BRAIN SIGNAL ANALYSIS AND CLASSIFICATION BY DEVELOPING COMPLEX NETWORK TECHNIQUES

Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

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By

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ABSTRACT

Brain signal analysis has a crucial role in the investigation of the neuronal activity for diagnosis of brain diseases and disorders. The electroencephalogram (EEG) is the most efficient biomarker for the analysis of brain signal that assists in the diagnosis of brain disorder medication and also plays an essential role in all the neurosurgery related to the brain. EEG findings illustrate the meticulous condition, and clinical content of the brain dysfunctions, and has an undisputed importance role in the detection of epilepsy condition and sleep disorders and dysfunctions allied to alcohol. The clinicians visually study the EEG recording to determine the manifestation of abnormalities in the brain. The visual EEG assessment is tiresome, fallible, and also high-priced. In this dissertation, a number of frameworks have been developed for the analysis and classification of EEG signals by addressing three different domains named: Epilepsy, Sleep staging, and Alcohol Use Disorder.

Epilepsy is a non-contagious chronic disease of the brain that affects around 65 million people worldwide. The sudden onset tendency of the epileptic attacks vulnerable their sufferers to injuries. It is also challenging for the clinical staff to detect the epileptic-seizure activity early enough for determining the semiology associated with the seizure onset. For that reason, automated techniques that can accurately detect the epilepsy from EEG are of great importance to epileptic patients and especially to those patients who are resistive to therapies and medications. In this dissertation, four different techniques (named Weighted Visibility Network, Weighted Horizontal Visibility Network, Weighted Complex Network, and New Weighted Complex Network) have been developed for the automated identification of epileptic activity from the EEG signals. Most of the developed schemes attained 100% classification outcomes in their experimental evaluation for the identification of seizure activity from non-seizure activity.

A sleep disorder can increase the menace of seizure incidence or severity, cognitive tasks impairments, mood deviation, diminution in the functionality of the immune system and other brain anomalies such as insomnia, sleep apnoea, etc. Hence, sleep staging is essential to discriminate among distinct sleep stages for the diagnosis of sleep and its disorders. EEG

provides vital and inimitable information regarding the sleeping brain. The study of EEG has documented deformities in sleep patterns. This research has developed an innovative graph-theory based framework named weighted visibility network for sleep staging from EEG signals. The developed framework in this thesis, outperforms with 97.93% overall classification accuracy for categorizing distinct sleep states

Alcoholism causes memory issues as well as motor skill defects by affecting the different portions of the brain. Excessive use of alcohol can cause sudden cardiac death and cardiomyopathy. Also, alcohol use disorder leads to respiratory infections, Vision impairment, liver damage, and cancer, etc. Research study demonstrates the use of EEG for diagnosis the patient with a high menace of developmental impediments with alcohol. In this current Ph.D. project, I developed a weighted graph-based technique that analyses EEG to distinguish between alcoholic subject and non-alcoholic person. The promising classification outcome demonstrates the effectiveness of the proposed technique.

Doctor of Philosophy Declaration

I, *Supriya Supriya*, declare that the PhD thesis entitled *Brain Signal Analysis and Classification by Developing New Complex Network Techniques* is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Signature: [redacted] Date: 26-01-2020

ACKNOWLEDGMENTS

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Special thanks to Prof. Hua Wang for the excellent feedback on the applicability of this research and also for some fantastic discussions on EEG signal analysis. I am grateful to all the members of our department.

My sincere appreciation goes to my honourable parents and close family members for encouragement and support. Finally, my husband Akashdeep Singh and son Conan Singh deserves the dedication of this thesis.

Declaration on EEG Database used

I, *Supriya Supriya*, declare that the PhD thesis entitled *Brain Signal Analysis and Classification by Developing New Complex Network Techniques* have used three different types of EEG databases: Epileptic EEG databases, Alcoholic EEG database and Sleep EEG database. And all these databases have been collected from online repositories, publicly available for research purpose. There is no use of animals and human in this research.

Signature: [redacted] Date: 23-03-2020

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PUBLICATIONS

The following publications associated to the PH.D. Dissertation.

1. S. Supriya, S. Siuly and Y. Zhang, "Automatic Epilepsy Detection from EEG Introducing a New Edge Weight Method in the Complex Network", *Electronics Letters*, vol. 52, no. 17, pp. 1430-1432, 2016.

2. S. Supriya, S. Siuly, H. Wang, G. Zhuo and Y. Zhang, " Analyzing EEG signal data for detection of epileptic seizure: Introducing Weight on Visibility Graph with Complex Network Feature ", Australasian Database Conference (ADC 2016), Sydney, 2016. (associated to chapter 4)

3. S. Supriya, S. Siuly, H. Wang, J. Cao and Y. Zhang, "Weighted Visibility Graph With Complex Network Features in the Detection of Epilepsy", IEEE Access, vol. 4, pp. 6554-6566, 2016. (associated to chapter 5)

4. S. Supriya, S. Siuly, H. Wang and Y. Zhang. “An efficient framework for the analysis of Big Brain Signals Data” Australasian Database Conference (ADC 2018), Gold Cost, pp. 199-207). Springer, Cham. (associated to chapter 6)

5. S. Supriya, S. Siuly, H. Wang and Y. Zhang,“EEG Sleep Stages Analysis and Classification Based on Weighed Complex Network Features”, IEEE Transactions on Emerging Topics in Computational Intelligence, 2018, (associated to chapter 7)

6. S. Supriya, S. Siuly, H. Wang and Y. Zhang “Automated Detection of Epileptic Seizure using Complex Network Features”, BMC Bioinformatics (submitted and associated to chapter 8)

7. S. Supriya, S. Siuly, H. Wang and Y. Zhang “Automated Epilepsy Detection Techniques based upon Graph-theory”, IEEE Transactions on Network Science and Engineering (revision submitted).

CHAPTER 1

INTRODUCTION

The brain has been recognized as an incredibly intricate phenomenon in the world. The brain comprises approximately 100 billion neurons with the interconnection of 100,000 km or larger in addition to the storing capacity of around 1.25×10^{12} bytes (Hofman 2012). It is the core controller of the body by sending and receiving the information in the form of electrical signals termed action potentials. The primary challenge is to use this information to advance an improved understanding of serious disorders related to the brain like Alzheimer, strokes, epilepsy, dementia, and Brain tumors, etc. According to the World Health Organization, approximately 2 million Australians are suffered from a brain disorder. The pattern of the action potentials is fluctuating in brain disorders, and it can be best intelligible with the assistance of Electroencephalogram (EEG). EEG is the core authorized biomarker that aids to enhance the understanding of mental condition and behavior, to preclude or diagnose any abnormal condition that occurs.

The human brain responds to every single stimulus by generating action potential or electrical signals. Due to high temporal and spatial resolution, the EEG is an efficient tool to translate the brain signals into neuroscience text. This neuroscience text depicts the meticulous condition and clinical content of the brain functioning. In addition to this, EEG is non-invasive, easy to use and have cost-effective set-up in the research lab also. As a result, it is favorite amongst researcher and clinicians. Consequently, EEG is becoming the most imperative tool which assists in the diagnosis and ministration of brain abnormalities and disorders. The clinicians visually examine the EEG recording to discover the presence of abnormalities in the brain (Siuly & Zhang 2016). The visual EEG inspection is tiresome and fallible. Moreover, finding traces of abnormal activity by experts' neurologist through visual examination of EEG is a challenging issue and cannot be considered as a very reliable procedure (Siuly, Li & Zhang 2016). In addition to this, EEG analysis not only assists in the diagnosis of management the anti- disorder medication but also plays a crucial role in all the neuro-surgery related to the brain. As a result, there is continuously an obligatory of automated EEG analysis and classification technique that assist the clinicians for the diagnosis of brain abnormalities and also reduce cost and time. Due to the limitations of the traditional approaches for the analysis and processing of EEG data to detect abnormalities, this research work proposes graph-theory based techniques for the analysis and classification of EEG signals to detect abnormalities. The main focal point of this dissertation is epilepsy detection. In addition to this, sleep stage classification and Alcohol use syndrome are also considered for EEG signal analysis.

The proposed techniques explore the hidden dynamics of different EEG signals under diverse circumstances and effectively extricate dissimilar class of EEG signals. The research in this dissertation work can facilitate the neuro-clinicians to fetch valuable knowledge about brain fettle for the diagnosis of brain deformities.

1.1 Research Motivation

A key focus of this research work is epilepsy detection. Epilepsy has been recognized as one of the most chronic brain dysfunction among neurological diseases (Siuly et al. 2019). When there is a manifestation of more than two seizure attack concurrently, then epilepsy is declared. Around 50 million population at the world level are suffered from this epilepsy syndrome (Alcin et al. 2016). According to WHO, the epilepsy occurrence rate per year is 2.4 million, and it can affect any age group. The premature death rate of epileptic patients is two to three times higher than the normal healthy person (Acharya et al. 2012). According to the Australian Bureau of Statistics, more than 250,000 Australians at present have epilepsy.

EEG is the extensively examining tool for diagnosing disorders, treatment, and therapy planning related to epilepsy disorder. EEG data are complex as well as high-dimension in nature. Some clinics archives the EEG data on the paper. A half-an-hour EEG recording consumes around one cubic foot of paper (Alarcon et al. 1995). The development of digital recording system has overcome the paper recording issues of EEG and also provided the ambulatory recording facilities. Lamentably, the digital and ambulatory systems have introduced new challenges to the clinicians by introducing a large amount of data. In order to detect epilepsy, the clinicians have to visually examine the EEG recording of great length (Hassan, Siuly & Zhang 2016). The visual EEG inspection is tiresome, fallible and even not cost effective because the cost of studying the EEG is high. In addition to this, finding traces of seizure activity by experts' neurologist through visual examination of EEG cannot be considered as a very reliable procedure. As a result, there are necessities of automated seizure detection techniques that assist the clinicians for the diagnosis of epilepsy by computer-based analysis of EEG and also reduce high cost, fallacy and long haul of examination. This research study has also considered two other brain disorder research problems related to EEG analysis and classification named sleep staging and classifying alcoholism dependent EEG signals from normal EEG.

Sleep staging classification is currently an urgent and emerging research area in the healthcare community. Sleep is an intricate process that is directly affecting the several brain functions. The role of sleep is not completely acknowledged so far. Sleep disorders are a great and under-cognized problem that are untreated at the worldwide. A large number of population in the world is affected by Sleep disorders. Sleep stages identification helps in the diagnosis of sleep disorders such as Insomnia, sleep apnea, Parasomnias, Narcolepsy, Sleep Hypoventilation, Bruxism, and restless legs syndrome, etc. (Saper et al. 2010). Therefore, WHO, the American Psychiatric Association and some professional sleep societies are actively engaged in the research of sleep disorder classification system (Morin & Espie 2012). WHO predicted that more than 100 million population have Obstructive Sleep Apnea and 936 million suffer from sleep apnea. According to the Australian Bureau of Statistics, the population around 9% of Australian adults are diagnosis for sleep disorders. Sleep deprivation also leads to strokes, cardiovascular disease, and other neurological syndromes, for example, Alzheimer's, migraine and Parkinson's, etc. EEG signals are visually analyzed by the specialists to recognize the sleep patterns. On the basis visual interpretation of EEG sleep pattern, the expert classifies it into their appropriate sleep staging. Each stage is concomitant to particular waves of the brain and neuronal activity. The manual staging of sleep data from EEG signals is laborious, susceptible to error and resource-intensive.

The alcohol use disorders (AUDs) is one of brain phenotype, which not only deteriorates the brain but also develops the cerebral and mobility impairments (Oscar-Berman & Marinkovic 2007). Alcohol consumption syndrome is the utmost ubiquitous disorders in the communal (Acharya et al. 2012). WHO proclaimed that AUDs is the third most risk factor for the contribution of other diseases (named cancer, neuropsychiatric diseases, Dementia, cardiovascular disease, Cirrhosis, infectious diseases, depression, pancreas disease, etc.) and consequences in 2.5 million deaths per year ("Alcohol" 2020). EEG signals are one of the promising measure that is used for the detection of alcohol use disorders. Therefore, EEG signals classification and analysis techniques are used to identify the alcoholic subject from normal in order to determine AUDs.

Innumerable approaches have been anticipated for EEG analysis and classification for epilepsy detection, sleep staging classification and alcoholism detection from EEG signals. However, the existing techniques do not fulfill the gap between non-linear EEG and their underlying dynamical behavior. Moreover, the adoption rate and research development in this field are still hindered by some fundamental problems inherent within the big data paradigm. Furthermore, brain abnormality detection comprises of visual inspection of long-term EEG recording of several days by the expert neurologist. The non-stationary and complex nature of EEG signals make this task more error-prone, time-consuming and even expensive. All of these points motivate us to introduce a new graph theory-based framework for the analysis of big brain EEG data. The graph-theory based approaches characterize a hidden sight of brain activity and brain-behavior mapping. The graph theory not even helps to understand the underlying dynamics of EEG signals at microscopic, mesoscopic, and macroscopic level but also provides the correlation among them.

The proposed methods in this research work pave the way in the field of automated EEG signals analysis based on graph theory. The automated EEG analysis techniques developed in this dissertation will diminish the endeavor of human supervision and render the EEG analysis task more effectively.

1.2 Problem Statement and Solution

The information regarding the neurological disorders can only be evaluated by extracting functional condition of the brain. This research study aims to analyze the EEG signals in order to find the following research problems.

Problem 1. It is always a challenging issue for the researchers and neurologist to detect Epilepsy automatically from EEG signals. EEG comprises vast information about the functional state of the brain. Moreover, at present still, the EEG is manually investigated by the expert clinicians to discover the Epilepsy smidgeons. Epileptic patients have a greater risk of other complications such as Bleeding into the brain, Brain tumors, Cerebral palsy, Alzheimer's disease (in the later stage of life) and Autism disorder, etc.

Solution. This research study develops several graph theory based new algorithms for automated detection and classification of Epileptic seizure from EEG signals.

Problem 2. Presently the diagnosis from Big Brain Signals Data (EEG) is an onerous challenge for current medical discipline because they are the humongous quantity of information (great in size and dimension). Investigating these unmitigated volumes of data still consider a big challenge for the reason that of its complex diversity and visibility as well richness in context. The brain signals are an imperative epitomize of brain information, as a result, BBSD processing is indispensable.

Solution. This research introduces a framework for analyzing the humongous quantity of information (BBSD) generated from the brain that can assist in the development of intelligent decisions system for identification of anomalies.

Problem 3. Sleep staging classification is currently an exigent and emerging arena of research in the health communal. Sleep stages identification helps in the diagnosis of sleep disorders like Insomnia, Snoring, Obstructive Sleep Apnoea, Sleep Hypoventilation, Bruxism, and Narcolepsy, etc. The manual analysis of sleep EEG signals is error-prone and resource-intensive. These limitations lead to the development of automated sleep stages classification system for EEG signals.

Solution. This research work developed an effective algorithm to analysis and identifies different sleep stages from the EEG signal and automatic classification of sleep stages.

Problem 4. Alcoholism dependency is an acute syndrome which shows its impact on the neurons functionality in the central nervous system and also on the behavior of the affected person

Solution. In this research study, a graph-theory based framework is developed which helps to differentiate between alcoholism dependent EEG signals and non-alcoholic EEG signal.

1.3 Research Objectives

The key impetus of this thesis is to explore graph theory based EEG signals analysis for the detection or classification of brain abnormalities. Three categories of EEG signals are used for analysis named epileptic EEG data, sleep stage database and alcoholic EEG signals that are publically online presented. The performance of the newly developed methods is scrutinized with the existing methods in the specified domains of EEG signals. The objectives of this dissertation are summarized as follows:

1. To develop graph-theory based techniques for epilepsy detection.
2. To explore the feasibility of weight in the graph approach for the identification of brain anomalies (epilepsy, alcohol use disorders and sleep staging classification) from EEG signals.
3. To study the state-of-the-art in EEG signals analysis for the detection of brain disorders and enhance the performance.
4. Build up a new approach to extract informative EEG brain signal features from the complex network which can provide valuable information regarding EEG brain signals.
5. To identify the complex network features that can effectively distinguish epileptic from non-epileptic section of EEG, alcoholic from non-alcoholic EEG and awake from sleep section EEG signals.
6. To develop an automated EEG analysis and classification techniques for abnormalities detection form EEG.

1.4 Dissertation contribution

The dissertation contributions are demonstrated in the following points:

1. Investigate the EEG signals of epileptic seizure activity by developing weighted network frameworks.
2. Explore the network topologies or statistical parameters from different EEGs

3. Develop a weighted graph based framework to identifying distinct sleep stages from an EEG channel.
4. Identifying the epileptic EEGs and alcoholic EEGs with the help of one technique.

The Brief information regarding the contribution points are discussed below:

1. **Investigate the EEG signals of epileptic seizure activity by developing weighted network frameworks**

   Firstly, a Weighted_Complex_ Network Based Framework (WCNBF) is developed to detect epileptic seizure from distinct EEG signals. The framework is tested on the benchmark epileptic EEG database with 5 discrete types of EEG signals and achieved 100% accuracy performance for classifying the EEGs of seizure and healthy subjects. Secondly, Weighted Visibility Network Based Framework (WVNBF) is developed to identifying epilepsy from EEG signals. In WVNBF, the link weight technique helps to identify the instant fluctuation associated with seizure activity. The WVNBF accomplishes higher performance of classification accuracy for different test-problems allied to distinct EEG signals. The WCNBF and WVNBF has the limitation of dependency on the selection criteria for constructing the links amongst vertices. This limitation is overcome by developing the new weighted complex network (NWCN) technique. The NWCN technique is tested on Bonn university Epilepsy data as well as on the focal EEG signals (Bern-Barcelona database) and achieved 99% accuracy for Bern-Barcelona database and 100% for Bonn University database.
2. **Explore the network topologies or statistical parameters from different EEGs**

   This research study has used different network parameters such as modularity, average degree and average weighted degree to explore the three different fields: Epileptic EEGs, Sleep EEGs and Alcoholic EEGs. In addition, a new parameter is also developed named "Edge Weight Fluctuation (EWF)". This study discussed the changes explored in these parameters corresponds to distinct EEGs states such as the average weighted degree start increases during epileptic activity, modularity has high value in the period of awake as compared to different sleep states.
3. **Develop a weighted graph based framework to identifying distinct sleep stages from an EEG channels**

This study developed weighted graph based framework for classifying different sleep stages. Simulation analysis was executed by using Lorenz-series and Rossler-series, to check the noise robustness of the developed technique. The experimental finding proves that weighted graph are the competent tool for the evaluation of sleep quality from EEGs. It is also noticed that the modularity and AWD are high during awake and low during different sleep states (S1 to S4).

4. **Identifying the epileptic EEGs and alcoholic EEGs with the help of one technique.**

   The study developed one single technique named weighted horizontal visibility network (WHVN), which can effectively detect the epilepsy as well as helpful to differentiate the EEGs of alcoholic subjects from non-alcoholic subjects. The 10-fold cross-validation approved the effectiveness of the developed technique with different classifiers.

1.5 Dissertation Framework

This treatise comprises of total nine chapters. Each chapter has its own significant role in this research work. Figure 1-1 illustrates the overall structure of the thesis. Brief information about each chapter are discussed below:

Chapter 2 presents the fundamental knowledge related to human brain system and EEG signals, which is essential to comprehend the research work in this treatise. Subsequently, this chapter also provides some important concepts concomitant to epilepsy disorder, EEG sleep pattern and its classification as well as alcohol disorders that use are mandatory for this research study. The broad information about the specific topic can be obtained from the related references.

Chapter 3 covered the pertinent literature as well as state-of-art about various existing EEG signals analysis and classification techniques. Each existing method has a rich body of content associated with it. It is out of scope for this dissertation to describe every technique in great length. This primary goal of this chapter is to provide brief information for the guidance. The detail information about them is available in the relevant references.

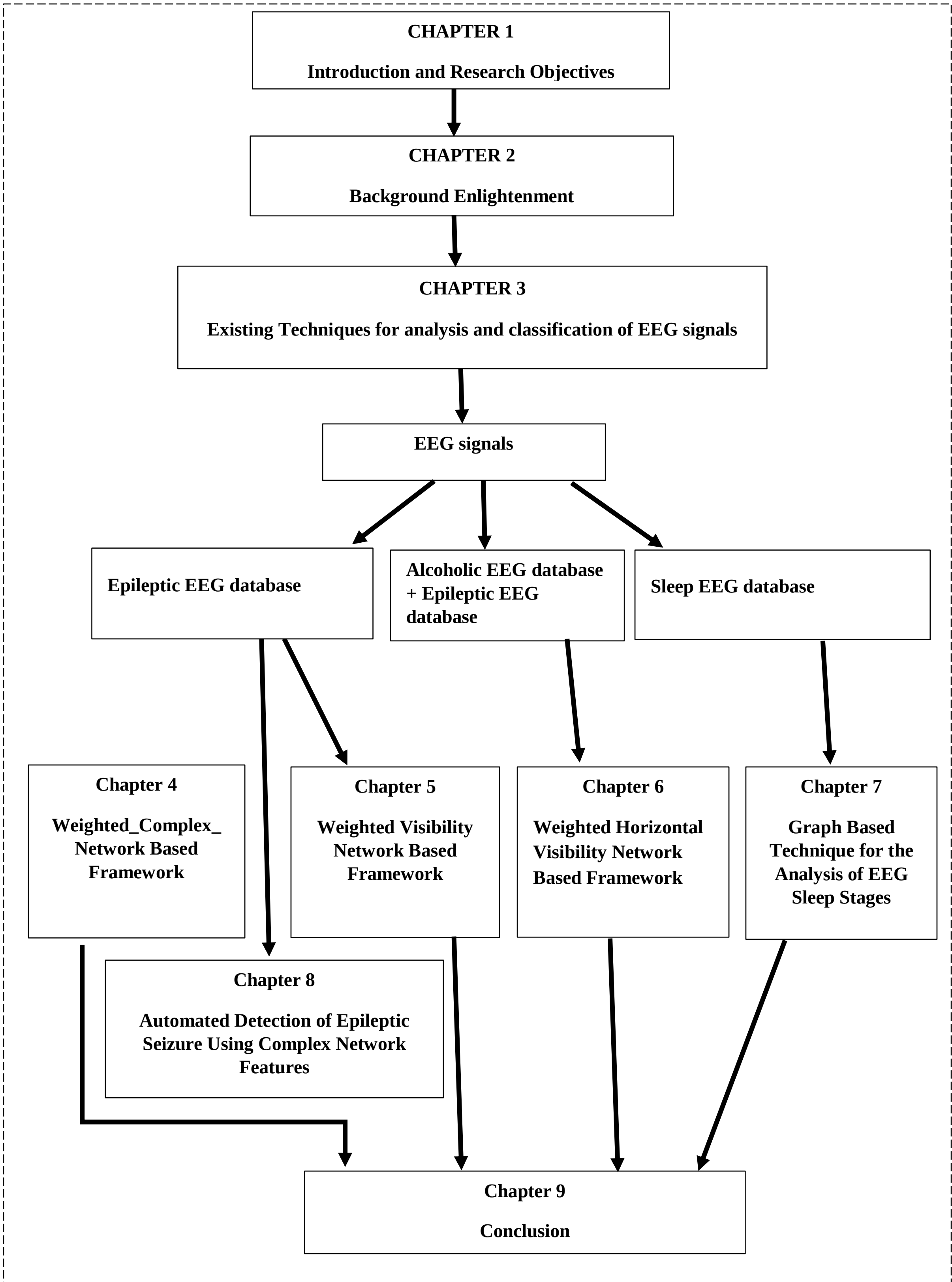


Figure 1-1: Illustration of the overall structure of the Dissertation

Chapter 4 is the first experimental part of this dissertation. This chapter introduce a new approach for automated detection of epilepsy syndrome from EEG with the help of graph theory. This chapter presents an innovative edge weight method for visibility graph in the discovery of epilepsy from EEG. This research study was the first in the field of epilepsy detection, to introduce the idea of edge weight and average weighted degree (as feature set) in the visibility graph. The proposed algorithm is 100% effective for classifying epileptic EEG signals from the non-seizure EEG. This research study also investigated the effect of segmentation and non-segmentation of EEG signals in epilepsy detection when the complex network-based approach is used with edge strength. The exhaustive valuation is based on the experimental performance of different classification problems or test cases. The 10-fold cross validation is implemented with the help of Support vector machine (SVM) and Discriminant Analysis (DA) families of classifiers.

Chapter 5 introduce the idea of community detection as a statistical parameter for epileptic seizure detection from EEG with the help of the visibility graph. In addition to this, a new edge weight algorithm is also developed for the visibility graph. The Weighted Visibility Network Based Framework (WVNBF) developed in this chapter helps to distinguishing different EEG signals. According to WVNBF, the first step is to transform the EEG signals to weighted visibility network (WVN). In the second step, the two graphical parameters named modularity and average weighted degree are excavated from the WVN. These parameters helps to characterize the EEG signals based graph effectively. In the third step, these features are evaluated by employing two popular supervised classification methods: SVM and KNN classification. The classification task is performed on five different sets of EEG signals. The higher classification outcomes exhibits that the developed methodology is effective as well as promising for epilepsy detection.

Chapter 6 describe the new idea of an effective data analysis framework for Big Brain Signals Data in biomedical signal processing. In this research work, a new graph theory based idea is proposed by introducing weight mechanism on the horizontal visibility graph for EEG signals analysis and named as 'weighted horizontal visibility network (WHVN)'. This method is developed to discover the hidden patterns from big time-varying EEG signal data. Two graph theory based measures named: Average Weighted Degree, and Average degree are extracted from WHVN. Different machine learning classifiers: naive bayes, SVM with different kernel functions i.e. linear, rbf and polynomial kernel, discriminant analysis with linear and quadratic discriminant were used to evaluate the performance by using 10-fold cross-validation. The WHVN framework is verified on two different benchmark EEG signal database: epilepsy related EEG database and alcoholic related EEG database.

Chapter 7 focuses on the sleep stage classification with the help of weighted graph based approach. The main aim of this investigational research is to study the significance of edge strength approach in multi-category classification problem as sleep-stage classification is a multi-category classification. The noise-robustness validation of the proposed research is evaluated by performing the simulation analysis of two disparate time-series named: Lorenz time-series and Rossler time-series.

Chapter 8 present the new idea for mapping the time-series EEG signals into a complex network. In addition to this, a new feature is also developed named fluctuation difference for extracting the indispensable information from EEG signals to attain the high-performance results in epilepsy detection. Two different kinds of epileptic benchmark EEG databases named Bern-Barcelona EEG database and Bonn University EEG database are used. Simulation analysis is performed on the two variant chaotic signals named as Henon map and Logistic map. ANOVA test is also conducted to validate the statistical significance of the proposed methodology.

Chapter 9 summarized the conclusion with inclusive results. Furthermore, it presents the auxiliary findings on the basis of the information demonstrated from this research. In addition this, the outlook about the future focus of this research is also discussed.

CHAPTER 2

BACKGROUND ENLIGHTENMENT

This dissertation aimed to develop different techniques that can efficiently perform the classification of distinct EEG signals and assist in the development of a computerized detection system for the diagnosis of brain abnormalities. For the development of an efficient automated system for EEG data classification, it is essential that we should have proper information about EEG signals. For that reason, this chapter presents general and important information about how EEG signals are generated and why they are significant in the diagnosis of brain maladies. This chapter is schematized as Section 2.1 comprise the information about the anatomy of the human brain. Section 2.2 explore about brain's communication system. Section 2.3 elaborates on the electroencephalogram (EEG). In the section, 2.4 information about Epilepsy and EEG's importance in Epilepsy diagnosis are covered. Section 2.5 comprehend Sleep stage classification and EEG in sleep staging. Section 2.6 has brief information about alcohol use disorder. The significance of the automated detection system for the diagnosis of abnormal brain conditions is presented in section 2.7. The whole chapter is concluded in summary at the end.

2.1 Anatomy Of Human Brain

The Human brain is one of the splendid and mystifies marvels of creation. It is an amazingly complex phenomenon with three-pound mass (weight) and administers all our body functions from breathing to intelligence, cognitive to heartbeats, etc. Nedergaard & Goldman 2016. A better cognizance about its working mechanism will enable neuroscientist to comprehend the mental state and assist in preventing or diagnosis any brain anomalies that occur. Protectively enclosed by the skull, the brain is comprised of brainstem, cerebellum, and cerebrum. Figure 2-1(a) illustrates the brain parcellation (Miller, 2011).

Brainstem: Brainstem is elementary and primitive part of the brain. The brainstem is responsible for connecting the cerebrum to the spinal cord. Being present at the bottom section of the brain, it acts as a primary portion to process the coming signals (Goldstein & Naglieri 2011). It controls and synchronizes the homeostatic functions, blood pressure, circadian rhythm, heart rate, visceral functions, etc. Brainstem abnormalities lead to Central Sleep Apnea, Weber's syndrome, Raymond-Cestan syndrome, Wallenberg syndrome, Brain Stem Seizures, brain stem infarction, etc. (Hurley et al. 2010).

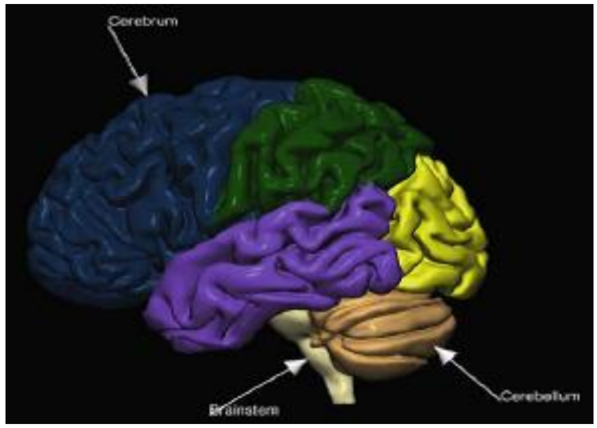
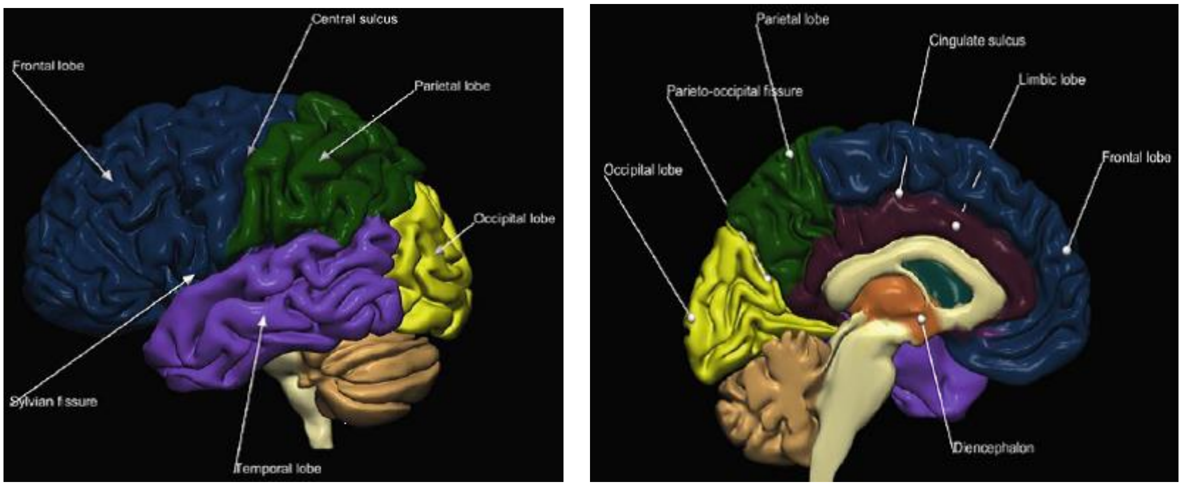


Figure 2-1: Illustration of the brain parcellation (Miller, 2011).

Cerebellum: Cerebellum is also known as the "little brain" as well as the 2nd largest portion of the brain. It is allied to other important parts named as the spinal cord, diverse cerebral and brainstem, etc. (Roostaei et al. 2014). The circuitry of the cerebellum plays a vital role in motor learning and its control, balance maintenance, cognitive functions, vision and other functions like processing of the language, thinking, etc. By weight, it is 10% of the cerebrum and comprises of around 80% of the total neurons present in the brain (Herculano-Houzel 2009). Cerebellum disorders are stroke, Ataxia, cerebral palsy linked epilepsy, and sleep disorders are commonly present among people with cerebellum maladies.

Cerebrum: The cerebrum has been acknowledged as greatest in size and principle portion of the brain. Its major functions are senses, thoughts, emotional responses, and movements' control. The cerebrum encompasses: left as well as right hemispheres known as cerebral hemispheres, deep gray nuclei, and diencephalon (Haines & Mihailoff 2018). Both hemispheres seem similar but perform different functions. Each cerebral hemispheres is responsible for controlling the opposite area of the body, i.e. if a brain tumor happens to the left hemisphere then its effect will be shown on the left arms or left parts of the body. Each hemisphere have different



(a) (b)

Figure 2-2: Illustration of the surfaces of cerebrum into lobes (a) Lateral view (b) Medial view (Miller, 2011).

fissures that parcellated it into the following 5 lobes (Miller, 2011) and figure 2-2(b) illustrates these three lobes:

i. *Frontal Lobe:* This part is responsible for Broca's area functions like speaking as well as writing; motor strip functions like body movements; intelligence and emotions, etc.
ii. *Parietal Lobe:* This lobe performs the functions like spatial as well as visual perceptual; hearing; language interpretation; sensory strips like a sensation of temperature, physical sensation or hurts, etc.
iii. *Occipital Lobe:* This lobe is the controller of Brodmann area 17 and controls the visual interpretations like color, lightening, etc.
iv. *Temporal Lobe:* This lobe operates the functioning Wernicke's area like language development; auditory perception, and memory, etc.
v. *Limbic lobe:* The circuitry of the limbic lobe is connected with complex functions like memory; understanding and behavior etc.

Cerebrum dysfunctioning results in Idiopathic occipital epilepsy, Frontotemporal dementia, Parietal lobe epilepsy, Alzheimer's disease, Temporal lobe epilepsy, Limbic epilepsy, etc.

2.2 Brain's Communication System

The human brain is comprised of two categories of cells named as glial cells and neurons (also known as nerve cells). Glial cells are responsible for the protection, nourishing, and structural support of the nerve cells. Whereas, neurons are responsible for information transmission in the brain.

The nerve cells convey information via a concomitance of two types of signals: Electrical and Chemical. The neurons are of different shapes and sizes but have four common constituents named as an axon, soma, synaptic terminals, and dendrites. The important part of soma is the cell nucleus which is responsible for RNA (Ribonucleic acid: important in many biological roles) production. Dendrites play a source of receiving chemical input by other neurons. Synaptic terminals are the tiny gap through which neurons transmit signals to each other. The communication of information by the neurons to other cells is possible by axons. Neurons communicate with each other in order to maintain the general, all-inclusive state of the brain.

Our memories and thinking are the after-effects of the occurrence of the patterns associated with electrical as well as chemical actions in the brain. The action or message communication is only possible between two neurons when their input wire (dendrite) and output wire (the axon) interact at particular intersections (named as synapses). Figure 2-3 illustrates the simple view of how communication occurs among neurons (Darbas & Lohrengel 2018).

Chemical signals known as neurotransmitters are transformed into electrical signals. Figure 2-4 illustrates how the sodium ion with positive-charge passes into the neuron with the help of voltage-gated-sodium-channels present in the membrane of the cell body and axon terminal. Afterward, it rapidly generates (in ms) Action Potential (AP) to the axon terminal (Lovinger 2008).

The action potential when terminating at excitatory synapse then results in an Excitatory Postsynaptic Potential (EPSP) and when ending at inhibitory synapse then producing

Inhibitory Postsynaptic Potential (IPSP) (Sanei & Chambers 2013). Action potentials are instigated by different kind of stimuli like pressure, sound vibration, temperature, etc. The AP is only generated when stimuli exceed a certain threshold level. Basically, this AP is known as the information communicated by nerve cells.

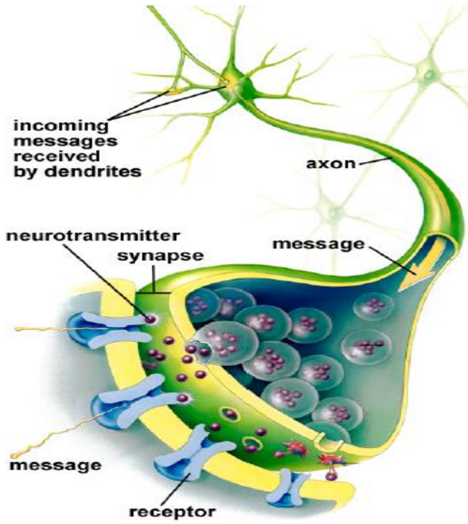


Figure 2-3: Illustration of the communication among two neurons through synapse (Darbas & Lohrengel 2018).

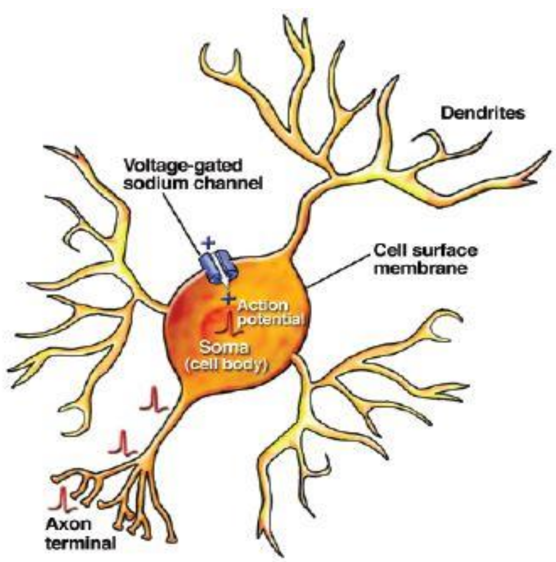


Figure 2-4: Illustration of the Action potential (Lovinger 2008).

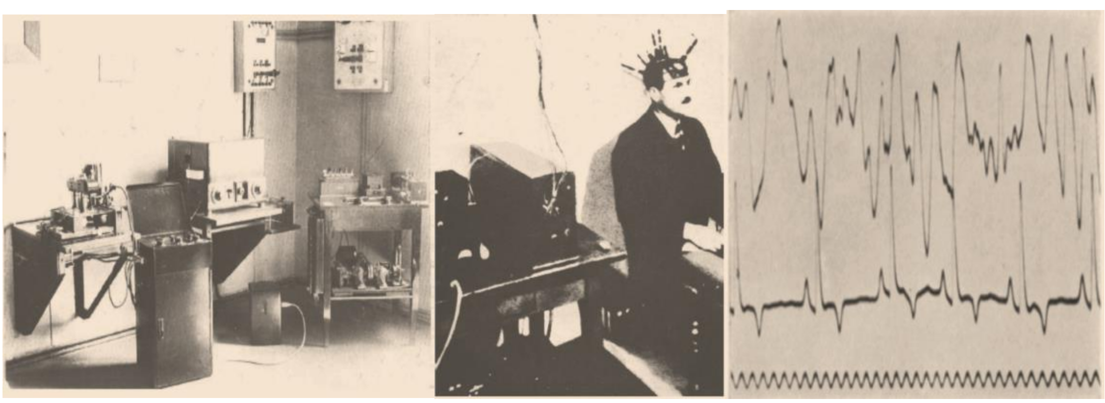
The above discussion clearly demonstrates that by measuring the electric-activity of the brain, it is easy to uncover the working mechanism of the brain, the state of mind and diagnosis or treated various brain disorders.

2.3 The Electroencephalogram (EEG)

The Electroencephalogram (EEG) is an electrophysiology technique that records (graphical display) the time-varying electrical activity (signals) present in the brain by attaching the electrodes to the human scalp.

2.3.1 Origin Of EEG

Richard Caton, a British scientist, is the first person who registered the electrical signals of the brain of a living creature (animals) by placing two electrodes on its scalp and recorded with the help sensitive galvanometer in 1875. Hans Berger, a German physician, was the pioneer of recording the human EEG. In 1924, he captured the EEG of the human scalp with the help of Siemens double coil galvanometer (Sanei 2013). Figure 2-5 illustrates the EEG recording attempt by Hans Berger.



(a) Hans Berger EEG Lab (b) EEG recording attempt (c) Early EEG recording by Berger

Figure 2-5: EEG recording attempt by Hans Berger in 1920s (Sanei 2013).

2.3.2 EEG Recording

The EER recording system is comprised of the following units:

i. *EEG Electrodes*: Metal disc attached to the human scalp in particular positions in order to record the brain activities or waves;
ii. *Amplifiers*: The amplitude range of the human scalp when measured by electrodes are 10 to 100 μV, and the amplifiers are required to intensification the level of the signals;
iii. *Filters*: The EEG signals necessitates filters to attenuate the effect of noises. High-pass, low-pass, and notch filter are mainly used;
iv. *Recording Unit:* It is used to maintain the permanent recording of EEG signals. Initially the EEG recording was captured on the papers, but currently, digital EEG is considered as a promising tool to capture the EEG signals because it eases the paper storage problems.

The EEG signals are worked as a signature of the brain's neuronal activities. The EEG signals are collected with the help of multiple-electrode placing in the interior of the brain, from the scalp and from the cortex. The neuronal activity captured by the EEG is the summation of EPSPs and IPSPs generated by a large number of pyramidal neurons that are present near each capturing electrodes (Ebersole 2003). Figure 2-6 illustrates how the electrodes are aligned into the six regions over the scalp (Ahani et al. 2014). The naming of each electrode is comprised of two integrant: the region and location of the brain. E.g., FZ represents the Midline Frontal, and the even number symbolize the location of the right hemisphere and odd number denote the location of the left hemisphere. The detail information about EEG electrodes standards and naming is available in (Duffy et al. 2011).

The EEG signals are captured in different formats. The signals that are captured from the scalp with the help of scalp electrodes are termed as EEG, from the inside of the human brain with the help of subdural electrodes are named as intracranial EEG (iEEG) and from the cortex by using cortical electrodes are labeled as electrocorticogram (ECoG).

Various configurations are proposed for electrode localization like 10-20, 10-10, and 10-5 international system, but 10-20 are recognized as the most used and common system (Jurcak, Tsuzuki & Dan 2007). Figure 2-7 illustrates the standard 10-20 and 10-10 electrode placement system (Duffy et al. 2011). An EEG channel represents the pair of the electrode with waveform characterizes the potential

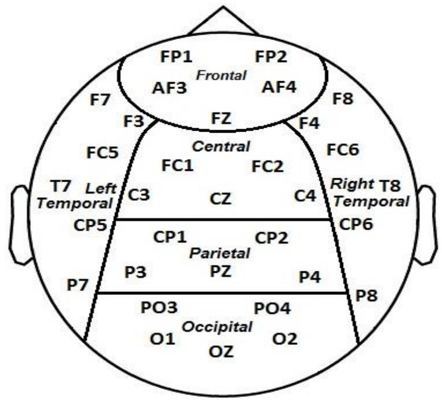


Figure 2-6: Illustration about how the electrodes are aligned into the six regions over the scalp (Miller, 2011).

difference among them. EEG is monitored via montage whereas the montage is the arrangement of the EEG channels in an ordered and logical manner. A number of diversity exist for montages in different labs of EEGs. But the most common montages are a bipolar montage, referential montage, average reference montage and Laplacian montage (Epstein 1992).

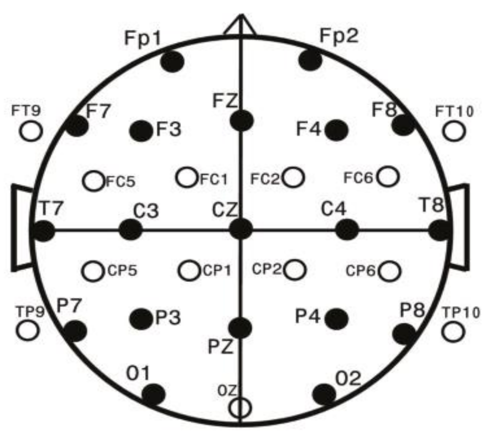


Figure 2-7: Illustration of the standard 10-20 and 10-10 electrode placement system with black circle illustrate the 10-20 electrode placement system and open circle illustrate the 10-10 electrode placement system (Duffy et al. 2011).

2.3.3 EEG Evaluation

The above-mentioned sections clearly depict that the EEG signals provide essential and distinctive information about brain activity by recording the characteristics of underlying neuronal activity. EEG finding plays a mainstay role in the diagnostic exploration and clinical evaluation of numerous medical problems. Following are the examples of few (Adelman 1987; Teplan 2002):

i. To monitor the coma or stupor, alertness, and death due to brain reasons.;
ii. Localizing the area that is damaged due to stroke, brain tumour and injuries in the head.
iii. To generate the bio-feedback situations.
iv. For servo-control of general anaesthesia.
v. To monitor or measure cognitive engagement.
vi. For monitor and measuring brain growth or development.
vii. To identify brain disorders
viii. For investigating the sleep physiology and maladies.
ix. To test the effects of epileptic drugs and convulsive drugs.
x. For alcohol effect on brain etc.

Generally, the clinicians visually examine the EEG recording to investigate the medical conditions. The visual EEG inspection is tiresome, fallible and even not cost effective because the cost of studying the EEG is high. As a result, there is continuously an obligatory of computerized EEG analysis techniques that assist the clinicians for the diagnosis of various medical conditions and also reduce cost and time (Adeli, Ghosh-Dastidar & Dadmehr 2007). The various brain disorders and its states are diagnose from EEG by the clinical experts on the basis of brain rhythms or brain waves, which is well explained in the next section.

2.3.4 EEG of Brainwaves

The visual analysis of the EEG includes the inspection of the presence of symmetry, the amplitude of the signal, morphology as well as continuity or discontinuity in the EEG signals, etc. The neurophysiological mechanisms of the brain are depicted with the help of brain waves. Figure 2-8 illustrates the different brain waves which have been taken from (Georgieva et al. 2014). Brain rhythms denote the distinctive patterns of massive neuronal activity and are represented in the following different frequency bands (Tatum 2014):

i. ***Infraslow:*** This EEG activity has a frequency range from 0.0 - 0.5 Hz. It is generally detected in the neonatal EEG, before and in the duration of epileptic activity. In addition, it is also observed in arousal and sleep duration. It arises in the non-neuronal networks named as glial networks. Evidence proved that it plays a crucial part in numerous physiological and pathological medical states (Schomer & Da Silva 2012).

ii. ***Delta:*** This EEG activity involves the frequency scale from 0.5 - 3.5 Hz. It is observed in a deep sleep, posterior slow wave of youth, elderly people and in infants. It is dominant in case of learning inability, severe attention deficit hyperactivity disorder, injuries in the brain, problem in thinking, etc. (Abhang, Gawali & Mehrotra 2016).

iii. ***Theta:*** This EEG activity has a frequency scale from$> 3.5\ to < 8.0$. It is associated with the drowsiness, creativity, emotional feeling, sensation and memory. It is more observed during anxiety, behavioral inhibition etc. It is mainly presents in children and elderly people. Too much theta waves leads to attention deficit hyperactivity disorder, depression and hyperactivity etc. (Corsi-Cabrera et al. 2000).

iv. ***Alpha:*** This EEG activity comprises the frequency scale from 8 - 13 Hz. It was first detected in occipital cortex of the brain during relaxing and closed eyes states of the subject. However, recent research has found the presence of alpha in various awakening tasks in different regions of the brain. It is associated with momentary memory storage and cognitive processes (Adelman 1987). A 10 Hertz rhythm observed in the precentral cortex during the rest state is known as mu rhythm whereas, if it is observed from the superior temporal lobe then termed as tau rhythm (Luster, Petersen & Garcia-Rill 2015). Alpha rhythm is also known as posterior dominant rhythm.

v. ***Beta:*** This EEG activity is associated with the frequency scale from 13 - 30 Hz. This activity detected in the frontal regions of the brain. It is further partitioned into two bands named: low beta with a frequency scale from 13 - 21 Hz and high beta with a frequency scale from 21 - 30 Hz. The beta activity provides information about alertness, concentrating, anxiety, or subject under medications and also helps in decision making, etc. (Kaufman 2007).

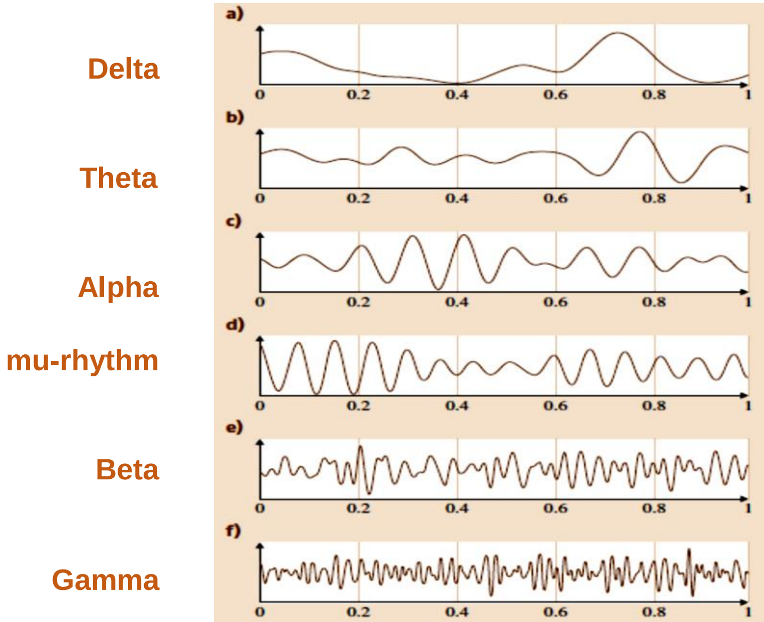


Figure 2-8: Illustration of different brain waves that are commonly used for analysis (Georgieva et al. 2014).

vi. ***Gamma:*** This EEG activity has a frequency from 30 - 80 Hz. It is important for voluntary motor activities, learning, and information processing (memory). Low level of gamma activity is generally observed in brain disabilities or learning issues (Jia & Kohn 2011).

vii. ***High-Frequency Oscillations:*** This EEG activity has a frequency >80 Hz. It is further sub-divided into ripples with a frequency scale from 80 - 250 Hz and fast ripples with a frequency scale from 250 - 600 Hz. The EEG activity with frequency from 600 - 1000 Hz are known as very fast ripples (Zijlmans et al. 2012).

Different types of anomalous patterns of the EEG signals are representing the abnormalities in the brain. Below are the examples of a few abnormal waves (Aminoff 2012), (McGrogan 1999):

- *Slow waves:* Any rhythm that is slower than the normal waves or rhythm is considered an abnormality.

- *Spikes or Sharp waves:* These waves are very fast in nature and resemble in appearance but have different durations. Spikes are lasting for < 70ms whereas, sharp waves have the duration of 70 to 200ms.
- *Spikes and wave:* This activity is the combination of the above two abnormalities. This abnormal patterns usually occurs repetitively at a rate of around 3 Hz.
- *Depression*: This pattern is associated with the duration in which the amplitude of the signal decreases.
- *Burst-Suppression:* This pattern is described as a burst of high voltage as well as mixed-frequency EEG activity parted by interims of marked quiescence for few seconds or sometimes for several minutes.

The instabilities in the pattern of brainwaves lead to serious health issues like epilepsy, bipolar disorder, sleep problems, insomnia, Attention deficit hyperactivity disorder and migraines, etc. Clinicians and researchers are identified the brain-waves patterns to understand the neurological conditions using EEG. This thesis focuses on three brain research problems using EEG signals. The main focus is on automated Epilepsy detection by classifying different categories of EEG signals. In addition, sleep stage classification and Alcoholic data classification using EEG signals are also considered. Below is the brief information about these three medical problems

2.4 Epilepsy

Epilepsy is one of the most chronic brain syndrome recorded since 2000 BC. Circa 65 million people at the world level have epilepsy, and 80% are living in developing countries (Epilepsy Action Australia, 2018). World health organization anticipated that epilepsy occurrence rate per year is 2.4 million, and it can affect any age group. The premature death rate of a person with epilepsy is two to three times higher in comparatively normal healthy person (Acharya et al. 2013). Epilepsy happens with an incidence of 68.8/100,000 person-years and the age-adjusted incidence because of the epileptic seizure is approximately 44/100,000 person-years (Ramgopal et al. 2014). According to Epilepsy foundation Australia, Epilepsy is a serious neurological condition that comes under the list of top five causes of avoidable mortality in the age-group of 5 to 29 ("Sudden Unexpected Death in Epilepsy (SUDEP) | Epilepsy Foundation" 2020).

Epilepsy is the state of perennial unprovoked seizure attacks. When there is a manifestation of more than two seizure attack concurrently, then epilepsy is declared (Fisher et al. 2014). “Seizure” is a paroxysmal malfunction of the neurological activity precipitate due to the immoderate hypersynchronous of the neurons present in the brain. Seizure commencement is described by two contemporaneous events (Rossignol, Carmant & Lacaille 2016):

- Bursts with high-frequency of dendritic potentials;
- Abnormal hyper synchronization in the high population of excitable cells of the neural region present in the cortex.

Etiologically, the epilepsy is categorized into the following groups (Shorvon 2011):

- *Idiopathic Epilepsy:* This epilepsy is thought to have a genetic origin with no neuroanatomic or neuropathological anomaly;
- *Symptomatic Epilepsy:* Epilepsy with acquired conditions and associated with neuropathological or neuroanatomic abnormalities;
- *Cryptogenic Epilepsy:* An epileptic condition in which the cause of the abnormality is not clear or identified;
- *Provoked Epilepsy:* This epilepsy occurs due to certain factors of the environment or specific system.

Epilepsy is menacing brain dysfunction which increases the occurrence risk of other maladies like Dementia, Cardiovascular Disorders, Depression, Sleep Disorder, Migraine, Cognitive Impairment, Mental Decline (in the chronic condition), Brain tumors, etc. and effect other body parts and Pregnancy as well (Ghosh-Dastidar, Adeli & Dadmehr 2008). Epilepsy can affect anybody irrespective of person’s age, intellect, gender, cultural or social differences whereas it is scrutinized that the prevalence of epilepsy is on the peak during the early stage of childhood and also high in the late stage of life (Sheoran & Saini 2014). Hence it is very crucial to detect and properly classify the kind of epileptic seizure so that (Smith 2005):

- Proper pharmacological diagnosis can be provided;
- Optimal guidance about prediction and recurrence risk will be easily possible;
- The indication about auxiliary paraclinical treatment will be ease;
- The indication for non-pharmacological diagnosis (like surgical treatment, diet, etc.);
- Guidance on symptoms of genetic diagnosing can be provided.

2.4.1 EEG in Epilepsy Diagnosis

EEG disclose the manifestation of electrical discharges of the human brain. EEG reveals the patterns of different brainwaves that are associated with different kinds of epileptic seizures. It helps to identify the location of epileptic discharge. The EEG activity with frequency range >100 is termed as ripples are considered as a marker for the epileptic discharges. EEG has been recognized as one of the best medical tests which assist in epilepsy diagnosis as compared to other biomarker tools (Computerized tomography scan, Magnetic resonance imaging, Functional Magnetic resonance imaging, etc.) because EEG data exhibit high temporal and spatial resolution. Also, the epileptiform seizure activity can be clearly observed in the EEG of the epileptic patient even in the dearth of an epileptic-seizure attack (Siuly, Li & Zhang, 2016). In the cases of having uncertainty in the diagnosis of epilepsy or the reason behind paroxysmal spells is unclear, then EEG recording is contemplated as the most accurate and promising diagnosis test. EEG helps in the diagnosis of epilepsy by (Smith 2005):

- Analysis of paroxysmal neurological activities;
- Differentiation among parasomnias disorder and nocturnal epilepsy;
- Characterization of epilepsy type;
- Quantification of inter-ictal epileptiform discharges (IED) frequency and the severity of the epileptic seizure;
- Evaluating the epileptic subject for neurosurgical treatment to control the epileptic seizure.

EEG signals observed two categories of anomalous activity in case of epilepsy: ictal activity (during the seizure) and inter-ictal activity (between the epileptic seizures). Spiking is observed as a common form of abnormality in the inter-ictal state. These spiking features are present in the majority of epileptic patients, whereas, in the case of non-epileptic patients, this feature is shown in very less number of people. This is the reason behind, inter-ictal spikes are considered as crucial for an epilepsy diagnosis. During ictal state, a very different pattern of EEG signals is seen with rhythmical waveform (Hughes 1994). Figure 2-9 illustrates the common patterns of EEG signals which are observed at the start of an epileptic seizure in epilepsy patient (Fisher, Scharfman & Decurtis 2014). Figure 2-10 illustrate the EEG patterns of recording during the inter-ictal discharges and seizure onset (Fisher, Scharfman & Decurtis 2014).

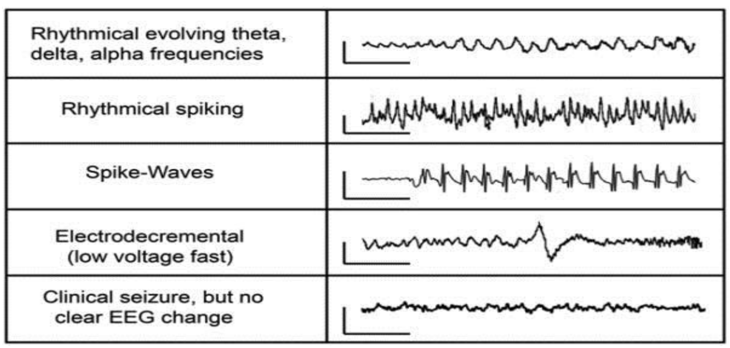


Figure 2-9: Illustration of common patterns of EEG signals at the start of an epileptic seizure in epilepsy patient (Fisher, Scharfman & Decurtis 2014).

2.5 Sleep Stage Classification

Sleep is a state of reversible behavioural with reducing perceptual engagement and unresponsiveness to the external stimulation or environment accompanied by convoluted and anticipated physiological changes (Keenan & Hirshkowitz 2011). We will spend approximately 27 years of our lifetime sleeping. Sleep influence human being in several ways like help in improving the memory recall, regulating the metabolism and reducing the mental fatigue, etc. Figure 2-11 illustrates how the sleep and wakefulness cycle is controlled by the brain neurotransmitters (Peplow 2013). Any disorder that includes sleep disruption or affects the sleep pattern is known as a sleep disorder.

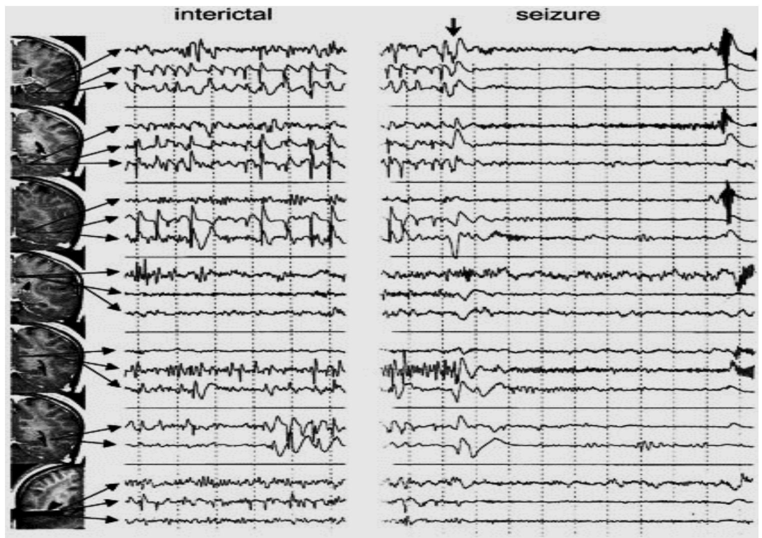


Figure 2-10: Illustration of EEG patterns of recording during inter-ictal discharges and seizure onset (Fisher, Scharfman & Decurtis 2014).

Sleep disorders comprise a wide range of maladies like insomnia, sleep-related movement disorders, sleep hypoventilation, sleep-related breathing disorders , narcolepsy, obstructive sleep apnoea and numerous other disorders (Ohayon 2011). International Classification of Sleep Disorders (ICSD) has sorted 80 sleep disorders into eight classes (Thorpy 2015).

It is anticipated by the world health organization that more than 100 million population in the world are suffered from obstructive sleep apnoea disorder (Benjafield et al, 2018). 3 million people at the world level have Narcolepsy (Anon 2019). Sleep disorder has an economic impact on Australia with a cost of $5.1 billion each year (Hillman & Lack 2013). Therefore, sleep study has drawn the attention of clinicians as well as researchers. Sleep is a heterogeneous state as it is a continuum of distinct states. For that reason, sleep staging is essential to discriminate between distinct sleep stages in order to ease an understanding of symptoms that facilitate for appropriate diagnosis of sleep and its disorders (Koella 1974).

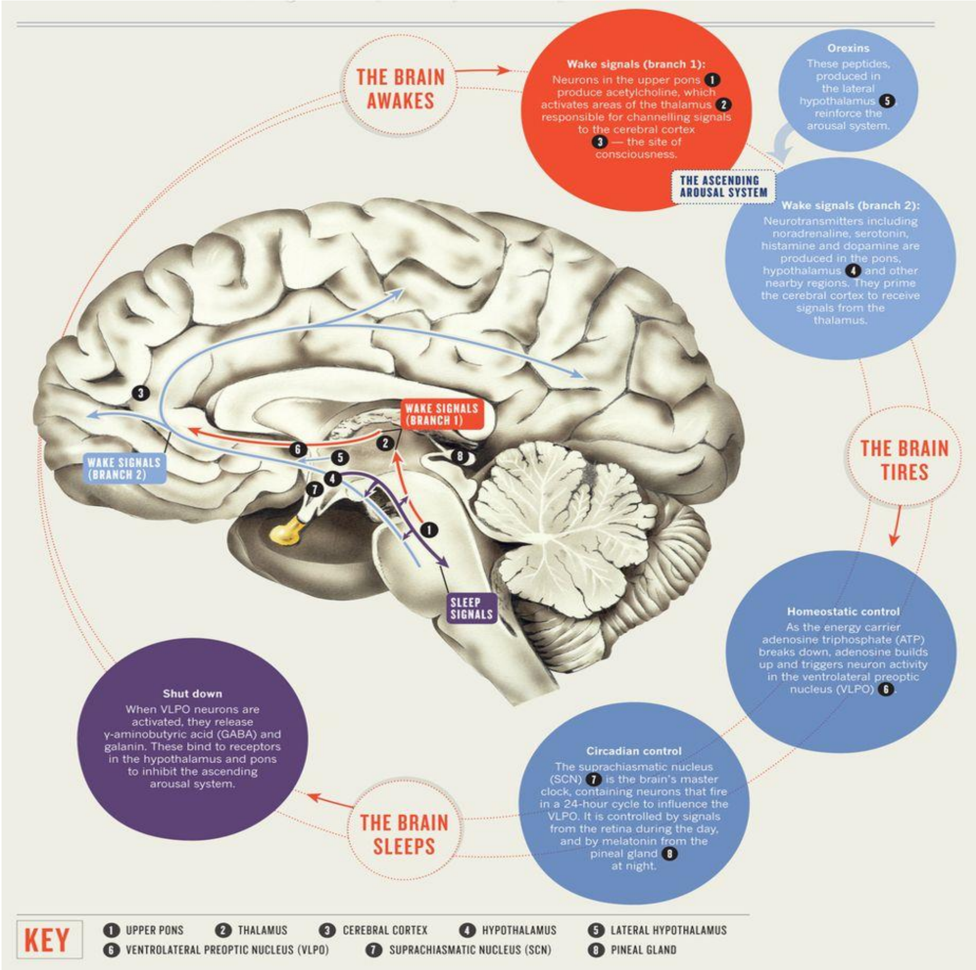


Figure 2-11: Illustration of sleep and wakefulness cycle that is regulated by brain neurotransmitters (Peplow 2013).

2.5.1 Sleep States

Sleep is categorized into two phases (Brezinova 1976; Zielinski, McKenna & McCarley, 2016):

- Rapid Eye Movement (REM);
- Non-Rapid Eye Movement (NREM).

REM phase of sleep occurs around 70 to 90 minutes after falling asleep. When we enter into REM phase, the breathing becomes irregular and rapid, the eyes start jerking rapidly behind the closed eyelid, the limbic muscles behaves temporary paralyzed, heartbeat rises, and blood pressure also increases, etc. REM involve the presence of low voltage and mixed frequency brain waves.

NREM phases include four stages: Stage 1, Stage 2, Stage 3 and Stage 4.

- *Stage 1*: It is also known as light sleep. The eye movement and muscle activities slow during this stage. During the initial cycle, it lasts from 1 to 7 mins;
- *Stage 2*: During this stage, the eye movements are stopped, and brain waves are also slower with an occasionally short burst of K complex or sleep spindles;
- *Stage 3*: There is an appearance of very slow waves known as delta waves interspersed with small and fast waves;
- *Stage 4*: During this stage, delta brain activity is present exclusively.

When sleep stages 3 and 4 are combined together then known as deep sleep. It is hard to wake up during deep sleep. Normally, a complete sleep cycle is of period or epoch of 90-110 mins. The first cycles of the sleep comprised comparatively short REM epochs and longer epochs of deep sleep. By the progress of night, REM epoch length increases and deep sleep decreases in length. At morning, Stage 1, 2, and REM are dominating (Zielinski, McKenna & McCarley, 2016. Sleep stages determination is essential in the clinical diagnosis and treatment sleep disorders (Zielinski, McKenna & McCarley, 2016). Figure 2-12: illustrates the different sleep stage cycle of 8-hour sleep with the repeating cycle of 90 mins (Peplow 2013). According to Rechtschaffen and Kales (R&K), sleep scoring benchmarks included REM, Stage 1, Stage 2, Stage 3, Stage 4, wakefulness sleep stages (Rechtschaffen 1968). Whereas, American Academy of Sleep Medicine (AASM) sleep scoring benchmarks involved W, stages N1, stage N2, stage N3, and R where N means Non-Rapid Eye Movement (Iber et al., 2007). Some researchers combine Stage 3 and Stage 4 as they discovered no major difference among them (Morgenthaler et al. 2008).

2.5.2 EEG Role in Sleep Staging

The frequency bands of the EEG manifest the important information about how cells, neurons and different regions of the brain regulate the distinct sleep states, wakefulness and also display anomalies due to associated pathologies (Zielinski, McKenna & McCarley, 2016). Figure 2-13 illustrates why EEG is considered as the best for sleep analysis as the sleep changes are easily recognizable in EEG. As we can see from Figure 2-13. that how different molecules and pathogens affect sleep regulatory molecules which in turn acts on neurotransmitters. The neurotransmitters change the ion channels that induce the fluctuations in EPSPs and IPSPs. These fluctuations are easily recognizable in the cortical EEG. Figure 2-14 illustrates different EEG activity associated with sleep stages (Zielinski, McKenna & McCarley, 2016).

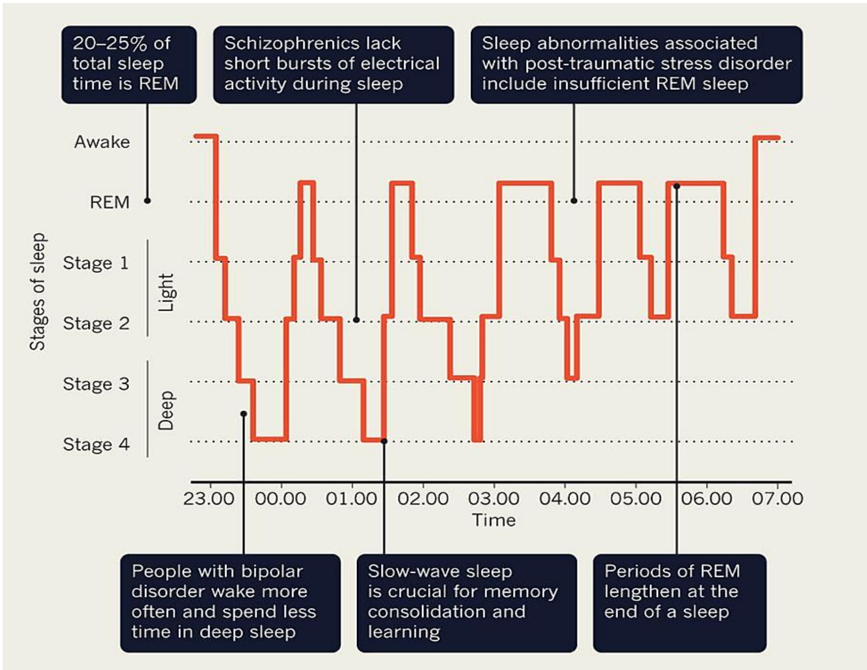


Figure 2-12: Illustration of 8-hour sleep with different sleep stages in repeating a cycle of 90 mins (Peplow 2013).

2.6 Alcoholism Detection

Alcoholism is defined as a state of drinking alcohol with the consequences of harming life in all aspects or compulsive alcohol usage. Alcoholism is also termed as alcohol use disorder (AUD). AUD not only affects the brain and body of the person but create problems in his/her social life. AUD leads to various detrimental consequences such as cognitive dysfunction, damage to brain cells, vision loss, depression, Wernicke-Korsakoff syndrome, cancer in the gastrointestinal (GI) tract, damage to cardiovascular as well as to immune and other systems, etc. Each year 2.5 million people died due to harmful alcohol intake at worldwide (Clapp, Wackernah & Minnick 2014). According to the Australian Bureau of statistics, the clinicians certified the mortality due to alcohol-induced is 70% in 2017 (Australian Bureau of Statistics

2017). The way by which alcohol caused harmful effects on the brain is still a wide and current interest in alcohol use research.

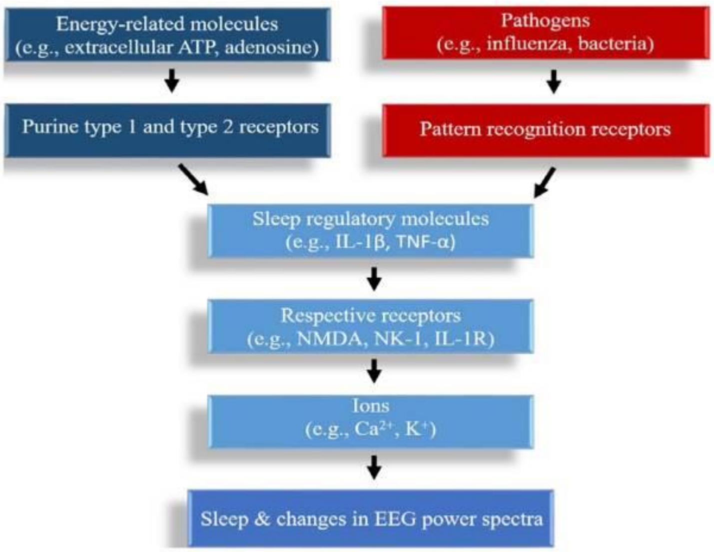


Figure 2-13: Illustration of how sleep regulatory molecules directly affect the neurotransmitters which in turn alter the sleep, and the changes are recognizable in EEG activity (Zielinski, McKenna & McCarley, 2016.

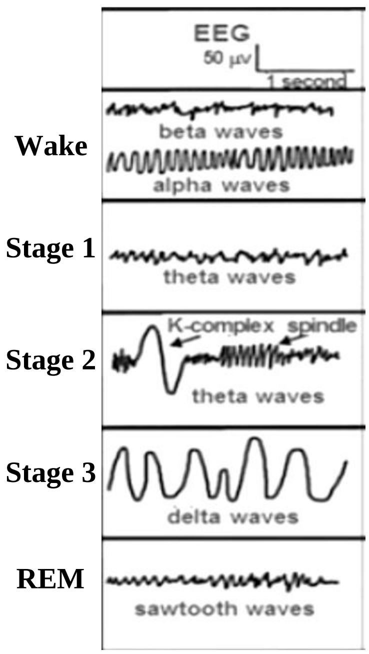


Figure 2-14: Illustration of different EEG activity associated with sleep stages (Zielinski, McKenna & McCarley, 2016).

2.6.1 EEG Role In Alcohol Use Disorder

The research study reported that there is a manifestation of increases in the theta and gamma activity of EEG during heavy alcohol consumption. While the low intake of alcohol represents variation in the alpha band (Jiajie et al. 2018). P3 components in EEG analysis performed as a useful biomarker for diagnosis the subject with a high risk of developing complications with alcohol (Plawecki et al. 2018). EEG is a promising biomarker tool for alcohol use research because the following affect of alcohol has been observed in the EEG of the alcoholic subject (Hershey 2019):

- Amplification in the components of frontal negative occipital brain waves;
- The amplitude of the P300 manifest reduction in alcoholic person as compared to non-alcoholic;
- The reduction in the excitability of pre-frontal cortical (PFC);
- Error-related negativity component of an event-related potential in an alcoholic person, manifest the amplitude reduction;
- Alcohol consumption exhibits a great change in the EEG of all the brain waves (alpha, beta, gamma, and theta) as well as in saccadic inhibition.

2.7 Automated EEG Analysis

Generally, the clinicians visually examine the EEG recording for epilepsy detection, for evaluation of the sleep stage to identify the sleep disorders and for the detection of alcohol use disorder. The non-stationary and complex nature of EEG signals make this task more error-prone, time-consuming and even expensive. The visual EEG inspection by the experts or neurologist is tiresome, fallible and even not cost effective because the cost of studying the EEG is high. Finding traces of seizure activity by experts' neurologist through visual examination of EEG is a challenging issue and cannot be considered as a very reliable procedure (Siuly, Wang & Zhang 2016). In addition to this, EEG analysis not only assisting in the diagnosis of brain disorders medication but also plays a crucial role in all the neuro-surgery related to the brain. If the EEG analysis data is reduced by the automated analysis systems, then more number of patients can be diagnosed effectively by the neurologist. M. Salinsky has described in his report of 83 patients are analyzed for seizure detection. The computerized detection system not only analyzed 22% of the seizures but also helps in saving or reduction of 1.3 days of hospital days for each admittance (Salinsky 1997). By considering the above information, this thesis developed a different automated framework for EEG signals analysis for different brain disorders.

2.8 Summary

This chapter has established the necessity of Epilepsy detection, sleep stage classification, and alcohol use disorder detection. In addition, it also explores the importance of EEG in different brain disorders identifications. Brief information about various important aspects has been covered, such as: how different brain constituents are working and responsible for various abnormalities, how neurons communicate with each other to maintain the generally all-inclusive state of the brain; EEG as a mainstay role in the diagnostic and clinical exploration of numerous medical problems; brain waves depict neurophysiological mechanisms of the brain; why it is very crucial to detect and properly classify the kind of epileptic seizure; the way by which EEG assists in the diagnosis of epilepsy. Furthermore, the influence of sleep on a human being; how neurotransmitters superintend sleep and wake cycle and how EEG manifest the important information about the distinct sleep states. Additionally, a concise sight is drawn upon AUD; why EEG is a promising biomarker tool for alcohol consumption research. In conclusion, the significance of computerized detection system for the diagnosis of brain abnormalities has discussed.

The next chapter will explore existing EEG analysis techniques as well as classification with the state-of-the-art and their limitations for clinical diagnosis.

CHAPTER 3

EXISTING TECHNIQUES FOR THE ANALYSIS AND CLASSIFICATION OF EEG SIGNALS

This chapter provides brief information about various EEG analysis and classification techniques. EEG analysis and classification is an important part for the diagnosis of brain disorders as EEG patterns are the real replication of the electrophysiological state of the brain at a particular time frame. As the primary research focus of this research study is on epilepsy detection, therefore, in this chapter, the various epilepsy detection techniques based on the different approaches of EEG signals analysis and classification are also discussed.

3.1 EEG signal analysis techniques

EEG analysis can be categorized into four domains: Time Based Analysis; Frequency Based Analysis; Time-Frequency Based Analysis, and Analysis by non-linear methods. Below is the brief introduction about the above four EEG analysis domains.

3.1.1 EEG analysis based upon Time domain

A time-domain approach based upon the analysis of EEG signals on particular time window by considering time as the variable of EEG signal. The time domain analysis comprises two main technique named Linear Prediction (LP) and Component Analysis (CA).

3.1.1.1 Linear Prediction: The linear prediction is a technique is used to compute the set of coefficients that will define the behavior of EEG signal by linear time-invariant (Pradhan & Dutt 1994). The linear prediction is a technique where the imminent outputs $\hat{y}\,(i)$ is the linear combination of input $x(i)$ and previous outputs $y(i-1), y(i-2), \ldots.., y(i-p)$.

$$\hat{y}\,(i) = \sum_{j=1}^{p} n(j) y(i-j) + \sum_{j=0}^{N} j(j) x(i-j) \quad . \tag{1}$$

In the equation (1) n and k represent the predictor coefficients. In EEG signal processing, the n predictor coefficients are generally considered zero and the imminent outputs $\hat{y}\,(i)$ is completely depend upon previous output i.e :

$$\widehat{y}\,(i) = \sum_{j=0}^{N} j(j)x(i-j) \quad . \tag{2}$$

3.1.1.2 Component Analysis (CA): CA is an unsupervised method that reduces the high dimensional data into feature sets. Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA) are the approaches based upon CA.

Principal Component Analysis: Karl Pearson developed PCA in 1901. Principal Component Analysis is a dimension –reduction technique which is based upon orthogonal transformation and reduces the high dimensional data into Eigenvector and also very successful in the EEG signal analysis (Ghosh-Dastidar, Adeli & Dadmehr 2008; Sheoran & Saini 2014). The principal components decomposition of Y can be defined as:

$$T = YW \quad . \tag{3}$$

In the equation (3), *Y* denotes the data matrix with zero empirical mean and *W* is the matrix of the principal component of *Y* and the columns of *W* are the eigenvectors of Y^TY.

Independent Component Analysis: In ICA, the multivariate signal is disintegrated into sub-constituent whereas these sub-constituent are non-Gaussian signals and not dependent on each other. ICA is used to find the hidden features presents in the EEG signals. The ICA transform is defined as:

$$h = Wx \quad . \tag{4}$$

in the equation (4), *h* denotes the sets of hidden components, or independent constituent and *x* signify the set of the observed data or original signal. W is missing matrix (Hyvärinen & Oja 2000).

Linear Discriminant Analysis: Similar to PCA, LDA is also used for dimensional reduction. LDA method is supervised in nature. It is based upon the linear combination of parameters that describe the data adequately. LDA is used in the case when the dimensions are based on independent variables for each and every observation.

3.1.2 EEG analysis based upon Frequency-domain

In the frequency domain, the hidden information of the EEG signals can be elaborated by decomposing the signals into pure sinusoidal waves with different frequency ranges. A frequency-domain approach based upon the analysis of EEG signals on frequency spectral estimation of statistical and Fourier Transform (FT) methods. The Spectral analysis is further classified into two parts named: Non-Parametric approach and the parametric approach.

3.1.2.1 Non-Parametric approach: In this approach, firstly the auto-correlation from the EEG signals are computed. Afterward, the FT is applied to the extracted auto-correlated data in order to extract the power spectrum density. The Welch method (Welch 1967) is considered as one of the best methods for extraction the Power Spectrum Density. Welch method include the decomposition of EEG signals into overlapping epoch sections. Afterward, the data window is applied to each section for calculation periodogram, and then the averaged of the periodogram is used to evaluate the Power Spectral Density.

3.1.2.2 Parametric approach: The parametric approach provides improved frequency resolution in comparison to the non-parametric approach. The parametric approach assumes apriori information about some parameters can help to characterize the EEG signals properly. The prior information can be useful to calculate the desired Power Spectral Density. During the parametric approach, it is supposed that the EEG signals are a stationary and random process. These stationary signal are considered as the output of a filter with white noise as input. After that, the parameters correspond to that filter are evaluated. There are various techniques to compute the filter parameters on the basis of the model used as a filter. The three best model are the Moving Average model, the Auto-Regressive model, and the Auto-Regressive Moving Average model (Ubeylı & Guler 2004).

3.1.3 EEG analysis based upon Time-Frequency domain

The Time-Frequency domain provides information about both the time and frequency mechanisms of the signal concurrently (Tzallas, Tsipouras & Fotiadis 2007). This technique is based upon the stationary principle and as a result window process is essential in the pre-processing stage. The

Time-Frequency domain can be categorized as (1) Wavelet transform; and (2) Hilbert–Huang Transform (HHT).

3.1.3.1 Wavelet transform: Wavelet transform (WT) is a spectral estimation method in which a function is represented as an infinite sequence of wavelets. A wavelet is defined as a small waveform with determinate energy and duration. In Wavelet transform, the primary function named mother wavelet is evaluated continuously along the time scale to achieve the wavelet coefficients. The wavelet coefficients provide information about the signal in both the time and frequency frame. In the Wavelet transform, the signal is decomposed into sub-bands, and relevant features are extracted from that subbands (Unser & Aldroubi 1996). The procedure is continued for the number of levels until the required results not achieved. The wavelet transform is of three kinds: Discrete Wavelet Transform, Continuous Wavelet Transform and Wavelet Packet Decomposition (WPD). Figure 3-1. illustrates the wavelet packet decomposition up to level 2. In the Fig.1, a_1 denotes the approximation coefficients, and d_1 symbolizes the detail coefficients at level 1 of WPD. Similarly, aa_2, da_2, ad_2, and dd_2 signifies level 2 WPD.

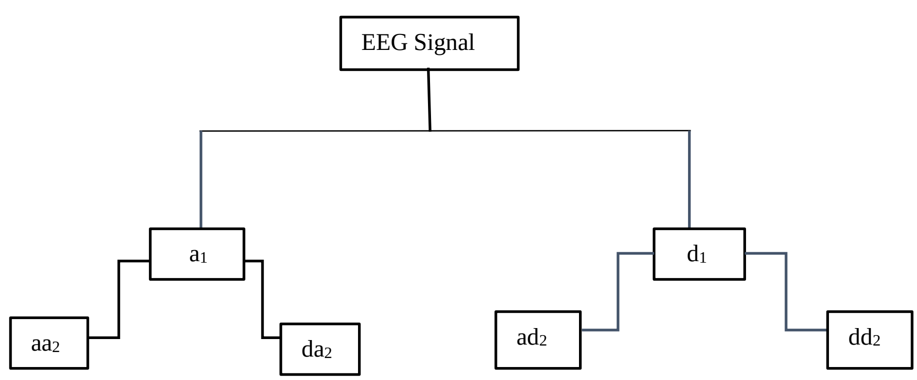


Figure 3-1: Wavelet packet decomposition upto level 2.

3.1.3.2 Hilbert–Huang Transform (HHT)

In Hilbert–Huang Transformation, there is decomposition of EEG signals into Intrinsic Mode Functions (IMFs) so that instantaneous frequency of the data can be achieved. In EEG signal analysis, IMFs is firstly extracted with the help of Empirical Mode Decomposition (EMD) afterward, Hilbert Transform is executed to every IMFs in order to achieve the instantaneous frequencies and amplitudes. Then, with the help of Hilbert-weighted frequency, the EEG signals are classified. EMD is the vital part of HHT as EMD can decompose the complex EEG signals into a fixed and small number of sub-parts (Oweis & Abdulhay 2011).

3.1.4 Non-linear methods of EEG analysis: Non-linear approaches are used in the analysis of EEG in order to characterize the complexity and fractal nature of EEG signals which cannot be described by the linear analysis (Müller, Jung & Ahammer 2017). Nonlinear methods are the more promising approach for describing the EEG signals as it can identify the non-linear coupling and phase locking within the harmonic of the same scale of frequencies. Below is the brief information about various non-linear parameters that are used in the analysis of EEG signals.

3.1.4.1 Higher Order Spectra (HOS): HOS is one of the promising non-linear technique for EEG signals analysis. HOS is basically a higher orders measures of the EEG signals. HOS can detect anomalies form EEG signals by identifying the non-linearity, nonstationary, non-Gaussian nature and phase locking among the harmonic constituents of the EEG signal. HOS is also termed as polyspectra. It can provide the spectral information about the higher order statistics. The HOS of Gaussian signals has zero statistical value (Acharya, Sree & Suri 2011). Therefore, HOS is a powerful noise immunity tool in the case of Gaussian noise. In addition to this, HOS is also preserving the phase characteristics of the EEG signals. Normalized bispectral entropy, normalized bispectral squared entropy, Mean bispectrum magnitude, and bispectrum phase entropy are the name of some HOS based parameters which can be extracted from bispectral for EEG signal analysis.

3.1.4.2 Higher-order cumulants: The cumulants are a set of measures that are the alternative to the moment’s distribution. The third order cumulant (third central moment) and higher order cumulants play an vital role in the analysis of the EEG signal (Yao 2000).

3.1.4.3 Recurrence Plot: Recurrence Plot (RP) is a graphical representation of the recurrences of the phase states in two-dimensional space. RP is useful in the analysis of EEG signals by identifying the hidden periodicities which are difficult to recognize in the different domains of EEG signals. It also helps to depict the non-stationary and non-linear character of EEG signals by visualizing the periodic behavior of EEG signals in the phase space trajectory. The RP illustrates the sets of pairs of times at which the EEG signal trajectory is at a similar place (Eckmann, Kamphorst & Ruelle 1987).

3.1.4.4 Recurrence Period Density Entropy (RPDE): In order to determine the periodicity of the EEG signal, the RPDE technique is advantageous. It is used to measure the periodicity of the EEG signal in the phase space without requiring any prior information about linear, Gaussian and dynamical aspects of EEG signals. RPDE is the illustration of non-linearity, non-Gaussianity and non-deterministic nature of the EEG signal (Little et al. 2006).

3.1.4.5 Recurrence Quantification Analysis: This technique is used to evaluate that how many times and how long the recurrences of EEG signals takes place in its phase-space. It is used to measure the complexity of the system. The Recurrence Quantification Analysis (RQA) is basically used to illustrate and measure the small-scale structural presentation of recurrence plots of EEG signals (Bhui & Senroy 2016). Mean diagonal line length, recurrence rate, longest diagonal line, determinism, longest vertical line, entropy, recurrence time, laminarity, and trapping time are the names of few parameters which are used to evaluates the RQA of EEG signals.

3.1.4.6 Approximate Entropy: Steven Pincus developed the idea of Approximate Entropy (ApEn) (Pincus 1991). It is a measure which is used to determine how regular and complex is the EEG signal are. For irregular and complex EEG signals, the ApEn measure high value. ApEn is an efficient tool for noisy and short data sample length with low computational cost. If X_N is a sequence consisting of N dimensions and $C_l(r)$ represents the occurrence of repetitive patterns with length l. Then approximate entropy of X_N, for a pattern of length l and similarity measure r is defined as:

$$ApEn(X_N, l, r) = \ln\left[\frac{C_l(r)}{C_{l+1}(r)}\right] \quad . \tag{5}$$

3.1.4.7 Sample Entropy: Sample Entropy is the extension and modified version of ApEn. It is a regularity or complexity measurement. It is used to measure the complexity of EEG signals (Richman & Moorman 2000). Sample Entropy includes the observation of patterns in EEG signals to check the degree of complexity in that. It does not count the measurement of the self-similar pattern. It has the main advantage over ApEn is that it is not restricted to sample length. During seizure activity, the sample entropy of EEG signals starts decreases.

3.1.4.8 Multiscale entropy: Multiscale entropy method is used to measure the complexity of EEG signals of finite length (Costa, Goldberger & Peng 2005). Multiscale entropy proved that the original data is more complicated than surrogate data. It is used to determine the complexity dynamics of EEG signals at multiple time scales

3.1.4.9 Fractal Dimension: Fractal Dimension (FD) is used as a parameter to detect and differentiate certain states of the physiological function of EEG signals. Fractal Dimension is one of the promising means for modeling the EEG signals which is highly complex and irregular in nature (Uthayakumar 2013). It is used to analyze the non-linearity as well as the chaotic aspects and behavior of the EEG signals. In the case of the information dimension, the Fractal Dimension is described as:

$$\mathrm{FD} = \lim_{\in \to 0} \frac{-\langle \log p_\epsilon \rangle}{\log \frac{1}{\epsilon}} \quad . \tag{6}$$

In the above equation, *p* signifies the probability and ϵ denotes the scaling factor.

3.1.4.10 Correlation Dimension: Correlation Dimension is a measure which quantifies the complexity of EEG signals (Grassberger & Procaccia 1983). Correlation Dimension is one of the categories of the fractal dimension. It is also used to differentiate among the deterministic chaos and random noise in order to identify the potential faults (Caesarendra et al. 2013). Correlation Dimension is generally computed by the GP algorithm which was developed by the Grassberger & Procaccia, 1983. Correlation Dimension is described as:

$$D_2 = \lim_{\epsilon \to 0} \frac{\ln \sum_{j=1}^{K(\epsilon)} p_j^2}{\ln \epsilon} \quad . \tag{7}$$

In the above equation (7), $K(\epsilon)$ symbolize the total numeral of hypercube with side length ϵ and covered the attractor, p_j denotes the probability of identifying a point in the hypercube *j*.

3.1.4.11 Hurst Exponent: Hurts describe an empirical descriptor an, the Hurst exponent (H) is used to define the natural phenomena related to the temporal nature of EEG signals (Hurst 1956). It is also applied for evaluating the randomness of a process. In addition to this, the fractal dimension is also correlated with the Hurst exponent. Hurst exponent is used to quantifying the self-similar, the amount of long-range dependency and also for the prediction of EEG signals. Hurst exponent H is described as:

$$H = \frac{\log(D|S)}{\log(T)} \quad . \tag{8}$$

In the equation (8), T signifies the duration of the EEG signals and $(D|S)$ defines the rescaled range value. D denotes the difference among the maximum and minimum deviation from the mean. S symbolizes the standard deviation. After plotting the $(D|S)$) versus T in the axes of log, the slope of the regression line estimates the H (Hurst 1956).

3.1.4.12 Largest Lyapunov Exponent: Largest Lyapunov Exponent (LLE) is used as a measuring unit to check the dependency of the process on its initial conditions. It is used in the analysis of EEG signals to quantify the chaoticity in that. It defines the rate of deviation of nearby trajectories. A positive value of Largest Lyapunov Exponent demonstrates the presence of chaos nature. LLE is defined as (Rosenstein, Collins & De Luca 1993):

$$d(t) = Ke^{c_1 t} \quad . \tag{9}$$

In the above equation, $d(t)$ denotes the average divergence at time t, K symbolize the constant that used for the normalization of initial separation and c_1 represents the exponential divergence of nearest neighbors.

3.2 EEG signal classification techniques

The EEG signals classification is a crucial step the neuroscience field for the brain disorders identification. An effectual classification technique plays a critical role to determine the individual's mental health by adequately classifying the EEG signals. Classification is basically an algorithmic process which is used to classify the unidentified sets of observations (testing class) into their appropriate categories via predefined observations (training class). Classification is implemented with the help of a classifier, a mathematical function, which maps input values into the right class (Siuly, Li & Wen 2013). In order to classify the EEG signals efficiently, the essential properties of the signals should be known in advance. The feature a measurable that quantify the characteristics and essential property of EEG signal. And the set of the numerical features is labeled as a feature vector. The feature vector of EEG signals is fed to the classifier to perform the classification task (Siuly, Li & Wen 2013). EEG signal classification can be categorized into two approaches named: Supervised Classification and Unsupervised Classification. In the following section, a brief outline of these two EEG classification approaches has been discussed.

3.2.1 Supervised Classification Approach: Supervised classification approach is a procedure to predict a function, by evaluating the features of the feature sets of which the class label is pre-determined. With the help of this function, the class label of the target is predicted. Supervised classification is comprised of a two-stage. In the first stage, a learning model is constructed for describing the known class categories for a data set. This learning prototype is constructed on the basis of the analysis of data sample and also on the idea for which the class labels are predefined. The data samples, in this case, are identified as the training set. In the second stage, the learned prototype is implemented to new (target) data sample in order to predict their class labels.

In general, the supervised classification techniques comprises of training the classifier on the basis of a pre-defined set of training samples, and when new data sample is provided to the classifier, it will distinguish that new data samples on the basis of the training experience (Osisanwo et al 2017). In supervised classification, the final aim is to develop a predict function p(x). This predict function is optimized with the help of mathematical algorithms in order to predict some valuable information when the input data samples (*x*) are passed into it. To clearly understand about supervised classification, let's assume the predict function p(x) is defined with the help of equation (10).

$$p(x) = h_1 + h_2 x \; ; \tag{10}$$

where $h_1$and h_2 are the constants. The main aim is to determine the correct value of $h_1$and h_2 so that the predict function can provide the most accurate results. It is only possible by optimizing the predict function *p(x)* with the help of the training sample. Each training sample is consist of the input value and their corresponding output value (class). The *p(x)* is trained with the help of enough training sample by adjusting the values of $h_1$and h_2 to make it more efficient and less wrong. This procedure is repeated until the best value of $h_1$and h_2 is achieved. In this manner, the predict function is trained, and the classifier is ready to perform some real-world predictions.

It is important to note that outlier is the primary source of error in the supervised classification, so it is essential to remove the outliers in the training data samples. An outlier is a data point that diverges from the complete pattern of the training data. The primary source of outliers is human error, measurement error, and experimental error, etc. The detection and elimination of outliers can increase the classifier performance (Domingues et al. 2018). The supervised classification techniques that are commonly used in the EEG signal analysis are Decision Table (DT), JRip (RIPPER), Random Forest (RF), Decision Tree (J48), Logistic regression, K-nearest-neighbor (KNN), Kernel estimation, Linear regression, Support vector machine (SVM), Gaussian process regression, Simple Classification and Regression Tree (CART) and Naïve Bayes (NB) etc.

3.2.2 Unsupervised Classification Approach: Unsupervised classification approach is based upon the training of an artificial intelligence system (AIS) on the basis of the non-classified or unlabeled information, and the AIS has to act on that non-classified or unlabeled information without any guidance. The unsupervised classification includes the grouping of the unsorted information on the basis of some quantify of integral ability (according to resemblances, similarities, the distance among the instance, variations and dissimilarities, etc.). In unsupervised classification, the classifier (AIS) is presented with the data that don't have the class label as well as uncategorized and the classifier has to predict the class of the testing data without any prior training. Therefore, in unsupervised classification, there is no pre-defined set of training samples from which the classifier can learn (Lin et al. 2016). The unsupervised classification is used to evaluate more complex task which cannot be attained by the supervised classification techniques. The ultimate objective of the unsupervised classification is to classify the complex data by learn more about the underlying dynamics or distribution in the data.

The unsupervised classification methods that are commonly used in the EEG signal analysis are K-means clustering, Density-based spatial clustering of applications with noise (DBSCAN), Hierarchical clustering, Generative Adversarial Networks classifier, Hidden Markov Models, Categorical mixture model, Expectation–Maximization (EM), Deep Belief Nets based classification, Blind signal separation based classification like Kernel Principal Component Analysis (Kernel PCA), Independent Component Analysis (ICA) etc.

3.3 Research summary in the field of EEG signals analysis and classification

As the main focus of this research work is to detect the epilepsy syndrome by analysis and classification of EEG signals. Therefore, this section provides an overview of the research work or state of the art in the field of automated detection of epilepsy disorder by analysis and classification of EEG signals.

Automated EEG based seizure detection for assistance in epilepsy syndrome was started in the early 1970s. Prior, Virden & Maynard 1973, introduce a device named as Cerebral Function Monitor (CFM) that monitor the long-term EEG without any supervisor. The device was able to detect tonic-clonic seizures on the basis of the high increase in the amplitude of the EEG signal. Latter on Babb, Mariani & Crandall 1974 designed an electronic circuit based seizure detection. Gotman & Gloor 1976, tried to identify and quantify the inter-ictal activity during a seizure with the help of small computerized system.

In 1982, Gotman individually developed a computerized automated epilepsy detection technique (Gotman 1982). Afterward, has been recognized as an avant-gardist who instigate the idea of automated computerized based epilepsy detection system. The proposed technique was not patient-specific in nature, (i.e., not specific to an individual). The method was based upon the discovery of sudden fluctuation in the rhythmic bustle of EEG signals within the frequency range of 3 to 20 Hz. For seizure detection, some experiments had been performed in which the amplitude of EEG signals is measured with respect to the background, the period of time and the periodicity of EEG signals. But the proposed algorithm was unsuccessful to detect epileptic seizure from that EEG signals in which the frequency bustle is high, and amplitude is low. In addition to this, it was not to detect epilepsy from that EEG signals in which the various frequency ranges exist. It was only able to detect the epileptic seizure with a frequency less than 20 Hz. Latterly, this technique was modified and used on the larger EEG database with 5303 hr recording. The main aim of this new methods was to consider the large temporal context of EEG data and to increase the specificity of the technique. The technique suffered from the detection delay drawback and therefore was not successful in implementing in a real-time application (Gotman 1990).

Qu & Gotman 1993, developed a new technique with the help of K Nearest Neighbor classifier for the automatic detection of seizure activity. The proposed method was patient-specific in nature. It helped to enhance the performance of the seizure detection as the EEG recording of individual-patient shows less inconsistency for the seizure and non-seizure activity but has the limitation on the detection of latency. They modernized this technique a number of times (Qu & Gotman 1995; Qu & Gotman 1997; Qu 1997). The major limitation of these above patient-specific methods was when it is tested on different types of epileptic patients; it did not provide good results. In addition to this, in case of multiple seizures present in one person, the favorable results in the sensitivity can be achieved by combining different classifiers. Later on, different researchers proposed different types of epileptic seizure detection techniques. Below is the brief information about various epileptic seizure detection methods.

Pradhan & Dutt 1994, analyzed that, a linear prediction is a promising approach for better analysis and visualization of EEG signal. In addition to this, the linear prediction method is an efficient technique to generate, store and transmit EEG signal. Altunay, Telatar & Erogul 2010, observed that when the linear prediction method is used to detect epilepsy, the energy prediction error feature increased during the seizure activity. Some other researchers also used the energy of the signal as a parameter for the detection of epilepsy disease (Yoo et al. 2013; Aloraiby et al. 2016; Baldominos & Ramon-Lozano, 2017). Xie, Jin & Krishnan 2011, attained 100% classification results by proposing a new feature in PCA and also used the energy of signal as a feature for epilepsy detection. Acharya et al. 2012, applied PCA with Gaussian Mixture Model classifier to detect epilepsy and abled to acquire clinical adequate results. Siuly & Li 2015, reported optimum allocation scheme based upon principal component analysis to distinguish epileptic EEG signals from normal. The motive of using PCA in the proposed study was to develop independent components and to diminish the dimensionality of the data set. Nam et al. 2002, implemented ICA to find the ictal activity in temporal lobe epilepsy and observed that there is increased in the laterization from 75% to 96% while seizure. Whitmer et al. 2010, investigated that ICA can efficiently distinguish different types of EEG signals with dissimilar sources. Arunkumar et al. 2012, found that ICA and Hurst exponent perform better in seizure detection as compared to PCA. Fathima et al. 2011, applied linear discriminant analysis by extracted the features named: variance, skewness, and coefficient of variation and achieved 96.9% classification accuracy with the linear classifier. Some researchers implemented the PC, IC, and LDA approach together for classifying the epileptic seizure with the help of support vector machine classifier and attained promising results (Gursoy & Subast 2008; Subasi & Ismail Gursoy 2010).

Adeli, Zhou & Dadmehr 2003, introduced the idea of automatic detection of the epileptic syndrome from EEG signals by analysis and characterizing the epileptiform discharges with the help of wavelet transformation technique. Jahankhani, Kodogiannis & Revett 2006, applied a wavelet transform method to extract the parameters and neural network based classifier for classifying the EEG signals. Subasi 2007, detected epilepsy from EEG signals with the help of wavelet transform based feature extraction method in the combination of expert model and observed that combination of experts model attained higher accuracy as compared to the individual neural network-based model. Ocak 2009, applied a discrete wavelet transform for the epilepsy detection from EEG by computing approximation and detail coefficients as the features. The proposed method was able to differentiate the seizure activity with 96% classification results. The study results also demonstrated that EEG signals with ictal activity exhibit non-linear behavior while normal EEG behaved like Gaussian linear stochastic system and also the approximate entropy decreases during an epileptic seizure. Acharya, Sree & Suri 2011, proposed epilepsy detection technique based upon higher order spectra cumulants from Wavelet Packet Decomposition coefficients and achieved 98.50% accuracy with SVM classifier. Zainuddin, Huong & Pauline 2012, developed a real-time approach for epilepsy detection from EEG signals with the help of wavelet transform. The feature sets named standard deviation, a minimum, and maximum measure of the wavelet coefficients were extracted from each and every sub-band. The research work included the study of the Gaussian wavelet, Mexican Hat wavelet, and Morlet wavelet by applying the wavelet neural networks classification technique. They reported 98% classification performance results with the conclusion that the Morlet wavelet having order four daubechies provide better results as compared to another wavelet.

Kannathal et al. 2005, implemented spectral entropy, renyi entropy, kolmogorov-sinai entropy, and ApEn in order to detect epilepsy and observed that in the period of epileptic discharge, the four entropies measures decreases. Later, Kannathal et al. 2005 used non-linear features named correlation dimension, Largest Lyapunov Exponent, Hurst Exponent, and entropy were applied to characterize the epileptic EEG signal as well as to differentiate epileptic signals from normal. The more than 90% classification accuracy depicts the significance of the algorithm. Pravin Kumar et al. 2010, presented the significance of entropy parameter for distinguishing the normal and epileptic as well as inter-ictal activity EEG signals. The parameters named wavelet entropy, sample entropy, and spectral entropy were extracted in the feature extraction phase. The two neural network based models (named recurrent Elman network and radial basis) were used for classifying the Epileptic EEG signals.

Nigam & Graupe 2004, applied artificial neural network based approach for epilepsy detection and reported 97.20% accuracy. Srinivasan, Eswaran & Sriraam 2005, applied approximate entropy as a parameter in Elman neural networks and probabilistic neural networks for classifying the epileptic EEG database. The 100% classification accuracy with Elman neural network revealed its importance in seizure detection field. Aslan et al. 2008, considered two different types of epileptic seizure named partial epilepsy and primary general epileptic disorder for analysis under the supervision of two expert neurologists. The radial basis function neural network classifier attained 95.2% accuracy, and a multilayer perceptron neural network classifier perform with 89.2% classification.

Mursalin et al. 2017, proposed a mixed approach for epilepsy detection by extracting parameters from time and frequency domain. Mean, skewness, mode, standard deviation, median, minimum, kurtosis, maximum, first, third and interquartile range, etc. were the parameters that extracted in addition to the maximum, minimum, mean and standard deviation of the wavelet coefficient features. In order to select the most promising feature, the correlation-based feature selection technique was implemented, and then the selected parameters were passed to the Random Forest classifier. The experimental outcomes depicted that the proposed study was a promising technique to classify different test cases of Bonn University epileptic EEG database.

Polat & Gunes 2007, used Fast Fourier Transformation based Welch technique with decision tree as a classifier to detect epileptic EEG signals and attained the classification performance results with 98.72% accuracy, 99.4% sensitivity, and 99.31% specificity. Later on, Polat & Gunes 2008, proposed a novel hybrid system for classifying the epileptic EEG signals by using Welch FFT technique for parameter extraction and Principal Component Analysis for dimension reduction. The proposed method was built upon an artificial immune recognition system and reported 100% classification accuracy. Kabir, Siuly & Zhang 2016, developed a seizure detection system with the help of logistic model trees. Aln et al. 2016, introduced a time-frequency (T-F) image based algorithm to identify epilepsy from EEG signals by using Grey Level Co-occurrence Matrix as a descriptor with Fisher Vector as an encoder and reported high-quality results.

Rana et al. 2012, presented a method to detect epilepsy from multi-channel by using phase slope index (PSI). The PSI was used to distinguish epileptic and normal activity from the EEG database. PSI quantified the link between two EEG channels and discovered the increased in the spatio-temporal interaction among the EEG channels, to categorized different EEG signals. The research study was implemented on the 258-hour-long EEG recording of 5 patients with different categories of an epilepsy syndrome. The methodology was implemented on two different epochs of EEG signals with the length of 20 sec and 60 sec. In the absence of any classifier, the proposed study achieved 100% classification accuracy for 20-sec epoch's length.

Chua et al. 2010, applied HOS approach for classifying normal, background and epilepsy seizure activity EEG signals. Parameters were extracted from the power spectrum and higher order spectra and analyzed by applying Gaussian mixture model classifier and Support Vector Machine classifier. It was reported that HOS based parameters are a more efficient approach to distinguish different EEG signals by attaining 93.11% accuracy. Martis et al. 2012, applied Empirical Mode Decomposition for the classification of normal, ictal and inter-ictal activity in epileptic EEG signals and achieved 95.3% classification accuracy.

Siuly, Li & Wen 2011, developed a novel clustering approach for classifying epilepsy from EEG by using least square support vector machine and reported 94.18% classification accuracy. Later on, Siuly & Li 2014, introduced a statistical system for classifying the multi-category EEG signals using optimum allocation approach for data representation based on definite time and variability of within a class. By using multiclass least square support vector machine as a classifier, the study claimed high-performance results for epilepsy detection. The importance of sampling approach was presented by Siuly et al. 2015, using random sampling and optimal allocation sampling-based approach for classifying epilepsy EEG signals. The study investigated that random sampling is a more promising approach for seizure classification as compared to the optimal allocation sampling. The proposed work used KNN, multinomial logistic regression with a ridge estimator (MLR), and SVM classifier. The KNN classifier provided 100% classification results.

Faul et al. 2007, presented the Gaussian Process probabilistic models for classifying the epileptic EEG signals. Niknazar et al. 2013, applied the recurrence quantification analysis approach as well as wavelet transform with order 4 to distinguish healthy, inter-ictal, and epileptic EEG signals. The alpha, beta, delta, theta, and gamma values were extracted from each sub-band. 98.67% classification result was attained after applying an error-correcting output coding classifier.

Guler, Ubeyli & Guler 2005, applied Largest Lyapunov Exponent parameter for the feed-forward neural network as well as for the recurrent neural network for classifying three kinds of

EEG signals with normal, inter-ictal and ictal conditions of epilepsy. The recurrent neural network provided more promising results with 96%, classification sensitivity, 97.38% for specificity and accuracy result was 96%. Shoaib et al. 2014, used wavelet energy as a parameter for the development of seizure detection processor with the help of SVM classifier. Belhadj et al. 2016, introduced the clustering method which was unsupervised in nature for epilepsy detection. Potential-based hierarchical agglomerative clustering method was implemented in combination with empirical mode decomposition. Euclidian distance as well as kolmogorov distance with Bhattacharya distance were calculated among the IMFs and used as input to the Potential-based hierarchical agglomerative clustering system. After applying the proposed methodology to the CHB-MIT epileptic database (Goldberger et al. 2000), they reported 98.84% classification performance results. Kabir et al. 2018, proposed the idea of a computer-aided analysis framework for the detection of epileptic disorder from EEG. K-means clustering approach was applied to determine various clusters of data by considering the similar and dissimilar behavior between the patterns of EEG signals. SVM, Naive Bayes as well as Logistic regression were used to classifying the normal and EEG signals with epilepsy. 100% classification accuracy was reported with SVM classifier.

3.4 Drawback of the Existing Techniques

From the above state of the art in the field of automated detection of the epileptic syndrome, it is clear that there are various methods are available for the analysis and classification EEG signals in order to detect epilepsy from EEG. But the above-described literature has some restriction and limitations. This section discusses the general drawbacks of the existing methods based on different approaches.

The time-domain approach includes only the time and magnitude mechanism of the EEG signal. It does not provide any information regarding the frequency based only the time and magnitude components of the signal of the EEG signals. Whereas, the more in-depth analysis of EEG signals also requisite the frequency mechanism of EEG signals. Time domain approach is less robust as compared to the frequency domain (Mursalin et al. 2017).

The non-parametric approach has the limitation of spectral leakage where the level of the EEG signal reduces, and the consequences can be easily shown in the whole frequency spectrum.

The non-parametric approach provided low-frequency resolution and suffered from great noise sensitivity. The parametric approach has the drawback of the absence of time mechanism of EEG signals whereas, the time component provides beneficial information about EEG signals. The short Fourier transform has the limitation of the fixed and definite size of the window and the resolution problem associated with the window size as the narrow scale window provides poor frequency resolution and wide-scale window provide poor time resolution. The Fourier transformation approach has not enough information about what frequency occur at which time-interval.

Time-frequency distribution based methods have the limitations of slow in speed as the time for computing the gradient ascent is high and extracted measures are inter-dependent. It is not able to provide efficient results if the signal suffers from noise, i.e. it is not a reliable analysis approach for EEG signals with artifacts. In addition to this, some restricted pre-processing steps need to be followed carefully for de-noising the signal which also increases the cost and time for analysis.

Wavelet Transform based techniques have the drawback of selection of an appropriate mother wavelet, the number of decomposition levels and the selecting appropriate features from specific sub-bands. In addition to this, Wavelet Transform performs well on multiscale structure but provide low efficient results for a single scale. The drawback of HHT is that IMFs takes long computational time if the database is extensive. In addition to this, the EMD is suffered from the problem of mode-mixing. Moreover, the mode-mixing is the primary reason behind the aliases in the time-frequency distribution and also the distinct IMF lose its physical uniqueness.

Power spectrum and autocorrelation functions are not able to provide any phase information about EEG signals. 2nd order measures find it challenging to analyze the EEG signals with non-Gaussian background noise. Whereas, higher order cumulants (moments and cumulants) are sensitive to the outliers in the EEG data sets. In the case of Gaussian density, the third and higher-order cumulants vanish.

The major drawback of applying the recurrence plot, RPDE and RQA is that the choice of recurrence threshold value (ε) to generate recurrence plot which covers sufficient recurrence points so that the generated recurrence plot provides enough and valuable information about the EEG signals. There is no proper guidance has been provided to decide the value of the ε threshold. In addition to this, the recurrence study of EEG signals at multiscale level generates numerous recurrence plots which will make the visual analysis infeasible. The major problem during the serialization of recurrence plots includes the compromisation of the spatial neighborhood data values.

Approximate Entropy suffers from the limitations of lacking in relative consistency for the choice of parameters and dependability on the EEG signal length. Approximate entropy and sample entropy measures the degree of regularity of EEG signals on a single scale. There is no direct link between regularity and complexity of the EEG signals. These traditional entropy methods analysis the surrogate data which are generated from the original data. And during surrogate data generation practice, there are chances of loss of some critical information and data degradation. In addition to this, approximate entropy, sample entropy, and multiscale entropy are significantly affected by the outlier because outlier alters the standard deviation of EEG signals which in turn affects the similarity criteria measurements.

The fractal dimension based techniques have some limitations like the choice of scaling range is a critical issue, and the fractal dimension measurements after applying the discretization on the EEG data is different from the continues EEG signals with unlimited details. In addition to this, it is not a robust method in the case to estimate the complexity of irregular graphs. Whereas, the Correlation Dimension has some shortcoming, i.e. the selection of the number of data points required for the consistent evaluation of the Correlation Dimension. The sensitivity and selection of estimate time-delay for the modernization of the phase space and also for noise effect.

The accurate evaluation of the time-dependent Hurst exponent is a big challenge. Hurst exponent has time as well as scale dependency. The H-index produces reliable results only if the right estimate method is executed, otherwise, it provides inconsistent results. In the case of Lyapunov Exponent based techniques, the major problem is the remodeled phase spaces which have additional dimensions in comparison to the actual phase space. The Lyapunov Exponent calculation based upon differences method has the shortcoming of the choice of a reasonable initial distance and the appropriate selection of the renormalization period.

3.5 Gap in Literature

The above-mentioned drawbacks of the existing methods clearly demonstrate that there is an obligatory of reliable automated seizure detection techniques that assist the clinicians for the diagnosis of epilepsy and also reduce cost and time. Nowadays, the graph-theory mechanism has provided innovative sights in epilepsy detection from EEG signals with the help of specific graph parameters (Ponten, Bartolomei & Stam 2007; Li et al. 2013; Tang et al. 2013; Bhaduri & Ghosh 2014). The graph-theory based techniques characterize a hidden sight of brain activity and brain-behavior mapping. The graph theory not even helps to provide a distinction between three spatial scales: microscopic, mesoscopic, and macroscopic of EEG signals but also provides the correlation among them. Therefore graph theory based framework can play a crucial role in determining the gap present in the EEG patterns (the gap in the existing techniques have also been discussed in the introduction section of subsequent chapters of this thesis). Graph theory harvests important information about the underlying brain connectome with the help of certain topological properties of the EEG signals network. The statistical features of the graph based upon EEG signals provide critical knowledge about dysfunction related to the structure and function of the brain with abnormalities.

3.6 Summary

This chapter presents a brief overview of different domains of EEG signals analysis named Time domain, Frequency domain, Time-Frequency domain, and Analysis on the basis of a non-linear approach. Then this chapter describes different approaches for classification of EEG signals named: Supervised classification and Unsupervised classification approach. In addition to this, a literature review in the field of automated epilepsy detection techniques is also discussed. The literature review includes a summary of the exiting techniques. Later on, the limitations of the existing methods are defined. In addition to that the gap in the literature is also discussed. The gap in the literature also depict that the existing statistical methods for analysis the EEG signals are not sufficient enough for detecting the brain abnormalities from EEG. The graph theory assists in determining the gap present in the EEG patterns. Therefore, in the following chapter, a novel graph theory based technique has been proposed for the automated classification of epileptic EEG signals from the normal.

CHAPTER 4

WEIGHTED_COMPLEX_NETWORK BASED FRAMEWORK FOR EPILEPSY DETECTION FROM EEG SIGNALS

In this chapter, a Weighted_Complex_Network Based Framework is proposed to identify one of the most challenging brain disorder named epilepsy disorder. Automated diagnosis of epileptic seizure activity using EEG signals is an area undergoing deep attention in medical science as well as in research disciplines. Because the traditional method of diagnosis relies on monotonous visual inspection by highly expert clinicians from long-lasting EEG recording. The branch of complex science named complex network has proved that the underlying dynamics of EEG signals is best defined if the strength amongst the nodes of the network is considered and evaluated. As the topological invariant of the network are closely associated to the underlying dynamics of EEG signals. This research study introduces an innovative edge-weight algorithm in the visibility graph for classifying epileptic EEG signals from the healthy EEG recording. This study aims to explore the efficacy of introducing the innovative edge weights idea as well as average weighted degree as an efficient network feature for identifying epileptic seizure activity by using five prevalent machine learning classifiers.

Some contents present in this chapter are already published in In Australasian Database Conference, Springer, Cham, 2016 [Publication 2]. And also in Electronics Letters, journal in 2016 [Publication 2].

4.1 Introduction

65 million population at worldwide are suffered from the critical chronic brain syndrome named as epilepsy (England et al. 2012). According to the World health organization, the epilepsy occurrence rate per year is 2.4 million, and it can affect any age group (Acharya et al. 2013). Almost one-third of epileptic patients experience seizures attack even with

medicated treatment (Ramgopal et al. 2014). The menace of SUDEP (Sudden unexpected death in epilepsy) in an adult epileptic patient is approximately 8-17% more and 34% in children epileptic patient. SUDEP is approximately 24 fold more in the epileptic patient as compared to the general (Hyvarinen & Oja 2000). During epileptic seizure attack, there is the incidence of abnormal electrical action in the brain because of the disparity of excitatory and inhibitory synapses present in the brain (Siuly & Li 2015). Epileptic patients have a greater risk of other complications such as Bleeding into the brain, Brain tumors, Cerebral palsy, Alzheimer's disease (in the later stage of life) and Autism disorder, etc. (Ghosh-Dastidar, Adeli & Dadmehr 2008). Epilepsy is diagnosed with the help of an EEG, which tracks the electrical activity occur in the human brain and records the diverse brain wave pattern. As brain exhibit complex interconnection among millions of billions of neurons, as a result, EEG recording is also having complex characteristics properties like non-linear and non-stationary in nature. The non-stationary and complex nature of EEG signals make the epilepsy detection task more error-prone, time-consuming and even expensive for the clinicians. Moreover, finding traces of seizure activity by experts' neurologist through visual examination of EEG is a challenging issue and cannot be considered as a very reliable procedure (Siuly et al. 2017). Despite the fact that numerous anti-epileptic drugs have been developed from the last decade still, one-third of epileptic patients continue to have a seizure attack in spite of treatment. In addition to this, EEG analysis not only help in the diagnosis of anti-epileptic medication but also plays a crucial role in all the neuro-surgery related to epilepsy. As a result, there is continuously an obligatory of automated seizure detection techniques that assist the clinicians for the diagnosis of epilepsy and also reduce cost and time.

Research in the arena of automatic epilepsy detection techniques started in 1982 when Gotman (Gotman & Gloor 1976) first time proposed an automatic method to detect the epileptic seizure and performed some experiments wherein the amplitude of EEG signals was measured with reverence to the background, the period of time and the periodicity of EEG signals. However, the proposed algorithm was unsuccessful in identifying seizure activity from that EEG signals wherein the frequency bustle is high, and amplitude is low. Later on, different techniques were proposed by different researchers for automated detection of epilepsy from EEG signals. Fourier Transform is one of the popular techniques to detect epilepsy (Gotman 1982; Gotman, Qu & Gotman 1993; Yadav, Agarwal & Swamy 2007;

Samiee, Kovacs & Gabbouj 2015) but suffered from great noise sensitivity and lack of spectral estimation. Wavelet Transform based seizure detection techniques (Hazarika et al. 1997; Adeli, Ghosh-Dastidar & Dadmehr 2007; Ocak 2009; Hassan, Siuly & Zhang, 2016; Islam, Rastegarnia & Yang 2016) have the drawback of selection of an appropriate mother wavelet. Time-frequency distribution based methods (Tzallas, Tsipouras & Fotiadis 2007; Tzallas, Tsipouras, & Fotiadis 2009; Boashash & Ouelha 2016; Alcin et al. 2016; Alcin et al. 2016 (b); Ghayab et al. 2018; Ghayab et al. 2018(b); Siuly et al. 2019) has limitations of slow in speed as the time for computing the gradient ascent is high and extracted measures are inter-dependent. Some researchers had proposed seizure epileptic seizure detection methods based upon the parametric analysis. Like Granger Causality (GC) parameter was used to recognize epileptic seizure from EEG (Bhardwaj et al. 2009; Murta et al. 2012; Epstein et al. 2014; Coben & Mohammad-Rezazadeh 2015). Even though GC is easy to implement but it has the drawback of sensitivity towards volume conduction and noise. Phase-based techniques (Mormann et al. 2000; Sabesan et al. 2008; Lobier et al. 2014; Shah 2014) has the limitation of uncertain results with the wrong choice of the phase difference. The traditional approaches have some restrictions, and drawbacks like the non-parametric approach have the limitation of spectral leakage where the level of the EEG signal reduces, and the consequences can be easily shown in the whole frequency spectrum. The parametric approach has the drawback of the absence of time mechanism of EEG signals whereas, the time component provides beneficial information about EEG signals. Power spectrum and autocorrelation functions are not able to give any phase information regarding EEG signals. The major drawback of applying the recurrence plot, RPDE and RQA is that the choice of the recurrence threshold value (ε) to generate recurrence plot which covers sufficient recurrence points so that the generated recurrence plot provides enough and valuable information about the EEG signals. Due to the limitations of the traditional approaches for the analysis and processing of EEG data to detect an epileptic seizure, the graph theory has become one of the key research fields in epilepsy detection.

Even though early discoveries in the neuroscience research also suggest the importance of graph theory in clinical interpretability (Bassett & Bullmore 2006; Ponten, Bartolomei & Stam 2007; Reijneveld et al. 2007; Ortega, Sola & Pastor 2008). Graph theory harvests important information about the underlying brain connectome with the help of certain topological properties of the EEG signals network (Bullmore & Bassett 2011). The statistical features of the network build from EEG signals provide critical knowledge about dysfunction related to the structure and function of the brain with epilepsy.

From the last few years, complex network-based EEG signals analysis for the detection or prediction of epileptic seizure are showing vast progress. Such as: Schindler et al. 2008, analyzed the complex network of different EEG signals earlier, later and for the duration of epileptic seizure activity. Network path length and cluster coefficient were used as parameters for the research. The major findings of the proposed research work that the two parameters were showed transformation in the network topology by shifting from random to regular then again shifted to random. Before the starting of the seizure attack, the clustering coefficient showed an increase in value. The synchronization of neurons was decreased for the duration of seizure attack and shifted towards the increasing level before finishing of the seizure attack. The proposed study encompassed with the drawback of a threshold value for the selection of cross-correlation function and edge matrices. Wilke, Worrell & He 2009, had applied graph measure to investigate the behavior of ictal activity in the epileptogenic networks. The out-degree parameter of the epileptogenic networks was used for the analysis. The major finding of the research study was that the out-degree parameter helped in the location of the seizure onset zone and gave information about the occurrence of the ictal movement in the brain. The research work had the limitation for the choice of optimal model order which varied according to the selection criteria. Bialonski & Lehnertz 2013, introduced the assortativity measure of the graph for the analysis of the epileptic EEG signals. Correlation coefficient and time lag were used to evaluate the interconnection of the signals. The major finding of this research study was that the positive degree-degree correlations feature of the network helps to characterize the seizure activity. In addition to this, the assortativity coefficient increased, and synchronization decreases for the duration of the epileptic seizure. The research study comprised with the shortcoming that the edge links are established using threshold value which was not certain. Ni et al. 2014, have done an analysis of EEG signals in order to check how the small-world or scale-free topology of the brain network related to the epileptic seizure. The multiple-mass neural model was used to extract the neural network statistics for the duration of the epileptic seizure. The main discovery of the proposed study was that the small world network and the scale-free network has a significant relation with the incidence of seizure attack. Petkov et al. 2014, used the computational model for understanding the underlying dynamics of the seizure activity in the functional network of EEG signals. The mean degree, degree variance, and local clustering coefficient were the measurements of the functional network used for the investigation. The research study concluded that the mean node degree parameter increased during epileptic seizure activity and degree variance parameter also played an important role in distinguished different EEG signals. Whereas, the clustering coefficient feature had not performed really well with the proposed methodology.

The above-cited techniques to detect epileptic seizure comprises of some shortcomings. But the common and major drawback that all of the above-mentioned techniques are having is the lack of edge strength in their proposed methodologies. The above-mentioned techniques of seizure detection from EEG signals using a network approach has considered that all the links of the network are equal in magnitude irrespective the nature of the EEG signals. Whereas, according to R. Polikar, different nodes of the network connect with each other through different intensities. And if we preserve the weight information on the graph, then we can achieve strong, reliable result (Polikar 2006). The strength of the edges plays an important role to analyze the existing information of the network. The edge strengths help in to discriminate between strongly important and potentially weak node. This information will further assists to understand the underlying dynamical information about the network. By considering the importance of weight in a network, this chapter introduces an innovative edge weight method in the Visibility Graph (VG) for epilepsy detection from EEG. The reason behind using VG for this research study is that VG technique plays a decisive role in several research fields like in the analysis of multifractal stochastic processes (Yang et al. 2009), econometrics field (Wang, Li & Wang 2012; Long 2013, hurricane data (Elsner, Jagger & Fogarty 2009), seismology (Telesca & Lovallo 2012), Human heartbeat dynamics (Dong & Li 2010; Shao 2010). Moreover, Ahmadlou, Adeli & Adeli 2010, first-time applied the VG in the brain signal analysis field to detect Alzheimer's syndrome and achieved very satisfactory results.

In this chapter, we proposed an innovative WCNBF founded on the graph theory for the automated analysis of EEG signals to extract the valuable information for the categorization of diverse kinds of EEG signals. Firstly, the time-series EEG signals are converted into Weighted_Complex_Network (WCN) with the help of VG theorem and by introducing innovative weight formula. Then, the statistical feature of the WCN is extracted in the feature extraction part. After that, the extracted feature is evaluated with the help two standard machine learning classifiers: SVM with several kernel functions and LDA. The performance of the Weighted_Complex_Network Based Framework is measured with the help of some sensitivity, specificity and accuracy parameters. The primary objective of this chapter is:

- To introduce weight in the edges of the visibility graph;
- To identify how efficient a weighted-visibility graph is for distinguishing the EEG signal of a healthy volunteers and epileptic patient in seizure zone;
- To introduce Average Weighed Degree as an efficient feature in the analysis of epileptic seizure activity from the weighted-visibility graph;
- To investigate the effect of segmented and unsegmented EEG signals for the identification and classification of epileptic seizure activity.

The experimental outcomes with 100% accuracy results demonstrate that our proposed WCNBF is proficient for discriminating between EEG signal of a healthy person and epileptic patient in seizure zone. As far we are aware of, this proposed WCNBF is truly newfangled and can be beneficial in the arena of automated detection of epilepsy and other neurological disorder. The rest of the chapter is systematized as: Section 4.2 comprised detailed information about the WCN based framework. The detailed information regarding EEG data used in this research project is available at Section 4.3. Section 4.4 covered experimental results with the required discussion about that. The conclusion is depicted in Section 4.5.

4.2 Weighted_Complex_Network Based Framework

This section of the chapter provides the complete description of the WCNBF for epilepsy detection from EEG signals. This WCNBF is using the following sequence of steps for the detection of epileptic seziure:

1. Transformation of EEG signals into WCN;
2. Topological features are extracted from the WCN of EEG signals;
3. Classification based upon the extracted feature sets;

4. Performance Measures

Figure 4-1 illustrates a schematic diagram of the WCNBF. Firstly, the EEG signals are converted into WCN. For the transformation of time-series EEG signals to WCN, each sample value of the EEG signal is considered as the vertex or node of the complex network. The links between different nodes are built on VG graph theorem. After that, an innovative edge weight theorem is introduced to compute the weight of the different links or edges in a WCN. As the WCN is formed then the statistical features of the network are extracted and features set are created. Afterward, with the help of classifiers and the extracted features set, the EEG signals are classified into their appropriate class (healthy or epileptic EEG signals). Then the performance of the anticipated framework is assessed via specific measurements. Following is the detailed elaboration of each step.

4.2.1 Transformation of EEG signals into Weighted_Complex_Network (WCN)

As WCN is based upon the VG, for that reason, it is essential to understand the VG first. Lacasa et al. 2008, proposed the idea of the Visibility Graph Algorithm to transform the time series into a network or graph on the basis of visibility character of geometry. The principle of VG is the theory of Euclidean plane, i.e., if each node denotes the point's position in the Euclidean plane, then the link between the allied nodes is only probable if there is visibility among them. This VG graph makes the visual analysis of the structural patterns of the network, easy at various time scales of the microscopic level to the macroscopic level (Ahmadlou & Adeli 2012). To understand the VG graph, let's assume G(N, E) denotes a graph with N number of the node and *E* is the total edges. $X=\{X_t\}_{(t=1,2,\ldots\ldots m)}$ symbolize a time-series. According to Lucas, if each data point (X_i) of the time series X is measured as a node (n_i) of the graph G (N, E). The edges among the nodes of the graph G (N, E) is only possible if they satisfied the following equation:

$$n_b < n_a + (n_c - n_a)\frac{t_b - t_a}{t_c - t_a}, c > b > a\,, \quad (1)$$

where, n_a, n_b and n_c are the nodes which relates with the data sample x_a, x_b, and x_c of the time series X and t_a, t_b and t_c are their corresponding time events. Figure 4-2 exemplify the VG of a small sample of time series data.

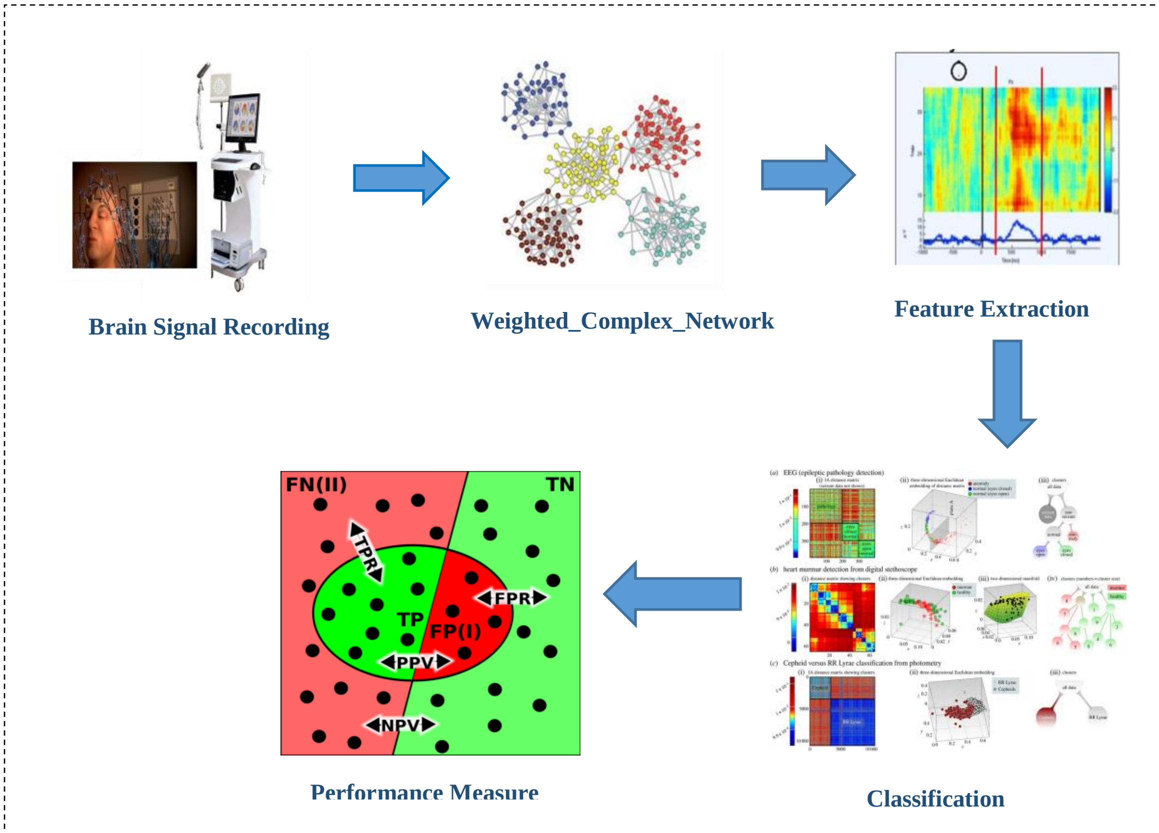


Figure 4-1: Schematic representation of the general sequence of steps followed by the Weighted_Complex_Network Based Framework.

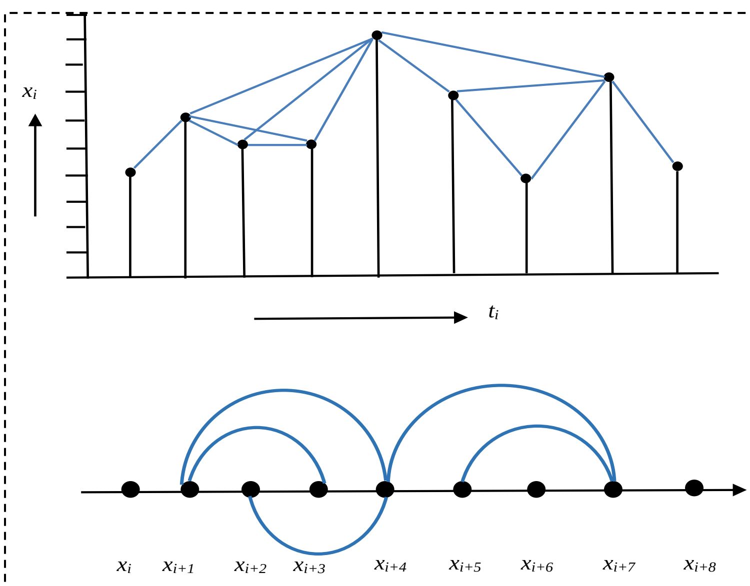


Figure 4-2: Illustration of Visibility Graph.

The WCN from EEG signals are comprised of the subsequent steps:

I. Consider an EEG time-series is symbolized as E= {E_t} $_{(t=1,2,\ldots\ldots m)}$ with m number of total data sample in it. Each sample point of E time-series is considered as node of the network with N ={n_i },*i=1,2,….k*, denotes the node sets and E ={e_i },*i=1,2….j*, represents the edge sets;

II. The link between all the nodes is generated on the principle of equation (1) of lucasa VG theorem;

III. Once the links or edges formed then edge weight is calculated. In this research work, I have developed the equation (2) for calculating the weight of the edges among distinct nodes:

$$w_{lm} = \left|\frac{n_m - n_l}{t_m - t_l}\right| \ , l < m, \qquad (2)$$

Where, w_{lm} denotes the weight of the edge among nodes *l* and *m*. t_m and t_l are the associated time event corresponds to nodes *l* and *m*. The weight of the edges are directional in nature. Once the edge weight amongst all the nodes are calculated then WVG is generated. Figure 4-3. illustrate the WCN of small segment of EEG signals of epileptic person during seizure attack with data sample values = {100, 124, 153, 185, 210, 220, 216, 222, 240, 265, 298, 330, 362, 381, 391}. I believed that the idea of introducing weight in the visibility graph for EEG signal analysis is really innovative and have not applied before.

4.2.2 Extraction of the network features from WCN

Extracting the relevant statistical feature of the network plays a crucial function during the classification of distinct EEG signals. In technical term, a feature embodies as a discernable dimension that can characterize the unique or distinguishable properties of a pattern or configuration. In the process of feature extraction, the vast EEG data is simplified into a feature vector on the principle of least possible loss of information (Siuly & Li 2014).

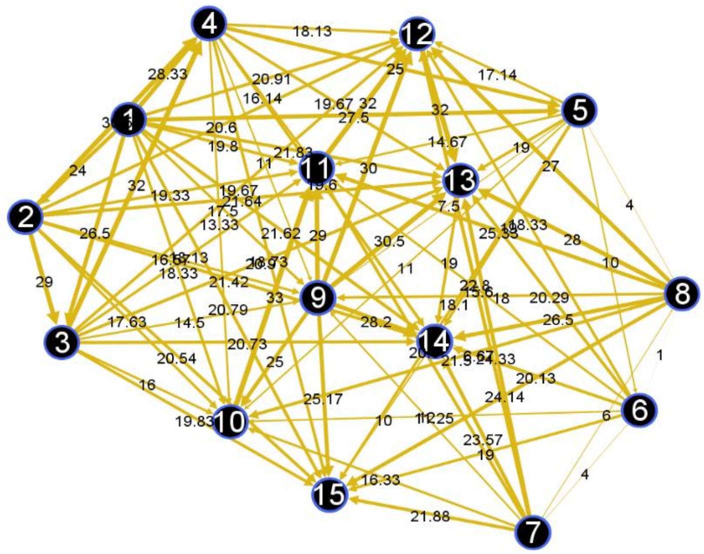


Figure 4-3: Illustration of WCN of EEG signal of an epileptic patient in seizure activity.

In this research work, Average Weighted Degree (AWD) is extracted as a feature from WVG to distinguish among the distinct class of EEG signals. As per my knowledge, AWD feature has not been applied before in the analysis of EEG signals. AWD feature is effectual to distinguish diverse EEG signals by discerning the underlying hidden pattern of EEG.

If $A_{l\times l} = \{a_{jk}\}$ denotes an adjacent matrix of WCN with *l* number of total nodes. a_{jk} symbolize an edge from node *j* to *k*. The value of $a_{jk} = 1$ if there is presence of link from node *j* to *k* and $a_{jk} = 0$ if there is no link among them. According to Antoniou & Tsompa 2008, the weighted degree of a node *j* is measured as the summation of all the edge weights of all the link joined to node *j* and is calculated as:

$$wd_j = \sum_{k\in N(j)} w_{jk} \ , \tag{3}$$

In the above equation (3), wd_j represents the weighted degree of node j; $N(j)$ denotes the neighbours of *j*; w_{jk} signifies the weight of the edge among node *j* and *k*. AWD is measured as the average mean of summation of all the edge weights incident on all the nodes of the network. As during seizure-activity, the EEG signals reveal sudden fluctuation which in turn affect the strength by which all the nodes are connected to each other. As a result, edge weight is affected and the result can be seen in AWD feature. Because AWD is directly proportional to the weight of the edges. In this way, AWD play a crucial role in the analysis of diverse EEG signals. The experimental outcome in section 4.4, clearly demonstrates the above-mentioned premise.

4.2.3 Classification

In the procedure of classification, a mathematical function named as a classifier, categorize the EEG signals with distinct class into their relevant class on the basis of feature sets. During classification, the whole EEG feature sets are partitioned into two portions: training group set and the testing groupset. The set of unidentified observation (testing group) is predicted or classified into the appropriate class by considering some criteria on the set of identified observation (training group). This research analysis used two eminent supervised classifiers of machine learning for evaluating the performance of the extracted feature AWD of the WVG. The two classifiers are: SVM classifiers and DA classifiers.

4.2.3.1 Support Vector Machine (SVM) classifier

SVM is described as set of techniques in which the linear functions make use of the hypothesis space with the feature space of high-dimensions and trained on the basis of the learning process with optimization principle for implementing a learning bias derivative as of statistical learning model (Jakkula 2006). The statistical learning model helps to generate a framework for analysis the problem of acquiring knowledge, to make predictions, to make decisions on the basis of the available data set. In general, it helps in selecting the hyper-plane space (Vapnik 1998). Generalization is the capability of a hypothesis on the basis of which it can perform accurate classification of the data not present in the training group. SVM is more proficient in means of not performing over generalization whereas overgeneralization is the major drawback of neural network classifies. The linear classifiers execute the classification on the principle of selecting the appropriate hyper-planes and are affected with the shortcoming of choosing that hyper-plane which is proficient at classifying the one group of data and does not perform better classification to other data sets. The SVM classifier overcomes this shortcoming by providing the idea of hyper-plane with maximum-margin and accomplish efficient classification. The maximum margin is expressed as:

$$margin = arg\min_{l \in D} d(l) = arg\min_{l \in D} \frac{l.w+m}{\sqrt{\sum_{j=1}^{d} w_j^2}} \ , \quad (4)$$

Where, *w* represent the weight vector and is orthogonal to hyper-plane; *l* denotes the input vector; *m* is the bias; *d* represents the margin of separation. The detail information about equation (4) and all of the parameters are available in Cristianini & Shawe-Taylor 2014. The hyper-plane is defined as subspace which has its dimension less than by one in comparison to the ambient space of it. In general, hyper-plane partition space into two portions. The standard equation of hyperplane is:

$$w \cdot l + m = 0 \quad . \quad (5)$$

The hyperplane based upon w and m provides the following function for the correct classification of the training sample or data.

$$f(x) = sign(w.l + m) \quad . \quad (6)$$

In the procedure of train the SVM, the following equation is used:

$$y_j(w.l_j) \geq 1 \ \forall \quad 1 \leq j \leq n \quad . \quad (7)$$

The equation (7) is solved to determine the hyper-plane with a maximum margin for the value of *w* if the y_j is the available data labels and l_j is the feature vectors (Boswell 2002). The dual formulation of the SVM classifier is represented as:

$$\min_{\alpha_j} \sum_{j=1}^{1} \alpha_j - \frac{1}{2} \sum_{j=1}^{1} \sum_{p=1}^{1} \alpha_j \alpha_p y_j \, y_j K(l_j, l_p) \quad 0 \leq \alpha_j \leq B \ , \forall j; \ \sum_j \ \alpha_j y_j = 0 \ , \quad (8)$$

where, *B* denotes the cost penalty, and α represents the Lagrange multipliers (Vapnik 1998). SVM used the concept of the kernel to map the non-linear input vector to the high dimensional. The function Φl is functioned as transformational function for mapping the input vector into a high-dimensional. The kernel function *K(l)* is defined in terms of dot product as:

$$K(l_j, l_k) = \Phi(l_j) \cdot \Phi(l_k) \quad . \quad (9)$$

Different categories of the kernel have been developed for SVM. The following three types of kernels are used in this research project (Boswell 2002):

- Linear Kernel function:

$$K(\mathrm{l_j}, \mathrm{l_k}) = l_j{}^T \mathrm{l_k} \quad . \tag{10}$$

- Radial basis kernel function is having ∂ as a tunable parameter:

$$K(\mathrm{l_j}, \mathrm{l_k}) = exp\left(-\frac{\|l_j - l_k\|^2}{2\partial^2}\right) \quad . \tag{11}$$

- Polynomial kernel function and *z* are a tunable parameter show variations from $1\ to \sim 10$:

$$K(l_j, l_k) = (l_j \cdot l_k + 1)^z \quad . \tag{12}$$

Following are the applications of the SVM for the binary classification:

A. Case 1: The data have h training points, and data is linearly separable in nature.

1. Construct matrix **M**, such that

$$M_{jk} = y_j y_k l_j \cdot l_k \ . \tag{13}$$

2. Find that value of α in which

$$\sum_{j=1}^{h} \alpha_j - \frac{1}{2}\alpha^T \boldsymbol{M} \alpha \ . \tag{14}$$

have a maximum value, with respect to

$$\alpha_j \geq 0\ \forall_j \quad \text{and} \quad \sum_{j=1}^{h} \alpha_j y_j = 0 \quad . \tag{15}$$

with the help of Quadratic Programming Solver

3. Compute $w = \sum_{j=1}^{h} \alpha_j y_j\, l_j$. (16)

4. Find the S which is a set of support-vectors via determining the indices where $\alpha_j > 0$.

5. Calculate

$$m = \frac{1}{N_u} \sum_{u \in S} (y_u - \sum_{v \in S} \alpha_v y_v \, l_v \cdot l_u) \quad . \tag{17}$$

6. Every new data point l′ is classified via calculating

$$y' = sign(w.l' + m) \quad . \tag{18}$$

B. Case 2: The data have h training points, and data is non-linearly separable in nature

1. Construct matrix **M**, such that

$$M_{jk} = y_j y_k l_j \cdot l_k \, . \tag{19}$$

2. Select an appropriate value for the cost penalty parameter B to deal with the significant level of misclassification.

3. Find that value of α in which

$$\sum_{j=1}^{h} \alpha_j - \frac{1}{2} \alpha^T \boldsymbol{M} \alpha \quad . \tag{20}$$

have the maximum value, with respect to

$$0 \leq \alpha_j \leq B \quad \forall_j \qquad \text{and} \;\; \sum_{j=1}^{h} \alpha_j y_j = 0 \quad ; \tag{21}$$

with the help of Quadratic Programming Solver

4. Compute $w = \sum_{j=1}^{h} \alpha_j y_j \, l_j \quad .$ (22)

5. Find the S which is a set of support-vectors via determining the indices where $0 < \alpha_j < B$.

6. Calculate

$$m = \frac{1}{N_u} \sum_{u \in S} (y_u - \sum_{v \in S} \alpha_v y_v \, l_v \cdot l_u) \quad . \tag{23}$$

7. Every new data point l' is classified via calculating

$$y' = sign(w.l' + m) \quad . \tag{24}$$

C. Case 3: The data have h training points as well as is non-linearly separable in nature and kernel function based classification

1. Select the appropriate kernel and map $l \mapsto \Phi(l)$

2. Construct matrix **M**, such that

$$M_{jk} = y_j y_k \Phi(l_j) \cdot \Phi(l_k) \, . \tag{25}$$

3. Select an appropriate value for the cost penalty parameter B to deal with the significant level of misclassification.

4. Find that value of α in which

$$\sum_{j=1}^{h} \alpha_j - \frac{1}{2} \alpha^T \boldsymbol{M} \alpha \quad . \tag{26}$$

have the maximum value, with respect to

$$0 \le \alpha_j \le B \quad \forall_j \qquad \text{and } \sum_{j=1}^{h} \alpha_j y_j = 0 \ ; \tag{27}$$

with the help of Quadratic Programming Solver

5. Compute $w = \sum_{j=1}^{h} \alpha_j y_j \, \Phi(l_j)$ (28)

6. Find the S which is a set of support-vectors via determining the indices where $0 < \alpha_j < B$.

7. Calculate

$$m = \frac{1}{N_u} \sum_{u \in S} (y_u - \sum_{v \in S} \alpha_v y_v \Phi(\, l_v) \cdot \Phi(l_u)) \ . \tag{29}$$

8. Every new data point l' is classified via calculating

$$y' = sign(w.\Phi(l') + m) \quad . \tag{30}$$

4.2.3.2 Discriminant Analysis (DA) classifier

R. Fisher is known as the developer of Discriminant Analysis (DA) classifier. DA played a critical role in classification to solve various problems (Sapatinas 2005). The discriminant analysis method is used to categorize the entities into mutually exclusive as well as exhaustive sets on the basis of quantifiable parameters or features of the entities. The DA classifiers are categorized into two categories: the first is linear discriminant analysis and the second is quadratic discriminant analysis. The major difference among LDA and QDA is that LDA classifier has a linear decision surface whereas, QDA have non-linear decision boundary. Both DA classifiers are based upon the simple probabilistic models with the conditional distribution of the data $P(L|w = j)$ for each class j. Predictions are obtained with the help of Bayes' rule:

$$P(w = j|L) = \frac{P(L|w=j)\ \mathrm{P(w=j)}}{P(L)} \quad . \tag{31}$$

Generally, the class with maximum conditional probability is selected.

Construction of the Discriminant analysis (DA) classifier: The DA classifier is built on the basis of two steps. The first step is to construct the building model of the classifier. The second step is how the unknown data sample is classified by the DA. Following are the structure of steps (Tharwat 2016):

Step I: Construction of building model of the classifier

1. Build a feature matrix L that have K samples such as $[l_j]_{j=1}^{K}$, each sample is signified as a column of p length , whereas l_j denoted the j^{th} sample;

2. Calculate the each class's mean $\mu_j(p \times 1)$ as in below :

$$\mu_j = \frac{1}{k_j}\sum_{j=1}^{k_j} l_j \ , l_j \in w_j, \quad \forall_j = 1,2, \dots, b \ , \tag{32}$$

where, k_j denoted the number of data samples in the j^{th} class, w_j are the sets of b classes.

3. For each class, compute the priori probability, i.e. $\mathrm{P}(w_j) = \frac{k_j}{K}$.

4. For each class, calculate the covariance matrix by using:

$$\sum_j = \frac{1}{k_j}\sum_{j\in w_j}(l-\mu_j)(l-\mu_j)^T, \ \forall_j = 1,2,\ldots,b \tag{33}$$

5. For all (class w_j, j = 1,2, ... , b) do

6. Compute the discriminant function (f_j) as

$$f_j(l) = \ln P(w = w_j|l) = P(l|w = w_j) \tag{34}$$

$$P(w_j) = \ln\frac{1}{\sqrt{(2\pi)^p|\sum_i \quad |}} exp\left(-\frac{1}{2}(l-\mu_j)^T \sum_j^{-1}(l-\mu_j)\right) + \ln(P(w_j)) \tag{35}$$

7. End for

Step II: How the unknown data sample (UNDS) is classified by the DA classifier

1. The input is the unknown data samples $(U(p \times 1))$.

2. The output will be the class label (w_j) .

3. for all (f_j, discriminant functions that are computed in Step I) do

4. Put the value of the UNDS (U) in the discriminant function (f_j).

5. end for

6. Class label (w_{max}) is assigned to the UNDS (U), whereas (w_{max}) denoted the class with maximum value of the discriminant function.

In LDA the covariance and means matrices are similar for both the classes whereas, the covariance and means matrices vary for each class in case of QDA.

4.2.4 Performance Measurement

The performance of the introduced framework is assessed by employing the following defined standard measuring parameters (Siuly & Li 2015) i.e.

- $\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive(TP)+False Negative(FN)}}$ (36)

- $\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative(TN)+False Positive(FP)}}$ (37)

- $\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+TN+FP}}$ (38)

4.3 EEG Database used in the research project

The WCNB framework has been implemented on the online available epileptic EEG database provided by Bonn University, Germany. The database is composed of five sets (symbolized Z, O, F, N, and S) of different categories of EEG signals. Each set inclosing 100 single-channel segments of EEG and the duration of each is 23.6-sec with 4097 data sample values. Set Z contained the EEG segments that are collected by recording the surface EEG of five healthy persons eyes open. Set O is the recording of the same healthy persons with eyes closed. F set comprised the EEG recording of five epileptic patients during the non-seizure interval from the epileptogenic zone of the brain. Set N included the EEG recording of the similar five epileptic patients during the non-seizure interval in the hippocampal formation region of the opposite hemisphere area of the brain. S set comprised the EEG recording of the similar five epileptic patients when the epileptic-seizure activity occurs. The recording of all the EEG sets was performed at a 173.61 Hz sampling rate and using a 128-channel amplifier system. The filter named band-pass was used with a value range of 0.53 to 40 Hz. The more detailed information about how this data was collected is available at (Andrzejak et al. 2001).

4.4 Experimental Evaluation of the WCNBF

This section presents the experimental exploration of the WCNBF. I have used MATLAB R2015b (with version 8.6, 64 bit) to perform the simulation analysis of theWCNBF. As per the WCNB framework, each channel of all the sets of EEG signals with 4097 data sample points are converted into the WCN first. After that, Average weighted degree parameter of the WCN is used as a statistical feature of the network and extracted to perform the classification. To execute the classification task, the above mentioned five sets of EEG signals are organized into the following four classification test problems:

- Test-Problem 1: Set Z and Set S.
- Test-Problem 2: Set O and Set S.
- Test-Problem 3: Set N and Set S.
- Test-Problem 4: Set F and Set S.

Cross-validation is a promising technique to assess the general performance as well as the potentiality of the classifier. In cross-validation, the segmentation is performed on the independent dataset to generate the training subset and validation subsets. The subsets are rotated for evaluations. In the end, the average of the outcomes of multiple evaluations is considered for reducing the variation of the evaluation performance. In this research, K-fold cross-validation has been performed with K=10 and named 10-fold cross-validation. In 10-fold cross-validation, the whole feature set is partitioned into 10 subsets randomly of equal sizes. During classification, one subset is used for the testing purpose, and the remaining 9 subsets are utilized as a training for the classification model. This procedure is repeated ten times, and at the end, the average of the evaluations (10) outcomes are considered. For the classification of the extracted AWD feature of the WCN, I have used SVM Linear, SVM Rbf, SVM Polynomial, LDA and QDA classifiers. The overall classification performances of the different classifiers in case of Test-Problem 1, 2, 3 and 4 are illustrated in the following Table 4.1, Table 4.2, Table 4.3, and Table 4.4.

Table 4.1 clearly describes that all of the five classifiers achieved 100% sensitivity performance during the classification task. Whereas the QDA and SVM_Poly achieved 100% specificity performance, SVM Linear and SVM Rbf attained 91% classification specificity,

Table 4.1: Overall classification performance of the different classifier for the Test-Problem

Different classifiers	Classification performance		
	Sensitivity (%)	Specificity (%)	Accuracy (%)
LDA	100	76	88
QDA	100	100	100
SVM_Linear	100	91	95.5
SVM_Rbf	100	91	96.5
SVM_Poly	100	100	100

and LDA reaches 76% of specificity performance during the classification task. The classification accuracy of different classifiers is: 100% for QDA as well as SVM_Poly, 96.5% for SVM Rbf; 95.5% for SVM Linear and 88% for the LDA classifier which is least among all the classifiers. Therefore, we can say that LDA classifier archived least classification outcomes in terms of specificity and accuracy for the Test-Problem 1. Whereas, the QDA and SVM_Poly classifiers are considered as more promising classifiers for classifying the Test-Problem 1 by achieving the 100% classification performance results. From the above discussion, it is clear that QDA and SVM_Poly classifiers can efficiently classify healthy EEG signals (eye open) and epileptic-seizure-activity EEG signals.

Table 4.2 presents the overall classification performances results for Test-Problem 2. The classification performance in terms of sensitivity are: 100% for LDA, SVM Linear and SVM Rbf classifier; 97% for QDA and 96% for the SVM Poly classifier. The classification performance in terms of specificity are: 94% for SVM Poly; 93% for QDA; 85% for the SVM Rbf; 83% for SVM Linear and 74% for the LDA classifier. The classification performance in terms of accuracy measurement of different classifiers are: 95% for QDA and SVM_Poly classifiers; 92.5% for SVM Rbf; 91.5% SVM Linear and 87% for LDA classifier. From the experimental outcomes of Table 4. 2, we conclude that among all the classifiers, the QDA and SVM_Poly classifiers can distinguish the EEG signals of healthy volunteers (eyes closed) and Epileptic-seizure-activity.

Table 4.2: Overall classification performance of the different classifier for the Test-Problem 2

Different classifiers	Classification performance		
	Sensitivity (%)	Specificity (%)	Accuracy (%)
LDA	100	74	87
QDA	97	93	95
SVM_linear	100	83	91.5
SVM_rbf	100	85	92.5
SVM_poly	96	94	95

Table 4.3 demonstrates the classification outcomes of all the five different classifiers for Test-Problem 3. The sensitivity performance of the Test-Problem 3 classification are: 98% for the LDA classifier; 96% for the QDA, SVM Linear as well as SVM Rbf, and 94% for SVM Poly classifier. The specificity results of the different classifiers are: 95% for SVM Poly; 86% for SVM Rbf; 82% for QDA as well as SVM Linear and 75% for LDA classifier. The accuracy outcomes of the different classifiers are: 94.5% for SVM Poly; 91% for SVM Rbf; 89% for QDA as well as SVM Linear and 86.5% for LDA classifier. The experimental outcomes illustrate that SVM Poly classifier is more prominent for classifying the Test-Problem 3 in comparatively other classifiers.

The classification performance for the Test-Problem 4 of the different classifiers are exemplified in Table 4.4. The classification sensitivity outcome of different classifiers are: 100% for LDA as well as SVM Linear; 99% for SVM Rbf as well as SVM Poly and 98% for QDA classifier. The classification specificity outcome of different classifiers are: 99% for QDA; 98% for SVM Poly; 91% for SVM Rbf; 85% for SVM Linear and 76% for LDA classifier. The classification accuracy outcome of different classifiers are: 98.5% for SVM Poly as well as QDA; 95% for SVM Rbf; 92.5% for SVM Linear and 88% for LDA. Therefore, the outcomes of Table 4. 4. signifies that SVM Poly archived higher accuracy performance when classifying the distinguished EEG signals present in the Test-Problem 4.

The experimental analysis performed in the Table 4.1, 4.2, 4.3 and 4.4 clearly depict that the classification performances of QDA and SVM classifier with polynomial kernel function are very close to each other for all the Test-Problem except for the Test-Problem 3. However, LDA classifier performed higher sensitivity results as compared to other classifiers. But the scenario of the experiments demonstrates that SVM polynomial kernel function classifier is more compatible with our WCNB framework and provide high classification outcomes for all the four Test-Problems.

Table 4.3: Overall classification performance of the different classifier for the Test-Problem 3

Different classifiers	Classification performance		
	Sensitivity (%)	Specificity (%)	Accuracy (%)
LDA	98	75	86.5
QDA	96	82	89
SVM_linear	96	82	89
SVM_rbf	96	86	91
SVM_poly	94	95	94.5

Table 4.4: Overall classification performance of the different classifier for the Test-Problem 4

Different classifiers	Classification performance		
	Sensitivity (%)	Specificity (%)	Accuracy (%)
LDA	100	76	88
QDA	98	99	98.5
SVM_linear	100	85	92.5
SVM_rbf	99	91	95
SVM_poly	99	98	98.5

The other objective of this research project is to evaluate the affect of segmentation on EEG signal analysis. For the purpose of segmentation, each single channel of EEG signals is partitioned into four segments and each segment of EEG has the duration of 5.9-sec with 1024 data points. As a result of the segmentation of each single channel, the resultant four segments are further measured as four independent channels for analysis. Therefore, for each set, if there are 100 channel then after segmentation, there will be 400 independent segments. From the above experimental investigation, it is an analysis that SVM polynomial classifier performed high classification outcomes with our WCNB framework, therefore the affect of segmentation and without segmentation is evaluated on the SVM poly classifier. Table 4. 5 present the overall classification performance of the WCNB framework with segmented EEG signals as well as without segmentation of EEG signals by applying the SVM poly classifier for all the four Test-Problems.

Table 4.5 describes that the specificity performance for the Test-Problems 1 is 100 % in both the case of segmented EEG signals as well as without segmented EEG signals. Similarly, the sensitivity and accuracy performance for the Test-Problems 1 are 100 % in both the case of segmented EEG signals as well as un-segmented EEG signals. Therefore, we can conclude that for Test-Problems 1, there is no effect of segmentation and un-segmentation

Table 4.5: Overall classification performance using SVM poly classifier for all the four Test-Problems by applying the segmentation and without segmentation of EEG signals.

Different Test Cases	Segmented EEG Signals			Un-segmentation EEG Signals		
	Specificity (%)	Sensitivity (%)	Accuracy (%)	Specificity (%)	Sensitivity (%)	Accuracy (%)
Test-Problems 1	100	100	100	100	100	100
Test-Problems 2	92.75	94	93.37	94	96	95
Test-Problems 3	95.25	93.75	94.5	95	94	94.5
Test-Problems 4	99	97.75	98.38	98	99	98.5

on the classification performance with our WCNB framework. For Test-Problems 2, the specificity performance is 92.75% for segmented EEG signals and 94% for un-segmented EEG signals. The sensitivity performance for the Test-Problems 2 is 94% in the case of segmented EEG signals and 96% for un-segmented EEG signals. The accuracy performance for the Test-Problems 2 is 93.37% in the case of segmented EEG signals and 95% for un-segmented EEG signals. The overall classification outcomes for the Test-Problems 2 depicts that the classification sensitivity, specificity and accuracy results are very close to each other in case of segmented and unsegmented EEG signals. For the Test-Problems 3, the specificity performance is 95.25% for segmented EEG signals and 95% for un-segmented EEG signals; the sensitivity performance is 93.75% for segmented EEG signals and 94% for un-segmented EEG signals; the accuracy performance is 94.5% in both the case of segmented as well as un-segmented EEG signals. Thus, it can be concluded that for Test-Problems 3, the classification outcomes of segmented and un-segmented EEG signals are closed to each other. Similarly in case of Test-Problems 4, it is analyzed that the classification results of

Table 4.6: Comparison analysis of accuracy performance of different Test-Problems classification with the existing state-of-the-art.

Test-Problem	Author	features	Accuracy
Test-Problem 1	Siuly, Li & Wen 2011	9	99.9%
	Nicolaou & Georgiou 2012	1	93.5%
	Samiee, Kovacs & Gabbouj 2015	-	99.8%
	WCNBF	1	100%
Test-Problem 2	Siuly, Li & Wen 2011	9	93.6%
	Nicolaou & Georgiou 2012	1	82.8%
	Kumar, Dewal & Anand 2012	1	92.5%
	WCNBF	1	95%
Test-Problem 3	Siuly, Li & Wen 2011	9	96.20%
	Nicolaou & Georgiou 2012	1	88%
	Xiang et al. 2015	1	87.6 %
	WCNBF	1	94.5%
Test-Problem 4	Siuly, Li & Wen 2011	9	93.60%
	Nicolaou & Georgiou 2012	1	79.94%
	Xiang et al. 2015	1	88.5%
	WCNBF	1	98.5%

segmented and un-segmented EEG signals are very close such as the specificity performance is 99% for segmented EEG signals and 98% for un-segmented EEG signals; the sensitivity performance is 97.75% for segmented EEG signals and 99% for un-segmented EEG signals; the accuracy performance is 98.38% for segmented EEG signals and 98.5% for un-segmented EEG signals. Therefore, from the experimental investigation from Table 4.5, it can be concluded that the WCNB framework is effective to produce high classification results in the case of segmented and un-segmented EEG signals. Moreover, the segmentation and un-segmentation of EEG signals have the almost the same impact on the classification performance.

Table 4.6 present the comparison analysis of the accuracy performance of different Test-Problems classification with the existing state-of-the-art. Table 4. 6 clearly revealed that the WCNB framework based upon graph-theory is more effective for categorizing diverse EEG signals in comparison to the existing cited methods.

4.5 Summary

This chapter firstly presents the idea behind the importance of edge-weight in the network for the detection of an epileptic seizure. Subsequently, WCNBF based on weighted graph theory is proposed. An innovative edge-weight computing method is developed in the visibility graph. In addition, a statistical parameter named Average weighted degree is used as a graph feature for feature extraction. The WCNBF is evaluated with five different classifiers: LDA, QDA, SVM Linear, SVM Rbf and SVM with polynomial kernel. The experimental outcomes explore that SVM Poly is more suitable and provide high classification results as compared to other four classifiers. Furthermore, the effect of segmentation on the EEG signals is evaluated. The investigational results depict that the WCNBF is not affected by the segmentation and un-segmentation of EEG signals. The experimental outcomes of segmented and un-segmented EEG signals are almost close to each other for different Test-Problems.

The experimental results of this chapter explain that the WCNBF is superior and effective for distinguishing the different categories of EEG signals. Plus, proficient for detecting the epileptic seizure activity from healthy subject's EEG signals. However, the classification accuracy for the Test-Problems 2, 3, and 4 is less as compared to Test-Problems 1. To increase the classification performance for these Test-Problems, it is needed to develop a different edge weight method and that is presented in the next chapter.

CHAPTER 5

WEIGHTED VISIBILITY NETWORK BASED FRAMEWORK FOR CLASSIFYING EEG SIGNALS TO DETECT THE EPILEPTIC SEIZURE USING MODULARITY AND AWD FEATURES

In chapter 4, a WCNBF framework has been developed for the analysis of EEG signals and for the classification of different test-problems based on epileptic EEG signals. The WCNBF provides good classification performance for one test-problem whereas for the other three test-problems, the classification accuracy is not good. To increase the classification performance for all the test-problems, this chapter 5, introduces the idea of Weighted Visibility Network Based Framework (WVNBF). WVNBF uses the modularity (which is a community detection parameter of the network) as an efficient feature of the EEG signals based network in the analysis of epileptic seizure activity. An innovative weight method is also introduced among the links of the vertices of the network. This chapter aims to develop WVNBF for classifying the diverse EEG signals to detect the seizure activity. This research also investigates how the modularity feature of the weighted network and visibility network performed altogether in the analysis of EEG signals for epilepsy detection or classification. Firstly the modularity and AWD features are individually analyzed using SVM linear kernel function classifier. The experimental outcomes revealed that by combining the modularity and AWD feature, more accurate results are attained in comparison to the individual feature. This remaining paper has been structured as: section 5.2 includes the importance of visibility graph-based network (VGBN) and the need for introducing the weight to the links of VGBN. Section 5.3 presents the complete description of the data set used in the experimental part along with the steps to construct the Weighted Visibility Network Based Framework. Section 5.4 comprises a detailed discussion about the experimental procedure and the results. Summary of the whole chapter is provided in section 5.5.

This chapter acquired some contents that are already published IEEE Access journal of volume 4 in 2016 (Supriya et al. 2016).

5.1 Introduction

Epilepsy is recognized as the common and chronic brain malady after the Alzheimer and stroke at worldwide. Epileptic patients are suffered from the anxiety of recurrent and erratic seizure attacks which also leads to epileptic attack or affect their quality of life as well as the life of their nearby friends and family members. The epileptic seizure attack sometimes brings the reason for short-term and long-term cognitive impairment and alternations in behavior (Meier et al. 2008). Therefore, automated epileptic seizure detection is the necessity of anti-seizure medicines, for the prevention of SUDEP and injuries allied to an epileptic seizure. EEG is a successful technique that plays a critical role to determine the individual's mental health for adequate detection of epilepsy disorder. Because epileptic seizure activity leaves their signature in the time-series EEG signals. In addition, EEG can easily measure the disproportionate, and synchronized pattern of the brain voltage that occurs during an epileptic attack (Siuly 2012). Because EEG data is available in time-series form therefore, time-series analysis techniques or methods are generally used for epilepsy detection. The existing epilepsy detection methods are present in a vast range from linear to non-linear techniques and mostly reliable on the traditional techniques (Hsu & Hsu 2005; Osterhage & Lehertz 2007; ; Vavadi, Ayatollahi & Mirzaei 2010; Hogan 2011; Musselman & Djurdjanovic 2012; Bellegdi & Arafat 2017;). However, these techniques are not sufficiently capable of perpetuating all the characteristics of EEG signals for example, non-stationary and chaotic nature (Campanharo et al. 2011). For that reason, there is requisite to develop new methods that can efficiently identify the epileptic activity from EEG signals and provide pertinent and important information.

The network-based EEG analysis is an alternate approach for visualizing the underlying as well as hidden patterns associated with time series (Zhang & Small 2006). The different properties of the network help in identify the different nature (such as chaotic or fractal behaviour) of time series. The statistical parameters of a network play a significant role in obtaining valuable information associated with time series data. In the recent era, the complex network has become the most nascent approach in the neuroscience for identifying the brain abnormalities (Stam & van Straaten 2012). The network-based techniques bring a new direction in the field of neuroscience for detecting the brain abnormalities via exploring the changes that occurs in the characteristic features of the named build from the EEG signals. EEG signals exhibit the multiple behaviors which are easy notable with the help of different attributes of the network as different EEG signals have different corresponding statistical features. The visibility graph algorithm (VGA) has the ability to inherit the various non-linear characteristics features of time series data (Lacasa et al. 2008). The VGA based time series analysis has the major limitation of not considering the link strength value among the vertices of the network. Whereas, all the links of the network have not the same strengths. As a result, after considering the limitation of the VGA based methods for epilepsy detection, this research study develops a new methodology for the analysis of EEG signals.

This research study presents an innovative methodology named Weighted Visibility Network Based Framework (WVNBF) based upon an innovative edge link method for classifying the seizure activity from non-seizure EEG signals. EEG signals originating from the epileptic seizure exhibit multi-fractal property due to the presence of non-linear behavior. An epileptic seizure can be identified from the WVNBF by extracting the comprehensive information from the structure of the WVNBF. The most significant approach is to decompose the WVNBF into collections of highly interlinked vertices named clusters and used an appropriate function that can accurately classify the Epileptic EEG signals. This research study considered that modularity and average weighted degree are the most effective feature of the network for this purpose.

The main reason for selecting these two features is that as these features have the ability to acquire the important and valuable information from the structural pattern of the network. The Weighted Visibility Network Based Framework is evaluated on four different research problems (test-groups) by using different machine learning classifiers. The experimentation with high classification outcomes for all the four different research problems proves the competence of the WVNBF. As per my knowledge, the link weight theory in the VGA with the modularity and AWD is totally novel in the field of epilepsy detection from EEG, and this WVNBF has not been applied in the past.

5.2 Importance of visibility graph-based network (VGBN) and the need for introducing the weight to the links of VGBN

A complex network is a subfield of complexity science that concerned with statistical physics, graph theory and also with data analysis. Currently, complex network is considered as an emergent approach for the qualitative and quantitative analysis of time-series data of EEG in term of fractality as well as long-range dependency. Among the several approaches of the complex network for studying the time series and its underlying dynamical information, VGBN is considered as one of more prominent approach. VGBN has the ability to characterize the EEG signals in terms of network theory by inheriting the dynamical properties of EEG data and representing in the form of statistical parameters of the network. Therefore, VGBN can utilize to attain valuable or significant information about EEG signals. Moreover, Liu et al. 2015, also reveal that VGBN exhibit noise robustness and not required any parameter selection (like time series to complex network method (Wang et al 2013) required threshold value and recurrence plot based network also be determined by threshold value (Thiel et al. 2004)). The state-of-the-art in the visibility graph also divulges that the topological invariant allied to VGBN play a significant role to understand the time series (EEG) data. As a result, VGBN can be considered as a competent technique in the scrutiny of EEG signals and also is the reason behind for used in this research study. The following paragraph demonstrates the different techniques based upon VGBN for the analysis of epileptic seizure detection or classification and their limitations as well.

Zhu, Li & Wen 2014 used VG algorithm to analyze the epileptic EEG signals. This research study used the public repository of Bonn University epileptic EEG database in which the EEG signal has a frequency of 173.61 Hz. Mean degree and Degree distribution features were used to distinguish between healthy, inter-ictal and seizure state of EEG signals. The Degree distribution features were able to satisfy the power law whereas, the Mean degree parameter of epilepsy activity showed remarkable variance from normal EEG signals when used LDA. On the other hand, the author used a small part of the whole database. In addition to this, the low degree nodes feature was not able to fully satisfy the power law. Tang et al. 2013, proposed the idea of using VG algorithm for epilepsy detection from high-frequency Electrocorticography (ECoG) signals with a frequency range of 100- to

200 Hz by using Butterworth Bandpass filter. The experimental data was collected from the Hospital of Peking University which comprises of ECoG signals of three epileptic patients. This research study focused on the comparative analysis between Graph index complexity (GIC), Sample Entropy and Lempel-Ziv Complexity parameters for the identification of Epileptic activity. The investigational results proved that the GIC feature was the most promising as compared to the other two features for the database used in the proposed study. Although, GIC was a good non-linear marker to detect epilepsy in case of high-frequency signals because it is sensitive to high-frequency fluctuations. However, GIC parameter also showed inconsistent results for some spatially independent channels. Hao, Chen & Zhao, 2016, have done the analysis and prediction of the epilepsy seizure attack by using the VG algorithm. The study was based on two features: Average Path Length and Clustering Coefficient. According to the research study, Average Path Length does not perform any significant output for the classification of the epileptic signals whereas the Clustering Coefficient feature produced quiet promising results. This research work was based on the small subset of Bonn university database. The drawback of this proposed methodology is that there were no performance measurements used for the evaluation of results. The research output was based on the visualization of the graph. As a result, it is hard to decide the classification performance of the proposed methodology without any performance evaluation measurement. (Olamat, Shams & Akan, 2017, developed a VG based algorithm to detect epilepsy seizure in which a particular size window was slide along the EEG signals to generate the segments. Then, each segment was considered as nodes and link between them was establish using VG algorithm. This research study claimed that the motifs of the complex network could be considered as a marker for the analysis of epileptic seizure activity. During seizure activity, the nerve tissue discharge was spatially extended which in turn increases the rate of connectivity among vertex-pairs and the presence rate of pre-eminent motifs. The proposed method included with the shortcoming of the limitation of window size. If the window sized above 10, then the proposed methodology was not able to provide valuable information about EEG signals. Wang et al. 2017, performed EEG signal analysis using VG, HVG and DVG approach to detect epileptic seizure in a patient with intellectual disability (ID) by collecting the data from Epilepsy Center Kempenhaeghe. The Mean degree (MD), Degree entropy (DE), Power-law degree power (DP), Assortativity coefficient (AC) and

Average shortest path length (SL) parameters were extracted in the feature extraction part after mapping time series EEG data into three different graph(VG , HVG and DVG) to perform statistical analysis and 5 fold cross-validation using Support Vector Machine (SVM) classifier with a Gaussian kernel. The major finding of this research was the graph parameters of HVG provided more promising results to discriminate epileptic EEG from the non-epileptic EEG signals as compared to VG and DVG. It was the author believed that the attained results might be not appropriate for automated epilepsy detection in actual clinical implementations. In addition to this, the seizure duration was very small in the EEG signals due to which the boundaries of the different stages of the seizure attack was difficult to distinguish.

The above-cited methods have some inadequacies. But the common and most important constraint of these techniques is about not considering an essential fact that links amongst the nodes of the network sustain strength and different links exhibit different values of strength. Moreover, the literature research in the discipline of network theory has also exposed that the binary network exhibit information only about the existence of links whereas, the preservation of information regarding the weight among the links of the vertices of network helps to determine more robust and reliable results (Polikar 2006). Because the presence of weight in the network links play a vital role in the determination of strong and potentially important links that exist in the network. For all of the above-mentioned reasons, this research study has developed a WVNBF to determine the weight of the links among different vertices of the network.

5.3 Data and Technique

This section provides extensive information regarding the WVNBF and the EEG data used in this research study. The structure diagram of the WVNBF is presented in Figure 5-1. Firstly, the EEG signals are transformed into Weighted Visibility Network. Subsequently, Statistical parameters of the WVN are extracted for classification, and finally, the performance is evaluated using standard parameters. Following is the detailed elaboration of each step.

5.3.1 Data

In this study, I have used the similar EEG database that I have used in my previous chapter 4 in section 4.3, i.e. http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3 which is made available by the Epilepsy Center stage 1 of Bonn, Germany. This EEG data is online available and encompassed with five different class of EEG signals with the class named: F, S, Z, O, and N. There are 100 channels of EEG signals in each class and each channel comprised with 4097 sample points with 173.61 sampling rate of 23.6s duration. The detailed information regarding this database is available at Andrzejak et al. 2001.

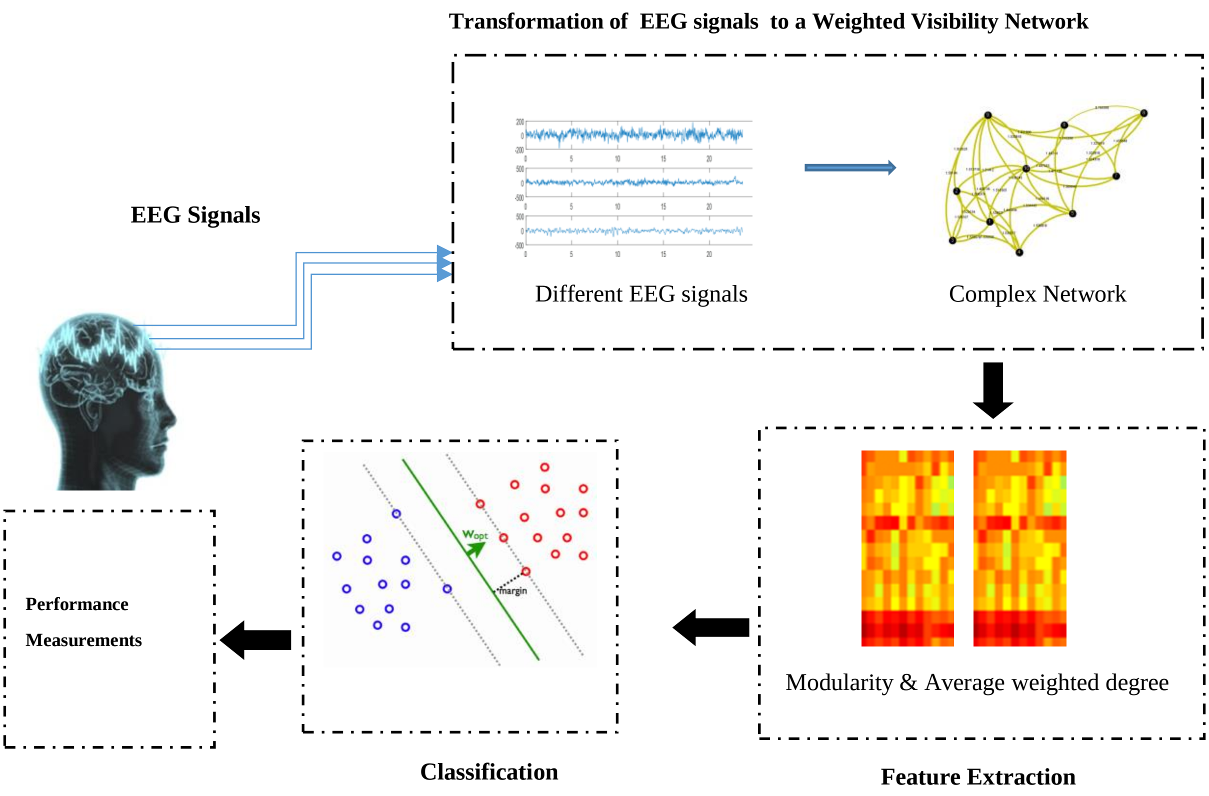


Figure 5-1: Schematic illustration of the general sequence of steps followed by the Weighted Visibility Network Based Framework.

5.3.2 Weighted Visibility Network Based Framework

The Weighted Visibility Network Based Framework comprised of four stages. The first stage is to transform the EEG signals to WVN. The second stage is the extraction of Modularity and AWD as statistical parameters of the network in the feature extraction. The third step is to evaluate the performance of the extracted features using supervised classifiers of the machine learning, and the final step is the use of different performance measurements for the valuation of the classification outcomes. Following is the more details about each step:

For the construction of WVN, the first phase is to consider that each sample point of the EEG signal is the vertex of the network. If G = (V, L) represent a network with V ={v_i };i=1,2,…n, is the set of n number of vertices and L = {l_i };i=1,2,…m , is the set of m number of links and E = { e_i };i =1,2,…n denotes an EEG time series signal then vertex v_i correspond to sample point e_i. The links among different vertices of the network are only possible if they satisfied the following equation which is based upon the visibility graph method.

$$v_b < v_a + (v_c - v_a)\frac{t_b - t_a}{t_c - t_a}, c > b > a \quad , \qquad (1)$$

where, v_a, v_b and v_c are the vertexes corresponding to the sample point e_a, e_b, and e_c of the time series EEG signal E and t_a, t_b and t_c are their equivalent time events. The more detailed information about the role of visibility graph for finding the links among the nodes is available at section 4.2.1. The next phase is to evaluate the weight of the links among the vertices of the network. This study introduces the following weight equation:

$$w_{ab} = arctan\frac{v_b - v_a}{t_b - t_a} \ , b > a \quad , \qquad (2)$$

where, w_{ab} represents the weight among the vertex v_a and v_b with their equivalent time events t_a and t_b. *arctan* denotes an inverse trigonometric function named arc tangent. This study consider the radian function value of the *arctan* for all the links weights of the network. In this research study, all the links are considered directional in nature i.e. link L_{12} hae direction from vertex v_1 to vertex v_2. In addition, the absolute value of the link's weight has been considered. After computing the links weight among all the vertices of the network, the final phase is the construction of WVNBF of an EEG signal. The below example demonstrates how WVNBF is constructed from the EEG signal and the significance of the links weight in the analysis of the EEG signal.

Example 1: Construction of the WVNBF from the time series EEG signal with value *E* = {10, 20, 30, 25, 50, 10, 70, 60, 65, 100} and associated equivalent time events *t* = {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}. Figure 5-2 illustrates the pictorial representation of the EEG signals *E* and elucidate how to calculate the value of link weight among different sample point. It can be seen from the Figure 5-2 that $E(t_1)$ =10 and $E(t_6)$ =10 exhibit same value whereas, at time interval t_7, there is fluctuation with the value $E(t_7)$ =70. As per the above-mentioned criteria for the construction of WVNBF from E. Each sample value of E is considered as the vertex of the network and links among all the vertices is computed using equation (1). The link weight among vertex between v_1 and v_7 is denoted as w_{17}, and w_{67} symbolize the link weight among vertex v_6 and v_7. The value of w_{17} and w_{67} is determined using equation (2), i.e.:

$$w_{17} = \left|arctan\frac{v_7 - v_1}{t_7 - t_1}\right| = \left|arctan\frac{70-10}{7-1}\right| = 1.471 = \alpha_1 \quad ; \tag{3}$$

$$w_{67} = \left|arctan\frac{v_7 - v_6}{t_7 - t_6}\right| = \left|arctan\frac{70-10}{7-6}\right| = 1.554 = \alpha_2 \quad . \tag{4}$$

Therefore, the above values of the w_{17} and w_{67} clearly demonstrate that the two vertices (v_1 and v_6) have similar value (sample value=10), but their link weight strength show a discrepancy when linked with third node (v_7). In addition, there is sudden fluctuation occurs at t_7 in Figure 5-2. Due to this sudden fluctuation, the link weight value increases. Therefore, the proposed link weight strength method helps to detect the epileptic seizure activity by identifying the sudden fluctuation and efficiently distinguish diverse categories of EEG signals. Table 5.1 depicts the vertices of the network correspond to the *E* time series EEG signal and the values associated with each vertex. Table 5.2 present the value of all the links of the network build from *E* and their associated weight value. L_{12} denotes the link among vertices v_1 and v_2. And computing all the links and their associated weight value, finally, the WVNBF is constructed. Figure 5-3 illustrates the WVNBF of *E* EEG signal.

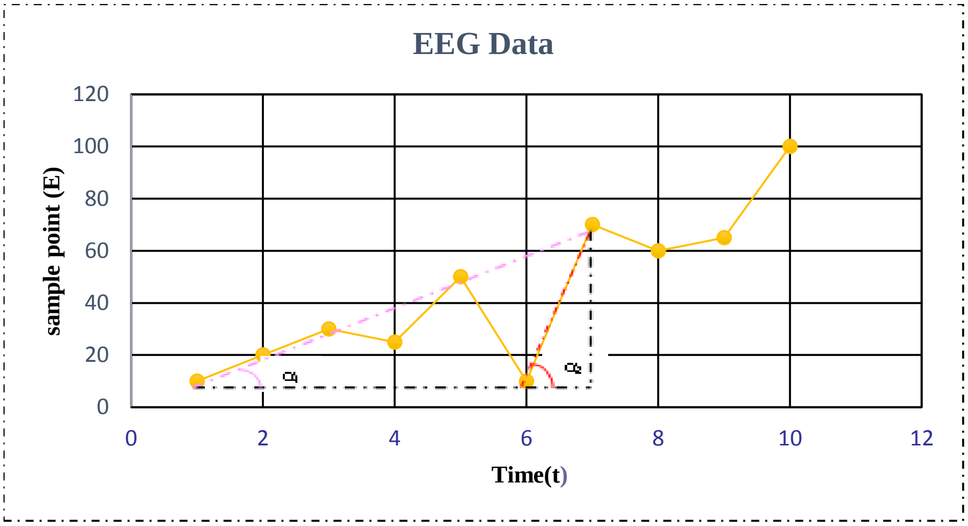


Figure 5-2: Illustration of EEG signals $E = \{10, 20, 30, 25, 50, 10, 70, 60, 65, 100\}$.

Table 5.1: The values associated with each vertex of the network correspond to the EEG signals E

EEG Signal E	Sample Points	Time	Vertices
e_1	100	t_1	v_1
e_2	124	t_2	v_2
e_3	153	t_3	v_3
e_4	185	t_4	v_4
e_5	210	t_5	v_5
e_6	220	t_6	v_6
e_7	216	t_7	v_7
e_8	222	t_8	v_8
e_9	240	t_9	v_9
e_{10}	265	t_{10}	v_{10}

Once the WVN of EEG signals is developed, the next step of the WVNBF is to implement the feature extraction process. Technically, feature extraction has a significant role in the classification of various categories of EEG signals. A feature is an identifiable measuring quantity acquired from the pattern and characterizes the distinctive properties. In feature extraction, the vast amount of EEG signal is simplified into vector sets named feature vectors

Table 5.2: Illustration of all the links and their associated weight value among different vertices of the a network of EEG signals E presented in Table 5.1

Links	Weight (w)	Links	Weight (w)	Links	Weight (w)
L_{12}	1.529	L_{13}	1.533	L_{19}	1.566
L_{14}	1.535	L_{15}	1.534	$L_{1\,10}$	1.516
L_{23}	1.536	L_{24}	1.538	L_{29}	1.510
$L_{2\,10}$	1.514	L_{78}	1.405	L_{89}	1.515
L_{34}	1.539	L_{39}	1.501	$L_{3\,10}$	1.508
L_{45}	1.530	L_{49}	1.480	$L_{4\,10}$	1.495
L_{56}	1.471	L_{58}	1.325	$L_{9\,10}$	1.530
$L_{5\,10}$	1.480	L_{59}	1.438	L_{79}	1.487
L_{67}	1.325	L_{68}	0.785	$L_{8\,10}$	1.524
$L_{6\,10}$	1.482	L_{69}	1.421	$L_{7\,10}$	1.509

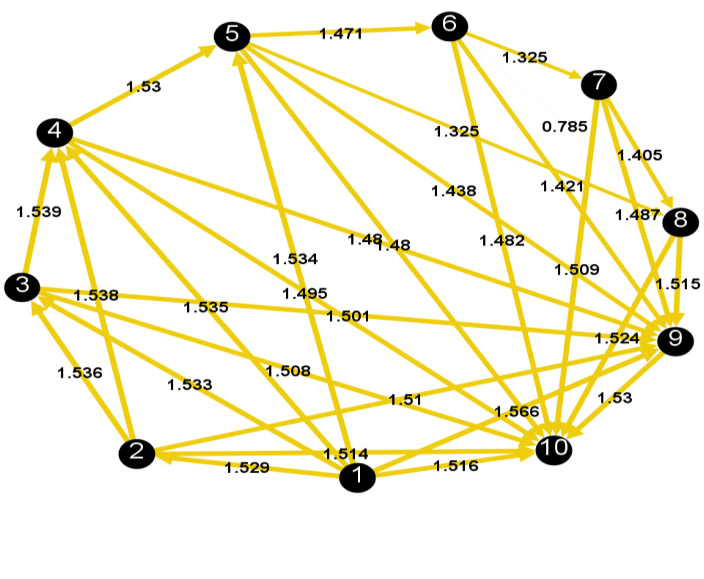


Figure 5-3: Illustration of WVNBF of EEG signal *E*.

on the principle of least possible loss of information present in the original signal. In this research, as an EEG signal is transformed to the WVN, therefore, graphical parameters are mined in the feature extraction part and used for the classification of different types of EEG signals. The measures of the network that are used as extracted features in this study for the epilepsy detection are named: Modularity (Q) and Average Weighted Degree (AWD).

Modularity is measured as a complexity function for a weighted graph to determine the quality of sub-division of the graph into the components or modules (Newman 2004). Newman was the first who introduce the idea of modularity. According to M. E. Newman, if M denotes the weighted adjacency matrix of the weighted network, then the modularity is measured as:

$$Q = \frac{1}{2w}\sum_{de}\left(M_{de} - \frac{k_d k_e}{2w}\right)\delta(C_d C_e) \quad . \tag{5}$$

where Q symbolize the modularity, M_{de} signify the weight of the links among vertex d and e. $k_d = \sum_e M_{de}$ represent the sum of the weight of links associated with the vertex e. C_d denotes the community in which vertex e lies and w. $\delta(C_d C_e)$ is 1 if $C_d = C_e$ else 0. This research work used the modularity feature that is developed by Blondel et al. 2008. As this method of modularity calculation is more simple and efficient to compute the community partition quality from a vast network. According to Blondel, when the module y combine into module z at that juncture the modularity gain is calculated as:

$$\Delta Q_{yz} = \left[\frac{\sum_{zn} + k_{y,zn}}{2w} - \left(\frac{\sum_{tot} + k_y}{2w}\right)^2\right] - \left[\frac{\sum_{zn}}{2w} - \left(\frac{\sum_{tot}}{2w}\right)^2 - \left(\frac{k_y}{2w}\right)^2\right] \quad , \tag{6}$$

where $\sum_{zn}$ symbolize the total weights of the links that come under module *z;* $\sum_{tot}$ represents the total weights of the links that are incident to the vertex in the module*;* $k_{y,zn}$denotes the sum of the weight of the links from the module *y* to module *z;* k_y signify the sum of the weights of the links incident to vertex *y; w* exemplifies the total weight of all the links in the graph. The modularity is a complex network feature which is used to measure the quality of the division of the complex network into clusters. The modularity measure developed by Blondel et al. 2008, is comprises of two stages. Firstly, recognize the small clusters with the help of optimization of modularity in a local manner. Secondly, in order to rebuild the new network, the vertices fit into the same clusters are combined together with vertices of the network are the communities. These two steps repeated iteratively until the maximum value of modularity is attained.

Average Weighted Degree (AWD) is the second parameter that is extracted in the feature extraction stage. If $A_{KxK} = \{a_{yz}\}$ symbolize an adjacency matrix with K number of vertices. Then A_{yz} =1 if the edge exists from the vertex y to z otherwise 0. The weighted degree of vertex y is the sum of the weights of all the edges linked to vertex y and is symbolized by (Antoniou & Tsompa 2008) :

$$wd_y = \sum_{z \in B(y)} w_{yz} , \tag{7}$$

where $B(y)$ indicates the neighborhood of vertex y and w_{yz} be a sign of the link weight among vertices y and z. The AWD is measured as the average of the total weights of the existing links on all the vertices in the WVNBF.

After extracting the modularity and average weighted degree features from the WVN of EEG signals, the next step of the WVNBF is to evaluate the significance of the extracted features by using classification. During classification, the unknown sets of observations named testing class are classified into their apposite group on the basis of known sets of observations named training class. Technically, a mathematical function is used in the classification named classifier, which predicts the true or apposite label of unknown observation based upon its training trialing. This research study has used two well-known machine learning classifiers named: SVM and KNN.

KNN is a supervised learning and non-parametric algorithm that classified the outcomes of new instance-query on the basis of the majority of the k-nearest neighbor class. The k-NN classification has been considered as one of the top ten data-mining methods (Zhang et al. 2017). It is robust to noise as well to large training samples. It performs the prediction by using local information which makes it adaptive in nature. It accomplishes the classification based upon the frequent class set of its nearest neighbors present at its feature space. The general steps of its algorithm are as follows:

1. The first step is the initialization, i.e. define k;
2. Calculate the test instance's distance from each training instance;
3. Sort the distances either in ascending order or descending order;
4. Then sorted distances are used to select the k-nearest neighbors;

5. Apply majority rule i.e., the label of test instance is predicted by using major class or group of its feature space with k most similar training instances.

There are several approaches to measure the distance in the k-NN algorithms such as Euclidean distance, Minkowsky distance, and Mahalanobis distance. The study has used the Euclidean distance. The euclidean distance among the vector a_s and b_t is calculated as following (Cover & Hart 1967):

$$d_{st} = \sqrt{\sum_{j=1}^{n} \left|a_{sj} - b_{tj}\right|^2} \quad , \tag{8}$$

A research study in the field of classification has proved that SVM is considered as a promising classifier in the discipline of biomedical science especially in the anomalies detections from EEG signals (Mehta & Lingayat 2007; Siuly & Li 2012). SVM has the excellent ability to handle the high dimensional as well as non-linear data. SVM is based upon hyper-planes for classification, therefore, provide enhanced empirical performance. Furthermore, efficient classification outcomes are attained by evading local minima. SVM is enriched with the special feature named classification based on the kernel function. This research used the three different kernel function of SVM for classifying EEG signals: Linear Kernel function, the radial basis kernel function and Polynomial kernel function. The more detailed information about the SVM mechanism or algorithm is available at section 4.2.3.1 of the previous chapter.

To evaluate the classification performance of SVM and k-NN, the sensitivity, specificity and accuracy measurements are used.

5.4 Evaluation of Results and Discussion

This section presents detailed information about the experimental results and discussion about them. The WVNBF is applied to the EEG Epileptic database described in section 5.2.1. The data is divided into four test-group which is shown in Table 5.3.

Table 5.3: Representation of EEG datasets into four test-group

Test-group	Data-set	Description
Group-I	Set A vs. Set E	EEG of healthy volunteers (eyes open) and EEG of epileptic seizure zone activity.
Group-II	Set B vs. Set E	EEG of healthy volunteers (eyes closed) and EEG of epileptic seizure zone activity.
Group-III	Set C vs. Set E	EEG of epilepsy patient during hippocampal formation area at seizure free zone region and EEG of epileptic seizure zone activity.
Group-IV	Set D vs. Set E	EEG of epilepsy patient non-seizure interval from the epileptogenic zone and EEG of epileptic seizure zone activity.

Tang et al. 2013, claimed that there is no advantage of using the large or great number of sample points during the transformation of time-series to network as the complexity quantification as well as the self- similarity in the nature of a network does not require many vertices. In addition, the segmented signals can also provide meaningful information. Moreover, the experimental outcomes of our previous chapter 4 also prove that the segmented and whole EEG signals do not show much difference in the classification performance. The segmentation of EEG signals also provides fast computation. By considering all of the above-mentioned points, WVNBF is implemented on the segmented EEG database. Every single channel of EEG signals with 4097 sample points is segmented into four parts in such a way that Seg1 contains 1024 sample point, Seg2 also contains 1024 sample point, Seg3 comprised of 1024 sample points, and Seg4 contain 1025 sample points. Each segmented part is associated with the data correspond to the 5.9-sec. These four segmented parts are further considered as four independent samples while implementing the WVNBF. As each set comprises of 100 channels and each channel contains 4097 sample points. After executing the segmentation task, there will be 400 independent segments for each set with 1024 sample points in each.

The first step of the WVNBF is to transform each segment into a WVN. Figure 5-4 illustrates the visualization of the WVNBF based upon the 50 sample points taken from one segment of set A. Whereas, Figure 5-5 illustrates the visualization of the WVNBF based upon the 50 sample points taken from one segment of set E.

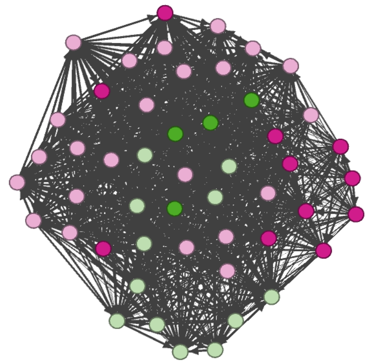


Figure 5-4: Illustration of WVNBF of EEG signal of a healthy person.

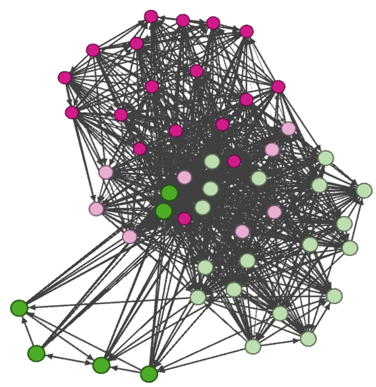


Figure 5-5: Illustration of WVNBF of EEG signal of an epileptic patient during seizure activity.

The different colours in the vertices of the above two figures represent the different communities in which they belong which is evaluated using the modularity algorithm. Moreover, both the figures also demonstrated that the WVNBF of different EEG signal exhibit different topological structure. The main objective of introducing the weight in the visibility graph-based network is to identify the sudden changes or fluctuations that happens during seizure activity. As in the period of seizure, the amplitude of the EEG signals shows immense changes or fluctuations. The proposed link weight technique helps to identify this sudden fluctuating changes because due to these sudden fluctuating changes the link weight values also start changes, which shows its effects on their corresponding statistical attributes or parameters of the WVNBF.

The second step of the WVNBF is to determine the modularity and AWD features from WVNBF of EEG datasets. Figure 5-6 illustrates the box-plot diagram of the feature named modularity corresponds to all the five sets with 400 segments in each set. It is clearly depicted in Figure 5-6 that, all of the five sets exhibit the different value of modularity. Moreover, set E shows the lowest value of the modularity parameter in comparison to the other four sets. The reason behind is that the value of the modularity parameter is evaluated by using Blondel method and should be lies in the range of [-1, 1]. The network has a stronger community structure if the value of modularity parameter is 1or close to 1. Therefore, Figure 5-6 depict that the sets A, D, B, and C exhibit a strong connection between their vertices inside the communities in comparison to Set E and also have a better division of the network. In short, during seizure activity, the modularity parameter starts to decreases.

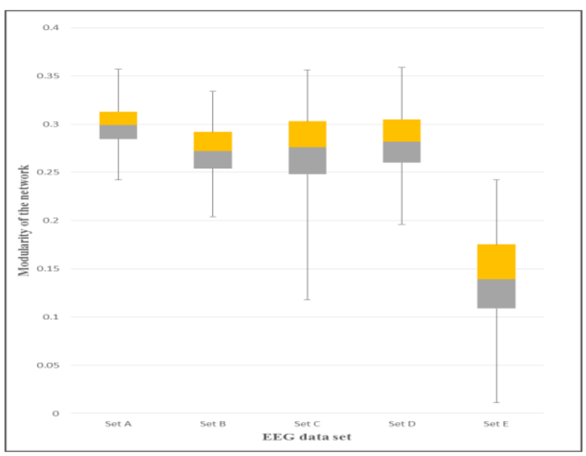


Figure 5-6: Illustration of the box-plot diagram of modularity feature of WVNBF of EEG signal of five sets.

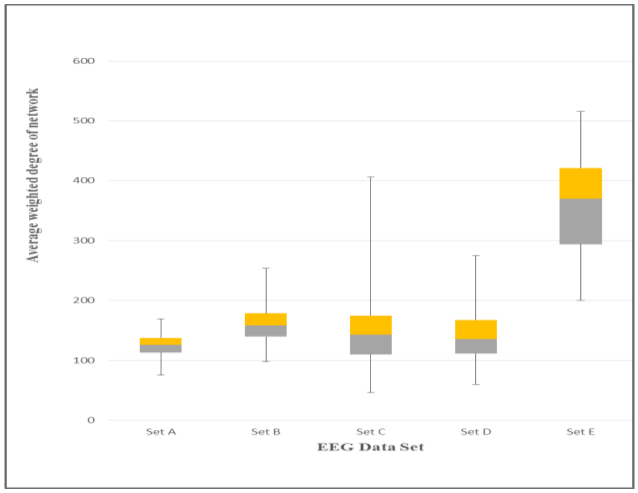


Figure 5-7: Illustration of the box-plot diagram of AWD feature of WVNBF of EEG signal of five sets.

Similarly, Figure 5-7. illustrates the box-plot diagram of the feature named AWD correspond to all the five sets and also depict that the set E exhibit the highest value of AWD parameter in comparison to the remaining four sets. The reason behind is that because of sudden fluctuation in the period of seizure, the value of links weights increases which in turn increase the AWD parameter. Therefore, the above analysis outcomes divulge that the Q and AWD parameters of the WVNBF of different EEG signal are capable of imitating their characteristic disparity and can play a key role in attaining the higher classification outcomes for different test-groups.

The performance of the extracted parameters: Q and AWD of WVNBF of different EEG signal are evaluated by applying the different classifiers. The classification performance of each feature is evaluated individually as well as also by combining the both (Q+AWD) parameters, and the experimental outcomes demonstrate that the combined feature sets provide high classification performances or results as compared to individual parameters. Therefore in this WVNBF, the classification task is implemented on the combined feature sets, i.e. Q+AWD. The classification is executed using SVM and k-NN classifier. The different categories of kernel functions available in SVM play a different and significant role. Therefore, this research has used three different kernel function of SVM named: SVM-linear, SVM-rbf, and SVM-poly. The choice of the k-value in k-NN classifier also affect the classification outcomes or performances. Therefore, different experiments have been executed to estimate the most apposite value of k. The experimental investigation discloses that k=3 and k=10 provide the most promising classification results for all the test-groups. Therefore, in this WVNBF, all the experiments study has used K=3 and K=10 value of k-NN classifier.

Table 5.4 presents the sensitivity performance of the classification on different test-groups by applying different classifiers on the combined feature set. It is visible from this table that all the five classifiers exhibit 100% classification performance in terms of sensitivity for the test-group-I. The classification sensitivity of Group-II for different classifiers are: 98.90 % and 97.30% in case of the k-NN classifier with k=3 and k=10; 99.46% for SVM-linear; 99.46% for SVM-rbf, and 99.47% in case of SVM-poly. For the Group-III, the sensitivity is: 96.50 % and 97.05% in case of the k-NN classifier with k=3 and k=10; 98.50% for SVM-linear; 98.50% for SVM-rbf, and 98% in case of SVM-poly. Whereas, the sensitivity of Group-IV are: 90.95% for SVM-rbf; 90.60% for SVM-poly; 92.30% for SVM-linear; 90.68% and 91.26% in case of k-NN classifier with k=3 and k=10. Table 5.4 clearly depicts that all the results of sensitivity performance for all the four groups are very close to each other whereas, SVM classifier provides high competence results as compared to the k-NN classifier.

Table 5.4: The classification performance in terms of sensitivity on different test-groups by applying different classifiers

Classifiers	**Classification Test-Group**			
	Group-I (%)	Group-II (%)	Group-III (%)	Group-IV (%)
k-NN(k=3)	100	98.90	96.50	90.68
k-NN(k=10)	100	97.30	97.05	91.26
SVM-linear	100	99.46	98.50	92.30
SVM-rbf	100	99.46	98.50	90.95
SVM-poly	100	99.47	98	90.60

Table 5.5 demonstrates the classification specificity of the combined feature set of WVNBF on different test-groups. It can be seen from this table that all the five classifiers exhibit 100% classification specificity for the test-group-I. The classification specificity of k-NN (k=3) classifier is 95.19% for test-group-II; 96.50% for test-group-III, and 92.34% for test-group-IV. The classification specificity of k-NN (k=10) classifier is 91.16% for test-

group-II; 98.97% for test-group-III, and 93.81% for test-group-IV. Similarly, the classification specificity for test-group-II is 93.86% in case of SVM-linear as well as SVM-rbf classifier; 98.50% in case of SVM-linear as well as SVM-rbf classifier; 90.24% for test-group-IV by SVM-linear and 95.26% by SVM-rbf. The classification specificity of SVM-poly classifier is: 95.21% for test-group-II; 98.49% for test-group-III and 96.25% for test-group-IV. It can be examined from Table 5.5 that the specificity results of all the classifiers are very close to each other for the four test-groups. Moreover, SVM-poly classifier has higher performance results for all the four test-groups in comparison to the remaining four classifiers.

Table 5.5: The classification specificity on different test-groups by applying different classifiers

Classifiers	**Classification Test-Group**			
	Group I	Group II	Group III	Group IV
k-NN (k=3)	100	95.19	96.50	92.34
k-NN (k=10)	100	91.16	98.97	93.81
SVM-linear	100	93.86	98.50	90.24
SVM-rbf	100	93.86	98.50	95.26
SVM-poly	100	95.21	98.49	96.25

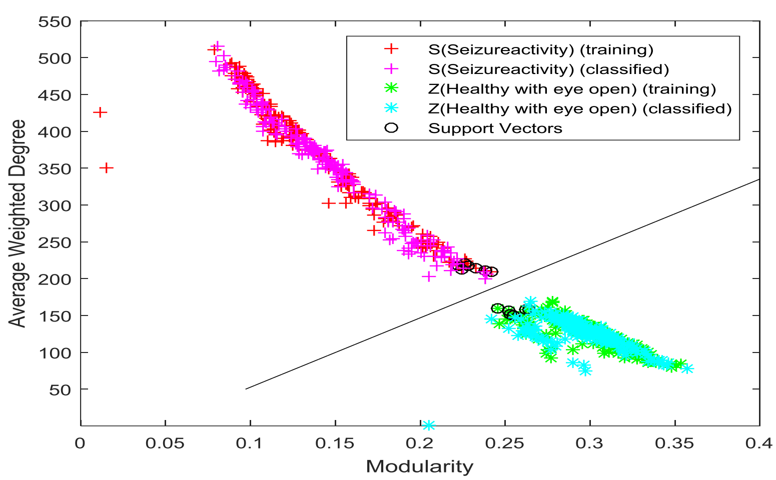
Table 5.6 demonstrates the accuracy performance of the combined feature set of WVNBF on the four test-groups while applying the different classifiers. The classification accuracy for the test-group-I is 100% in case of all the five classifiers. The classification accuracy of Group-II for different classifiers are: 93% and 94.25% in case of the k-NN classifier with k=3 and k=10; 96.50% for SVM-linear as well as for SVM-rbf, and 97.25% in case of SVM-poly. For the Group-III, the accuracy is: 96.50 % and 98% in case of the k-NN classifier with k=3 and k=10; 98.50% for SVM-linear as well as SVM-rbf, and 98.25% in case of SVM-poly. Whereas, the accuracy of Group-IV are: 91.25% for SVM-linear; 91.50% for k-NN classifier (k=3); 92.50% for k-NN classifier (k=10); 93% for SVM-rbf and 93.25% for SVM-poly classifier. Table 5.6 clearly depict that the accuracy outcomes of different classifiers are very close to each other in case of all the four test-groups. The SVM-poly classifier achieved the highest accuracy performance in comparison to other classifiers.

Table 5.6: The classification accuracy of different test-groups after applying the different classifiers

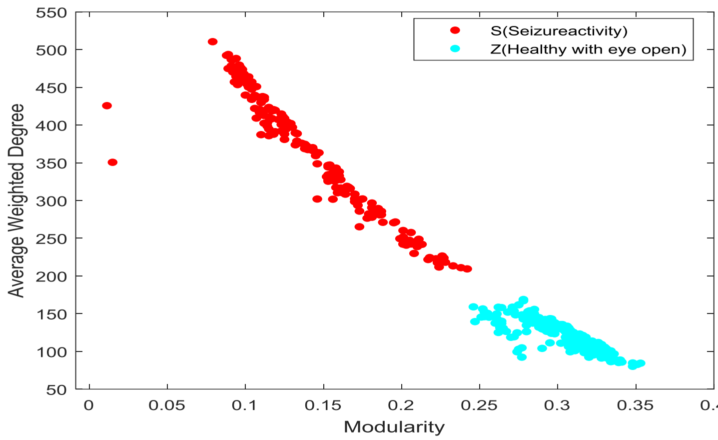
Classifiers	Classification Test-Group			
	Group I	Group II	Group III	Group IV
k-NN(k=3)	100	93	96.50	91.50
k-NN(k=10)	100	94.25	98	92.50
SVM-linear	100	96.50	98.50	91.25
SVM-rbf	100	96.50	98.50	93
SVM-poly	100	97.25	98.25	93.25

The classification specificity of Group-II for different classifiers are: 95.19% and 91.16% in case of the k-NN classifier with k=3 and k=10; 93.86% for SVM-linear as well as for SVM-rbf, and 95.21% in case of SVM-poly. For the Group-III, the sensitivity is: 96.50 % and 97.05% in case of the k-NN classifier with k=3 and k=10; 98.50% for SVM-linear; 98.50% for SVM-rbf, and 98% in case of SVM-poly. Whereas, the sensitivity of Group-IV are: 90.95% for SVM-rbf; 90.60% for SVM-poly; 92.30% for SVM-linear; 90.68% and 91.26% in case of k-NN classifier with k=3 and k=10. The classification performance of all the above four tables in terms of sensitivity, specificity and accuracy parameters for the test-group-I is 100% which clearly depict that the WVNBF is very much proficient at distinguishing the seizure activity from EEG signals associated with healthy persons.

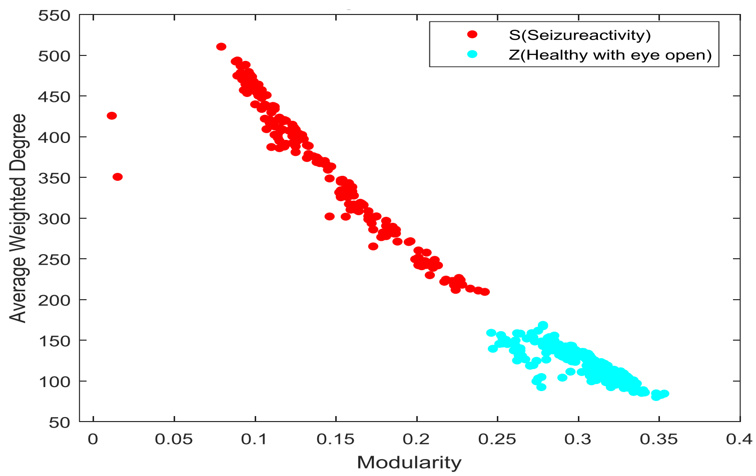
(a)



(b)


S(Seizureactivity)
Z(Healthy with eye open)
Average Weighted Degree
Modularity
550
500
450
400
350
300
250
200
150
100
50
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4

(c)


S(Seizureactivity)
Z(Healthy with eye open)
Average Weighted Degree
Modularity
550
500
450
400
350
300
250
200
150
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0
0.05
0.1
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0.2
0.25
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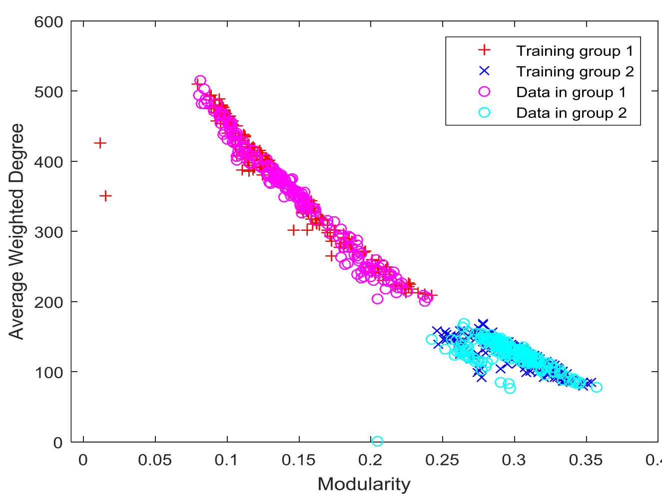
0.35
0.4

(d)


Training group 1
Training group 2
Data in group 1
Data in group 2
Average Weighted Degree
Modularity
600
500
400
300
200
100
0
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4

(e)

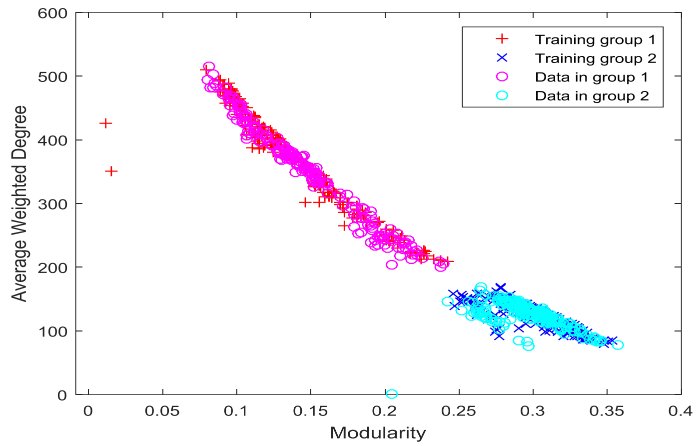


Figure 5-8: Illustration of the accuracy performance of different classifiers for the test-Group-I such as (a) SVM-linear, (b) SVM-RBF, (c) SVM-polynomial, (d) k-NN (k=3), and, (e) k-NN (k=10).

Figure 5-8 illustrates the classification accuracy with 100% performance for the test-Group-I with 1024 sample points after applying the different classifier such as Figure 5-8: (a) correspond to SVM-linear, (b) correspond to SVM-RBF, (c) correspond to SVM-polynomial, (d) correspond to k-NN (k=3), and, (e) correspond to k-NN (k=10). In Figure 5-8, the training group 1 represent the set E with seizure activity, and training group 2 signifies the set A with EEG signals of healthy persons (eyes open).

Table 5.7 reported the comparative analysis of the WVNBF with the different technique present in the state-of-the-art that has used similar Bonn EEG data for their experimentations. Table 5.7 clearly demonstrates that our WVNBF is the most promising with highest accuracy performance as compared to others.

Table 5.7: Comparison analysis of the WVNBF with the different techniques that are present in the state-of-the-art and also used the similar Bonn EEG data for their experimentations.

Classification Test-Group	Authors	Features	Accuracy (%)
Group I	Srinivasan, Eswaran & Sriraam 2005	5	99.6
	Guo et al. 2011	1	99.85
	Siuly, Li & Wen 2011	9	99.9
	Nicolaou & Georgiou 2012	1	93.42
	Zhu, Li & Wen 2014	2	99.0
	Husain & K.S 2014	-	99.8
	Ghayab et al. 2016	9	99.90
	Martinez-del-Rincon et al. 2017	1	99.85
	WVNBF	2	100
Group II	Siuly, Li & Wen 2011	9	93.6
	Zhu, Li & Wen 2014	2	97.0
	WVNBF	2	97.25
Group III	Siuly, Li & Wen 2011	9	96.20
	Zhu, Li & Wen 2014	2	98
	WVNBF	2	98.25
Group IV	Siuly, Li & Wen 2011	9	93.60
	Nicolaou & Georgiou 2012	1	83.13
	Kumar, Dewal & Anand 2012	-	93
	Zhu, Li & Wen 2014	2	93
	Riaz et al. 2016	6	93
	WVNBF	2	93.25

In conclusion, the above experimental analysis divulges that the two parameters of the WVNBF named: modularity and average weighted degree play a significant role in characterizing the underlying dynamics behavior or nature of different EEG signals. This research study also investigates that the chaotic nature of ictal EEG signals (signals in the period of epileptic seizure activity) makes them more difficult to partitions into different modules or clusters. The experimental results also demonstrate that among all the five classifiers the SVM-poly classifier is more efficient for providing higher performance results with the WVNBF.

5.5 Summary

This chapter introduces an innovative WVNBF for identifying or classifying the epileptic seizure. The WVNBF is developed by converting the EEG signals to WVN and introducing the link's weight in the form of arctan in it. The modularity feature and AWD feature are extracted from the WVNBF and evaluated using SVM and k-NN classifiers. The experimental investigation discloses that both the features help for identifying the sudden fluctuations in the EEG during seizure period. The links weight play the most important role in distinguishing the seizure EEG from non-seizure EEG signals. This research work explores that the WVNBF can be considered as the promising method for best describing the underlying dynamical pattern of EEG signals.

In the next chapter, a new method is introduced for analyzing the different types of EEG signals, and the method is tested on the Epileptic as well as on alcoholic EEG database.

CHAPTER 6

WEIGHTED HORIZONTAL VISIBILITY NETWORK IN THE ANALYSIS OF EEG SIGNALS

In chapter 5, a WVNBF has been developed for the automated detection of EEG signals and used the arctangent to calculate the weight of the links among all the nodes. The limitation of the arctangent based weight is that, its value lies between -1 to1 which will effect the value of the extracted parameters. To overcome this limitation, this chapter has used technique to calculate the link weight with the help of horizontal visibility graph. This chapter 6, presents an effective data analysis framework named based upon two different approaches named: horizontal visibility graph and machine learning methods for the analysis of EEG data. The Weighted Horizontal Visibility Network Based Framework (WHVNBF) is analyzing the different types of EEG signals by introducing the link weight technique in the horizontal visibility graph. An EEG signal is first mapped into the horizontal visibility network. After that, the link weight technique is introduced in it. Then the new network is named as weighted horizontal visibility network (WHVN). Two graph based measurements named: Average Weighted Degree, and Average degree are used for characterizing the EEG signals and are extracted in the parameter extraction process. The cross-validation approach with k=10 fold is used to test the effectiveness of the extracted parameters by applying the different classifiers named: Naive Bayes, linear and quadratic discriminant analysis, support vector machine with three different kernel function. The WHVNBF is tested on two different types of EEG database named: Epileptic EEG database and Alcohol-related EEG database. The experimental results demonstrate that the WHVNBF has the capability of analyzing and classifying the distinct types of EEG signals. This chapter is organized as: section 6.1 includes a detailed description of the horizontal visibility graph. Section 6.2 comprised of experimental data. Section 6.3 provides the detailed view of WHVNBF. The experimental results and discussion is present in section 6.4. Summary remarks are specified in Section 6.5.

This chapter acquired some contents that are already published in Lecture Notes in Computer Science Databases Theory and Applications, pp. 199–207, 2018 [245].

6.1 Horizontal Visibility Graph

Luque et al. 2009, proposed a Horizontal Visibility Graph (HVG) Algorithm which is easier to understand at a geometrical level as well as analytical level as compared to VG algorithm. HVG is based upon the comparison of the amplitude of data sample points of EEG signals. According to HVG, the link between two points only exist if there is a direct horizontal line between the points without being intersected by any other point. In order to comprehend the HVG graph, let's assume G (V, L) denotes a graph with V number of the vertex (node) and L number of links. A time series is denoted by Z= $\{Z_t\}$; (t=1,2,...z) is a time-series. According to Lacasa, if each data point (Z_i) of the time series Z is considered as a node, (v_i) of the graph G (V, L). The link among the nodes of the graph G (V, L) is only established if they satisfied the following equation:

$$v_i, v_j > v_k, \ \forall \ k \ |i < k < j \tag{1}$$

where, v_i, v_j and v_k are the nodes which relate to data points z_i, z_j, and z_k of, the time series Z and t_i, t_j and t_k are their corresponding time events. Figure 6-1 illustrate the HVG between different time series data points.

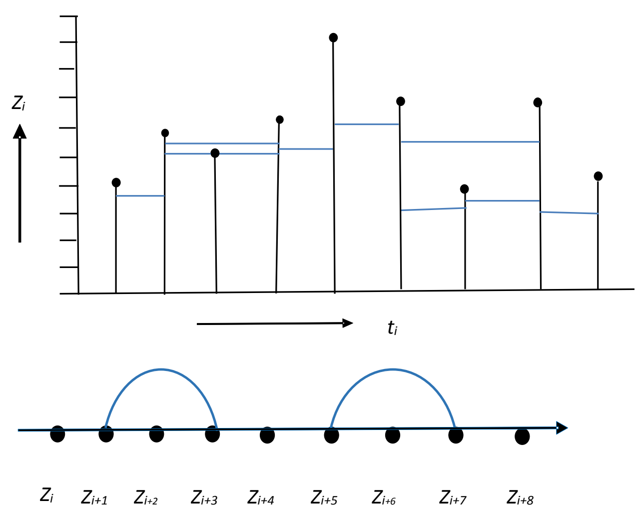


Figure 6-1: Illustration of the HVG between different time series data points.

The HVG technique has been used in the various field for the scientific purpose like in the analysis of heartbeat intervals (Madl 2016), financial time-series (Segberg & Skoglund 2017) and river flow fluctuations (Braga et al. 2016), etc. The following paragraphs provide information about some methods that have used the HVG technique in the analysis of EEG signals for the application of epilepsy detection or alcoholic data classification.

Liu et al. 2016, proposed a method to distinguish epileptic seizure activity from non-seizure activity by using the HVG algorithm and with the help of Degree Centrality parameter of a graph. The performance of the proposed methodology was check by the SVM classifier. It was claimed that Degree Centrality parameter of a HVG is a satisfactory marker for distinguishing ictal from inter-ictal EEG signals. The major limitation of the proposed methodology was that the Degree Centrality parameter provided low performance as the size of the data sample of EEG signal increases. Moreover, the classification performance results were not as high as compared to state of the art. Artameeyanant, Sultornsanee & Chamnongthai 2017, developed a feature extraction based methodology using HVG for epileptic seizure detection. Three classifiers named KNN, MLPNN, and SVM were used to analyze the ten statistical characteristics (Average degrees, average-clustering coefficient, transitivity, assortativity, density, central point dominance, closeness, average short path, the global efficiency, and network diameters) of a complex network. The authors achieved good classification accuracy results for the two databases used. However, the proposed methodology has some drawbacks as it is not appropriate for a large data sample of EEG signals. Furthermore, ten statistical characteristics of the complex network were used for classification which is time-consuming part as the number of feature sets increases, and the feature extraction part takes more computation time. Even the P-value test for the two databases showed a big difference in value for some characteristics and also was not quite promising. Liu et al. 2017, have done seizure analysis with the help HVG algorithm and proposed the idea of the new feature named Improved Degree Centrality (IDC) to classify different EEG signals and achieved 96.5% classification accuracy. The major problem of the proposed method is that the newly developed feature IDC is not able to provide high-performance results when combined with the classifiers. In addition to this, a small part of the database was used, and on the basis of that, it is hard to depict how the proposed methodology will behave when used to differentiate different types of EEG signals.

Zhu et al. 2014, proposed the HVG based method for classifying the EEG signals of alcoholic subjects from the controlled drinkers. Firstly, HVG based entropies (HVGEs), as well as sample entropy (SaE), are extracted from EEG signals. The selection of optimal channels for the identification of anomalies in alcoholics is based upon a statistical analysis technique. K-NN and SVM were used for classification. Only 87.5% accuracy was obtained after applying the 10-fold cross-validation algorithm for the classification of three HVG based features. After applying the optimal 13-dimension of horizontal visibility graph entropy features, 95.8% accuracy was attained. The above-cited methods of analyzing the EEG signals comprises of some inadequacies. But the common and major disadvantage of the above methods is the lack of link strength in their proposed methodologies. The preserving of link weight information on the network helps to obtain a more consistent result. The strength of the links plays an important role to analyze the crucial information of the network. Different nodes of the network connect with each other through different intensities. Therefore the WHVNBF has introduced the idea of link strength in the HVG.

6.2 Experimental data

This research work has used two different types of EEG databases named: Epileptic EEG database and Alcoholic EEG database. The epileptic EEG database used in this study is the same Bonn University EEG database that I have used in my previous chapter 4 and chapter 5. This study has used all the channels associated with five different sets (A to E) for this research work. The complete information about this database is presented in section 4.3 as well as also available at Andrzejak et al. 2001. The alcoholic EEG database is collected online from the Irvine Knowledge Discovery in Databases Archive UCI KDD, which is made available by the University of California (Bache & Lichman 2013). This database includes two different types of EEG recordings named as EEG recording of control subjects and EEG recording of alcoholic subjects, at sampling rate of 256 Hz. This database is acquired from 122 subjects, and 120 trails were completed by each subject. The complete information regarding this alcoholic EEG database is presented at Zhang et al. 1997.

6.3 WHVNBF Framework

This section elaborates the detailed description regarding the WHVNBF. Figure 6-2 illustrates the systematic drawing of the WHVNBF. This WHVNBF analysis the distinct EEG signals and comprised of four distinct processing modules. The first module is developed to transform the EEG signals into the WHVN. The second module includes information regarding different parameters of the network that are used for extracting the valuable feature of the WHVN. The third module comprised of different classification methods for efficiently categorized the feature set into their appropriate class. The fourth module is used to evaluate the performance of the WHVNBF on the basis of accuracy measurement.

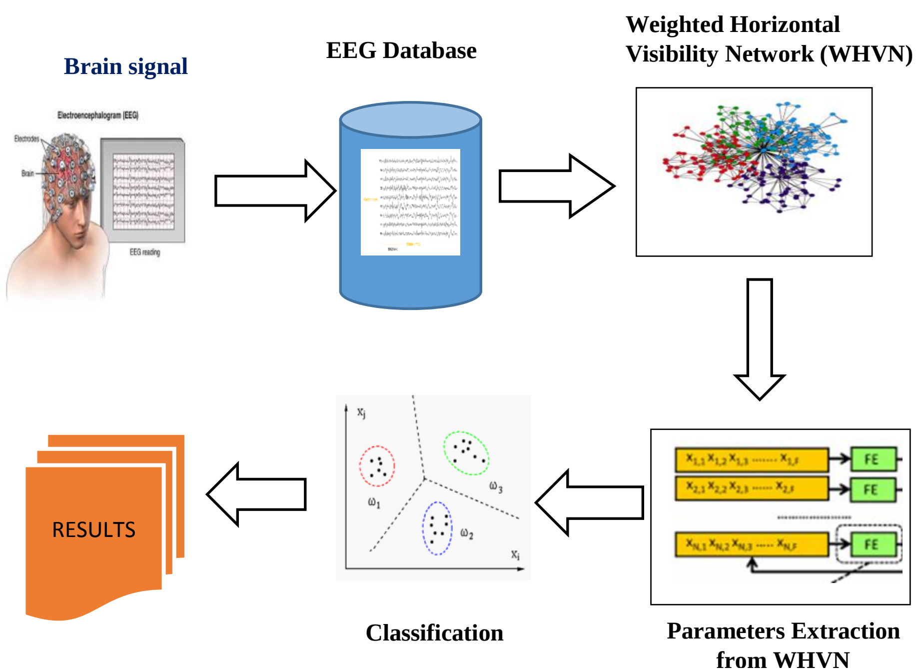


Figure 6-2: Illustration of the structural diagram of the WHVNBF.

6.3.1 Module I: Transform the EEG signals into the WHVN

To transform an EEG signal to WHVN, the first step is to consider that each data point of a time series EEG as a vertex of the HVG and the links between different vertices is calculated on the basis of the equation (1). Once the links are calculated among all the vertices, the next step is to find the link strength or link weight. The link weight is measured by using the following equation:

$$w_{ab} = \left|\frac{z_b - z_a}{t_b - t_a}\right|,\ a < b \quad , \tag{2}$$

Finally, WHVN is developed from the above steps. The horizontal visibility graph is used for the construction of WHVN for the below two reasons (Ahani et al. 2014):

1. The HVG has the ability to efficiently differentiate the random series form the chaotic ones;
2. The HVG is a geometrically simple plus analytically more solvable as compared to the visibility graph method.

6.3.2 Module II: Parameters Extraction from the WHVN

The parameter extraction is an indispensable step in the processing of pattern recognition as well as in machine learning. The main goal of the parameter extraction step is to extract a set of parameters or features from the WHVN based upon EEG signals. These parameters are informative relating to the desired or important properties of the EEG signals. Parameter extraction is also considered as a data rate reduction process because it helps to analyze the WHVNBF on the basis of a relatively small number of parameters without the loss of crucial information. This research study has used two parameters that are extracted from the WHVN named: Average weighted degree and Average degree. The Average Weighted Degree (AWD) of the WHVN is measured as the average of the total weights of the existing links on all the vertices in the WHVN. Whereas, the weighted degree of vertex *l* is the sum of the weights of all the links connected to vertex *l* and is symbolized as (Antoniou & Tsompa 2008):

$$wd_l = \sum_{z \in C(l)} w_{lz}\ , \tag{3}$$

where *C(y)* indicates the neighborhood of vertex *l* and w_{lz} be a sign of the link's weight among vertices *l* and *z.* The Average Degree (AD) of a WHVN *(*with *K* number of vertices and *L* number of links) is measured as the total number of links presents in set *L* in comparison to the number of vertices present in set K. It is already mentioned that the weight of the links are directional in nature and therefore the degree is counted in one direction. The Average Degree of a WHVN is measured as:

$$AD = \frac{|L|}{|K|} \tag{4}$$

6.3.3 Module III: Classification of the Extracted Parameters

In the pattern recognition approach, a particular pattern is studied for determining the class membership of that pattern. A pattern is encompassed of measuring vectors, and the vectors are allied with one of a particular class among the set of classes. Therefore, classification is also considered as the main theme of pattern recognition. The classifier associated with the classification task is derived with the help of training. The specific approach of classification is more appropriate for identifying the characteristics of the data and also for classifying the data. The preeminent classification approach is responsible for producing stable and consistent results. Therefore, the WHVNBF is tested on the different classifiers: naïve bayes, quadratic and linear discriminant analysis, and support vector machine with different types of kernel functions. The reason for using these classifiers is: the naïve bayes (NB) classifier have the ability to quickly converge in case of the conditional independence hypothesis, therefore required less training data. The SVM provides the high accuracy results in regards to overfitting whereas, to evaluate the adequacy of the classification and to achieve fast and accurate results, the LDA and QDA classifiers are implemented. The detailed information regarding all the above-mentioned classifiers is presented in Drotár & Smékal 2014.

6.3.4 Module IV: Performance Analysis

The performance of the extracted feature set is evaluated by using the different classifiers by measuring the accuracy parameter for all the different test groups of the classification process.

6.4 Results and Discussion

This section investigates the competency and consistency of the WHVNBF on two distinct EEG databases (Epileptic and Alcohol EEG database). MATLAB R2016b (with Version 9.1) is used for executing all the experimentations. 10-fold cross-validation was used to attain the consistent and reliable outcomes of all the experiments.

6.4.1 Experimental outcomes allied to Epileptic EEG data

The Epileptic database is distributed into the following four test-groups: which is shown in Table 5.3.

1. Group-I: Set Z vs. Set S
2. Group-II: Set O vs. Set S
3. Group-III: Set N vs. Set S
4. Group-IV: Set F vs. Set S

As per the WHVNBF, the different sets of the EEG databases are first transformed to WHVN and after that two distinct parameters are extracted from the WHVN. Figure 6-3 elucidates the boxplot diagram of AWD parameter associated with the 5 different sets of Epileptic database after applying the WHVNBF. Figure 6-3 depicts that the seizure activity (set S) shows clearly great deviation and have increased value of the AWD parameter in case of WHVN. Similarly, Figure 6-4 depicts the boxplot diagram of AD parameter associated with the 5 different sets of Epileptic database after applying the WHVNBF. Figure 6-4 illustrates that different sets of EEG signals exhibit different values of AD parameter. After extracting the two parameters, the next steps are to evaluate the performance of the two parameters using different classifiers.

Table 6.1 demonstrates the accuracy outcomes of the classification process for the Epilepsy database with different classifiers on the combined feature vector set (AWD+AD). Table 6.1 depicts that for the test Group-I, the accuracy of the different classifiers is 93% for LDA, 97% for SVM-linear, 95.50% for SVM-rbf and 100% for NB, QDA, and SVM-poly. For the test Group-II, the accuracy of the different classifiers is 93% for LDA, 94% for SVM-linear, 95% for SVM-rbf and 97% for NB, QDA, and SVM-poly. Similarly, for the test Group-III, the accuracy of the different classifiers is 89.50% for LDA, 95.50% for SVM-linear, 95% for SVM-rbf and 97.50% for NB, 98% for QDA and 98.50% for SVM-poly. For

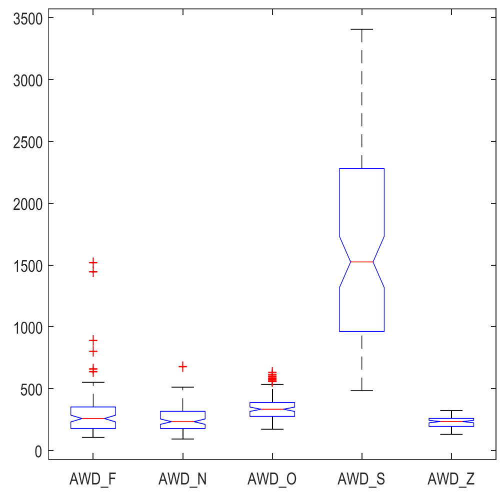


Figure 6-3: Boxplot diagram of AWD parameter allied to different sets of Epilepsy data.

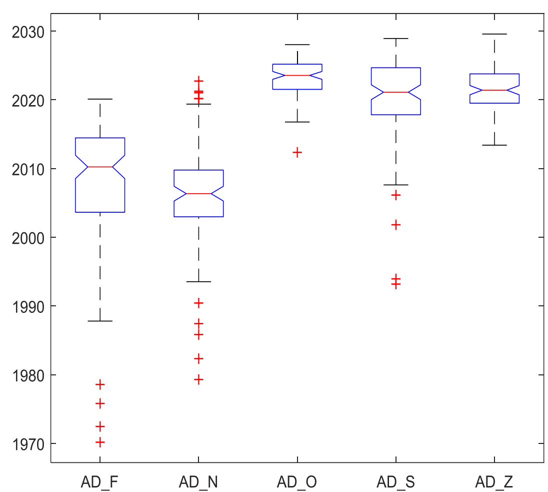


Figure 6-4: Boxplot diagram of AD parameter allied to different sets of Epilepsy data.

the test Group-IV, the accuracy of the different classifiers is 87% for LDA, 92% for SVM-linear, 92.50% for SVM-rbf and 91.50% for NB, 94.50% for QDA and 95.50% for SVM-poly. The experimental evaluation of the WHVNBF for different test groups with different classifiers demonstrates that the results of all the applied classifiers are very close to each other. But the SVM-poly provides the highest accuracy results for all the four test group problems as compared to others.

Table 6.1: The accuracy outcomes of the classification process for the different classifiers in the case of Epilepsy data.

Test-Groups	Naive Bayes (%)	LDA (%)	QDA (%)	SVM Linear (%)	SVM Rbf (%)	SVM Poly (%)
Group-I	100	93	100	97	95.5	100
Group-II	97	93	97	94	95	97
Group-III	97.50	89.50	98	95.50	95	98.50
Group-IV	91.50	87	94.50	92	92.50	95.50

6.4.2 Experimental outcomes for Alcoholic EEG data

This section includes the experimental outcomes of the WHVNBF with alcoholic EEG data. Figure 6.5 illustrates the boxplot diagram of AWD parameter associated with the different sets of alcoholic EEG data after applying the WHVNBF. Figure 6.5 demonstrates that in the case of alcoholic EEG signals, the AWD parameter exhibit low value as compared to the non-alcoholic-healthy subject. Similarly, Figure 6.6 illustrates the boxplot diagram of AD parameter associated with the different sets of alcoholic EEG data after applying the WHVNBF. Figure 6.6 shows that in the case of alcoholic EEG signals, the AD parameter exhibit very low value as compared to the non-alcoholic-healthy subject.

Table 6.2 demonstrates the accuracy outcomes of the classification process for the Alcoholic EEG data with different classifiers on the combined feature vector set (AWD+AD). Table 6.2 depicts that the accuracy of the different classifiers is 84.21% for LDA, 88.33% for SVM-linear, 87.08% for QDA, 89.17% for SVM-rbf and 87.08% for NB, and 90.42% for SVM-poly. The experimental outcomes of Table 6.2 elaborate that the SVM-poly provides the highest accuracy in comparison to other classifiers. Table 6.3 also depict the comparative analysis of the proposed framework with some existing techniques. And also proves that the accuracy output of proposed framework is very close to the existing techniques.

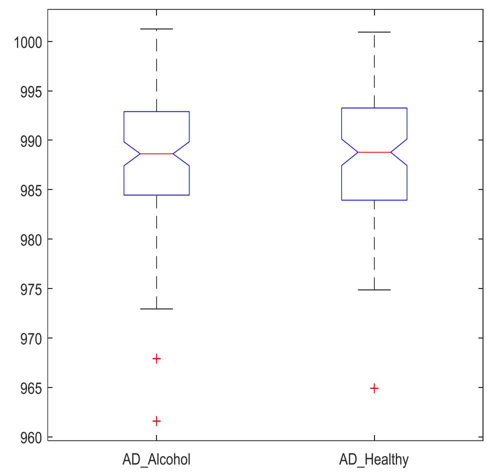


Figure 6.5: Boxplot diagram of AWD parameter allied to different sets of Alcoholic data.

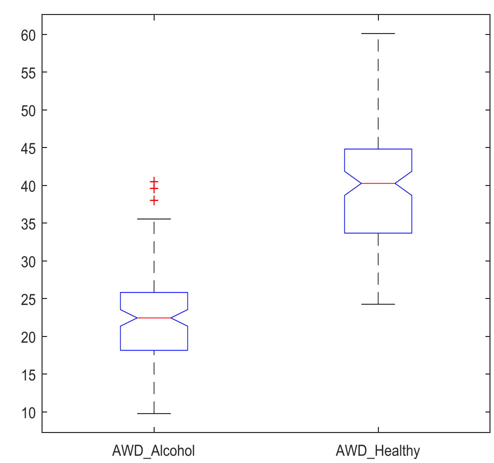


Figure 6.6: Boxplot diagram of AD parameter allied to different sets of Alcoholic data.

Table 6.2: The accuracy outcomes of the classification process for the different classifiers in the case of Alcoholic data.

Test-Group	Naive Bayes (%)	LDA (%)	QDA (%)	SVM Linear (%)	SVM Rbf (%)	SVM Poly (%)
Alcohol-EEG vs. Non-Alcoholic EEG	87.08	84.21	87.08	88.33	89.17	90.42

Table 6.3: Comparison analysis of the WHVNBF with the different techniques that are present in the state-of-the-art and have used SVM Classifier

Classification Test-Group	Authors	Accuracy (%)
Alcohol-EEG vs. Non-Alcoholic EEG	Acharya et al. 2012	91.70
	Zhu et al. 2014	95.80
	WHVNBF	90.42

6.5 Summary

This chapter presents an innovative framework for effectively analyzing the distinct EEG database with the help of HVG approach. The experimental outcomes of this study proved that the idea of introducing the link weight in the horizontal visibility graph plays a significant role in classifying the distinct EEG signals. Moreover, the average weighted degree, as well as average degree parameters of the graph, are also an important feature for characterizing the underlying dynamical properties of the WHVN. The efficiency of the WHVNBF is assessed by using six classification algorithms. The research results of classification also prove the proficiency of the WHVNBF. The next chapter includes a technique for classifying sleep stage data.

CHAPTER 7

GRAPH BASED TECHNIQUE FOR THE ANALYSIS OF EEG SLEEP STAGES

The current available methodologies for the identification of various sleep states present in EEG data are based upon the time as well as on frequency parameters. Whereas, the non-stationary nature of EEG data makes the existing approaches less reliable as the present available approaches are not able in providing efficient results if the signal suffers from noise. This chapter 7, presents a graph based automated technique for the identification of different sleep stages from the single-channel EEG data. The aim of this research study is to develop a Weighted Graph Based Technique (WGBT), based upon the visibility theorem for classifying different sleep stages. The validity corresponds to the noise robustness of the WGBT is evaluated by performing the simulation analysis using the Lorenz-series and Rossler-series. For the experimentation, two different rules named: American Academy of Sleep Medicine (AASM) rules and Rechtschaffen and Kales (R&K) were used for the scoring of EEG database. The higher accuracy performance for classification of distinct sleep states present in the EEG data proves that by introducing the link weight in the graph theory helps to achieve more competent outcomes as compared to the existing technique in the state-of-the-art. This chapter is schematized as: section 7.1 covers the introduction. Section 7.2 explains about the EEG database used for the experimentation. Section 7.3 provides a detailed information regarding the WGBT. Section 7.4 includes the simulation analysis for the noise robustness of the WGBT using the lorenz and rossler time series. Section 7.5 gives detailed information about the experimental outcomes, discussion, and comparison of the WGBT with the existing state-of-art approaches. Summary of the chapter is presented in section 7.6.

This chapter acquired some contents that are already published in IEEE TETCI journal, pp 1-112018 (Supriya et al. 2018).

7.1 Introduction

Sleep EEG data classification is an exigent and emergent topic of research interest in the healthcare community at presently. If different sleep stages are identified efficiently from the EEG signals then the diagnosis of various sleep maladies (such as insomnia, obstructive sleep apnoea, snoring, narcolepsy, sleep hypoventilation, and bruxism, etc.) become more easy and appropriately (Saper et al. 2010). As a result, different organizations named: The American Psychiatric Association (APA), World Health Organization (WHO), and other professional sleep societies are actively participating in the research of sleep disorder identification from EEG system (Morin & Espie, 2012). The research report also demonstrates that the sleepiness and drier fatigue is also the main reasons behind the fatal vehicle accidents upto 10 to 15% (Ohayon 2011). It is foreseeable that in 2020, the death rate because of vehicle-accidents will be 2.3 million at the world level and around 230,000 to 345,000 people will die because of the cause of sleepiness or tiredness (Ferrie et al. 2011). In general, the polysomnography (PSG) technique used for the identification of sleep anomalies. A PSG includes the data that is acquired from EEG, Electrooculogram, Electromyogram, and Electrocardiogram. EEG data epitomize the crucial information regarding the brain activities and majority of the sleep disorders leaves their signature of presence in EEG signals. Henceforth, the detection of distinct sleep stages from the EEG data is becoming the subject of continuous research interest.

This chapter has used the Sleep-EDF database (of EEG signals) for analyzing the distinct sleep stages. The analysis of EEG data for the identification of sleep stages may improve the detection and diagnosis of sleep disorders. Distinct approaches are developed for analysis the sleep EEG data such as correlation dimension as well as fractal exponent approach for sleep staging (Chouvarda et al. 2011), feature weighting method based upon the k-means clustering (Güneş, Polat & Yosunkaya 2010), non-linear measurement approach such as largest Lyapunov entropy, approximate entropy and Hurst exponent (Acharya et al. 2005), time-frequency based approach using random forest classifier (Fraiwan et al. 2012), complementary cross-frequency based coupling estimates approach (Dimitriadis, Salis & Linden 2018). The present techniques are less reliable as the present available approaches are not able to provide efficient results if the signal suffers from noise. By considering the above points, this research study developed a WGBT for automated classification of sleep stage data. Because network theory plays a decisive role in the neuroscience discipline for extracting the significant information from EEG data to identify the abnormalities (He & Evans 2010; Li et al. 2013).

This study used network based approach to perform the computational experiments. Firstly, each signals of EEG data is segmented to perform the fast computational experiments and after that each segment is assumed as the vertices and joining links are calculated using visibility network approach. The link strength formula is used to calculate the link strength, and then a weighted visibility network (WVN) is formed. From the WVN, average weighted degree, modularity and average degree parameters are used to extract the coherence characteristics of WVN and after that, KNN classifier is applied. The WGBT is verified on the benchmark Sleep-EEG database (Rechtschaffen 1968).

Zhu, Li & Wen 2014, applied a network-based method for the identification of sleep states, and have not considered the evaluation of the link weight in their proposed method. Whereas, the link weight performs an indispensable task in network-based investigation of a system. Because the different links have different value of the link strengths and all the vertices of a WG are linked with each other on the basis of the associated link strength. As a result, a WG approach is effective to identify the sudden fluctuations happening in EEG data allied to sleep behavior. The key benefit of WGBT over the present state-of-art in the cataloging of different sleep stages is that: this study used a link strength method and this link strength method is new as well as inventive in the classification of EEG sleep data. Additionally, the link strength helps in the easy recognition of the vacillation in EEG data using the three parameters. Because different classes of EEG data exhibit variations in their links weight, as a result, the parameters sets allied to the link weights will demonstrate a variation in their values.

The objective of this research study is to examine how the link strength method in network theory assistances for multi-class classification problem as classification of EEG data of sleep is a multi-class categorization problem. Furthermore, in this study, I want to evaluate the consequence of sorting the vector sets (of parameters) on the k-NN classifier. The main innovation of this research study is the use of modularity, AWD and average degree parameters in the analysis of sleep EEG at first time. The experimentation results substantiate that the WGBT is competence to the present techniques for two different standard groups of sleep scoring named: R&Ks and AASM with 97.91% and 97.93% of accuracy outcomes of the classification. Furthermore, it is also explored that by combining the feature vector sets, more suitable results are achieved in comparison to the individual feature vector. It is expected that that this WGBT will enhance the EEG sleep related diseases diagnosis and treatments in consistent manner and reduces the cost as well as time.

7.2 Experimental Sleep EEG

To measure the effectiveness of the WGBT, I used Sleep-EEG database that is online present (http://www.physionet.org/physiobank/database/sleep-edf) and available at the databank repository (Kemp et al. 2000). This EEG data is the recordings collected from 8 Caucasian males and females having the age group of 21–35 years and without the usage of any medicine. This research used two standard principle of sleep stage scoring named: R&Ks recommendations and AASM standards. According to R&Ks (Rechtschaffen 1968), the sleep periods have 6 distinct stages named: awake-fullness (awake), sleep-stage 1 (S1), sleep-stage 2 (S2), sleep-stage 3 (S3), sleep -4 (S4), and rapid-eye-movement (REM). Moreover, sleep stages S1, S2, S3, and S4 are signified as Non-Rapid-Eye-Movement (NREM). According to AASM recommendations, the sleep stages named S3 and S4 (of R&Ks) are joined into a single state, identified as slow-wave-sleep (SWS) or deep-sleep (Iber et al., 2007). The recordings encompass horizontal electrooculography, Fpz-Cz/Pz-Oz EEG. The EEG data is selected carefully and based on Pz-Oz channel in the time-interval of 00:00 a.m. to 5:00 a.m. The sampling rate of the recording is 100Hz and the length for each epoch are 30s and includes 3000 data sample points.

7.3 WGBT Technique

This section designed an effective technique for analyzing and categorization of different sleep states in the EEG data. The structural representation of the WGBT is revealed in Figure 7-1. As the Figure 7-1 portrayed that the WGBT comprises with four sub-phases: (a) Map the EEG data to WVN (b) Mining of the coherence characteristics, (c) Taxonomy, (d) The performance is evaluated for decision making.

For the mapping of EEG data to WGBT, I have used the VG theorem and link weight technique. Afterward, the coherence parameters of the WVN named: AD, modularity, and

AWD are mined in the parameter extraction process. Then, taxonomy is comprised with two stages: (i) Firstly, the extracted parameter vector sets are arranged in particular sequence such as ascending or descending. The parameter's values located at odd location are utilize for train the classifier and the remaining value is used for the testing. (ii) Next, the acquired parameter set is evaluating using k-NN classifcation. In this research, I have used the k-NN classifier because k-NN is very instinctive to label the known values on the basis of their similarity among observations in the training set.

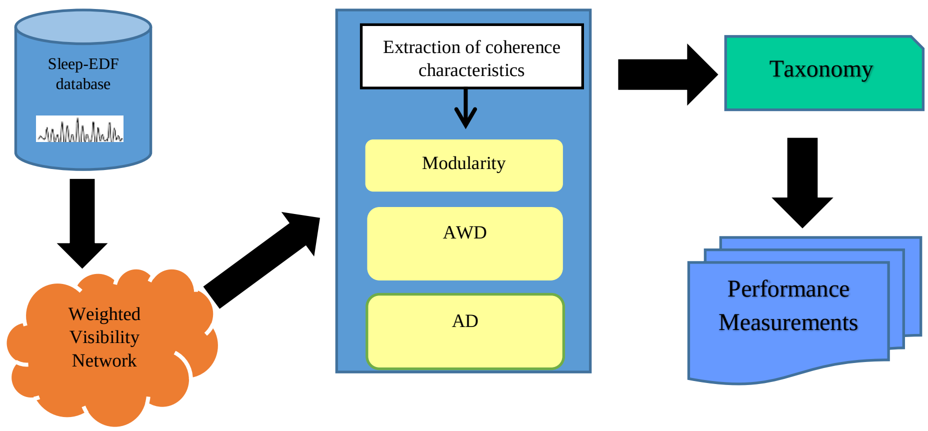


Figure 7-1: The structured representation of WGBT.

Mapping of EEG data to WVN

I have used the lucasa Visibility algorithm in order to map the EEG data to visibility network [110]. The main motive for the use of visibility algorithm (VA) in this research work is that as the VA is a significant approach for inheriting the dynamical features of the data that is available in time series form (EEG data is in the time series form). In addition, VA exhibits the property of noise robustness [205], as well as does not depend on the choice of selecting the value of some parameters (like as the selection of threshold value in case of TSCN [54] as well as recurrence network [249]). According to R. Polikar [195], the more reliable outcomes can be achieved by conserving the information regarding the weight in the graph. For that reason, I introduced the weight in the VA and given the name WVN. The weight feature plays a significant role for analyzing the vital or weak links present in the EEG network. And this analysis can further be helpful for determining the distinct types of dynamical underlying properties present in the EEG recording. The WVN is built on the basis of the following sequence of steps:

1. If *G(V, L)* signifies a network with *V* number of vertices and *L* number of links and a time series is denoted as $\{Z=Z_t;\ t=1,2,\ldots N\}$. Then it is considered that the mapping between Z_t and G(V, L) is possible by assuming that each data sample of Z_i as a vertex v_i of *G(V, L)*.
2. All the links present in *G(V, L)* is based upon the following VA equation

$$v_o < v_n + (v_p - v_n)\frac{t_o - t_n}{t_p - t_n}, p > o > n \quad , \tag{1}$$

where, v_n, v_o, and v_p are the vertices corresponds to the sample z_n, z_o, and z_p with the associated time t_n, t_o, and t_p.

The VA is developed on the principle of Euclidean plane with each vertex signifies the point's position and the links among the allied vertices is only exist if there is visibility amongst them. For clear understanding regarding the construction of VA from EEG signals, a small sample of EEG (Z) of Fpz-Cz channel with ten data sample has been taken, i.e., Z = {29.2674, 34.0535, 15.8256, 35.0718, 19.8989, 9.5121, 8.6974, 11.8542, 9.7158, -4.0315). Table 7.1 represents the EEG data sample and their corresponding vertices. Similarly, Table 7.2 represents the corresponding links value of the vertices presented in Table 7.1.

Table 7.1: EEG data sample and their corresponding vertices.

Small sample EEG	**Value of sample points**	**Vertices (v)**
Z_1	29.2674	V_1
Z_2	34.0535	V_2
Z_3	15.8256	V_3
Z_4	35.0718	V_4
Z_5	19.8989	V_5
Z_6	9.5121	V_6
Z_7	8.6974	V_7
Z_8	11.8542	V_8
Z_9	9.7158	V_9
Z_{10}	-4.0315	V_{10}

Table 7.2: Example of links corresponds to different vertices present in Table 7.1

Edges	Edges	Edges
L_{12}	$L_{7\,10}$	L_{18}
L_{16}	L_{17}	L_{25}
L_{23}	L_{24}	L_{29}
L_{26}	L_{27}	L_{28}
$L_{2\,10}$	L_{38}	L_{39}
L_{36}	L_{37}	$L_{3\,10}$
L_{46}	L_{47}	L_{48}
L_{34}	L_{58}	L_{45}
$L_{5\,10}$	L_{49}	$L_{4\,10}$
L_{68}	L_{56}	L_{67}
$L_{6\,10}$	L_{89}	$L_{8\,10}$
L_{78}	$L_{9\,10}$	

3. The next step is to calculate the weight of all the links presents in the G(V,L) which is computed from the succeeding equation (2):

$$w_{no} = abs\left(\frac{v_o - v_n}{v_o - v_n}\right), o > n \qquad (2)$$

Where w_{no} denotes the weight of the link connecting the vertices v_n and v_o and exhibit direction from n to o.

4. The final step is that WVN is constructed from the above three steps. Fig 7-3 illustrates the WVN from the small sample value of EEG data i.e. E={1.049, -3.079, -6.122, -4.65, -4.453, -1.509, -2.883, -3.276, -2.294, 1.442,3.993, 6.741, 8.606, 8.017, 5.662, 3.601, 4.778, 5.76, 2.619, 2.717, 3.601, 4.582, 7.428, 12.925, 15.476, 16.163, 13.612, 7.527, 3.012, 4.68, 5.564, 2.227, 3.797, 3.895, 2.717, -0.233, -6.51, -8.085, -6.907, -4.552, -3.079, -2, 1.049, 0.847, 0.847, -0.037, -1.313, -0.331, -0.233, -3.57}. The different colour of the vertices are representing the different groups or clusters in which the vertex belongs.

Parameter extraction is the process of analyzing the EEG signals to extricate the pertinent characteristics or parameters of the EEG data from WVN and represents them in a compacted form (reduce the dimensionality) suitable for classification or categorization by considering the minimum information loss. Parameter extraction has a significant role in the classification

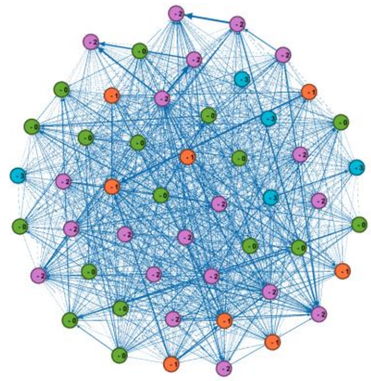


Figure 7-2: Illustrates the WVN from the small sample value of EEG data.

of distinct EEG signals. In this research work, I have extracted three statistical parameters of WVN named: modularity, AWD and Average degree that represent the significant characteristics of EEG signals. The detailed information regarding these three parameters is already provided in the previous chapters at section 6.3.2 and 5.3.2. After parameters extraction or mining, the subsequent stage is to organize the parameter vector sets in particular order: ascending or descending and then distribute the parameter sets in two portions: - (i) even place values of parameters sets and (ii) odd place values of parameter sets. After that, the classification method is completed. The classification is executed by considering the value at odd places as a training set for the classifier and the remaining values as a testing set for classification. I used k-NN classifier based upon machine-learning for ensuring the performance of all three parameters that are mined in the stage of parameter extraction. The kNN classifier has the property of naivest amongst other machine learning classifiers and exhibit robustness with respect to noisy as well as massive training data (Cover & Hart 1967). In addition, k-NN classifier is not based upon the selection of kernel parameters as in case of SVM classifier. Additionally, the k-NN rule attains consistently high accurateness, without a priori supposition regarding distributions associated to the training samples.

This research work, is evaluated with the help of well-known performance metric named accuracy.

7.4 Chaotic Analysis

The superiority of the WGBT is validated by applying the two different chaotic by nature benchmark time series analysis named: (i) Rosseler series and (ii) Lorenz series. This experiment also checks the behaviors of the WGBT with the noise. First, the analysis is executed on the lorenz series and secondly on rosseler series. In case of lorenz series, the implementation is performed firstly by applying the 1200 simulated sample points without noise and subsequently by introducing the noise in lorenz series with zero mean in addition to variance with 0.2. The following Lorenz equations has implemented (Lorenz 1963).

$$\frac{df}{dt} = s * (g - f) \tag{3}$$

$$\frac{dg}{dt} = r * f - g - fh \tag{4}$$

$$\frac{dh}{dt} = f * g - b * h \tag{5}$$

Where, *f, g, h* are correspond to the simulated time series; *s*, *n*, and *b* denotes the parametric values. The experiments is accomplished via assigning the random values to l_0, m_0 and n_0 between (0,1) and parameters has fixed value i.e. b=4, s=16, and r=45.92. For Lorenz and Lorenz using noise, the experiments are executed with the help of 10 repeated test-runs. Secondly, the analysis is executed on the rossler series by applying the 1200 simulated sample points without noise and subsequently by introducing the noise in rossler series with zero mean in addition to variance with 0.2. The following rossler equations has implemented (Rössler 1976).

$$\frac{do}{dt} = -p - q \tag{6}$$

$$\frac{dp}{dt} = o + ap \tag{7}$$

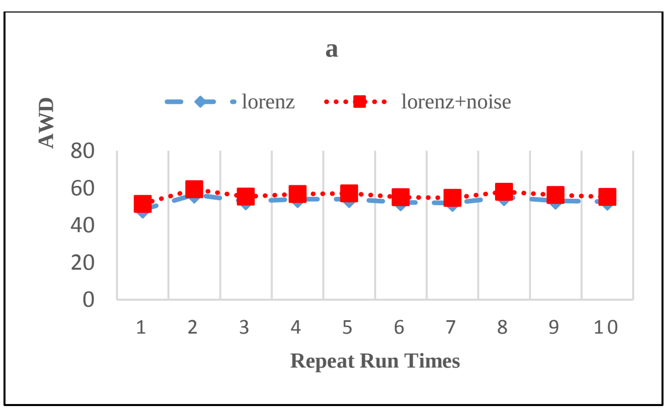
$$\frac{dq}{dt} = b + q(o - c) \tag{8}$$

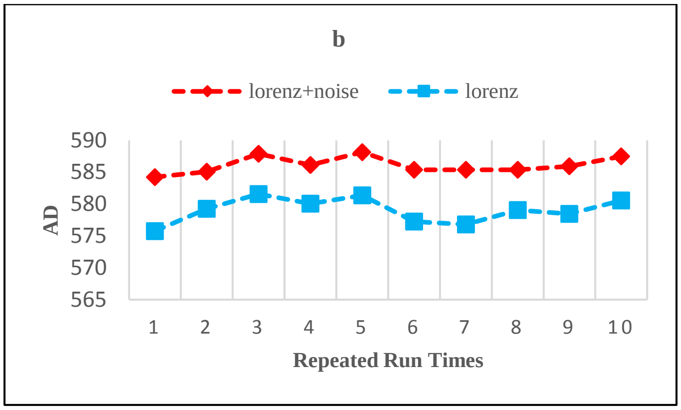
where, *o*, *p*, and q are correspond to the simulated time series; a, *b*, and *c* denoted the parametric values c=5.7, a=0.2, and b=0.4. In the case of rossler and rossler using noise, the experiments are executed with the help of 10 repeated test-runs. Figure 7-3 elucidates the behaviors of WGBT for the three parameters during the two chaotic series analysis. Figure 7-3(a, b, c) illustrates that all the three parameters of the WGBT (i.e. AWD, AD and Modularity) exhibit stability against noise. Figure 7-3(a, b, c) illustrates that the distance among Lorenz and Lorenz using noise is very less.

Likewise, the distance among Rossler and Rossler using noise is demonstrated in Figure 7-4(a, b and c) and is less in case of three paramters. Figure 7-4 (a) illustrates the AWD, Figure 7-4(b) illustrates the AD and modularity paramter is illustarted in Figure 7-4(c). From the above experimental results, it can be elaborate that the WGBT has robustness and stability against noises. Moreover, the three parameters of the WGBT also exhibit stability against the noise.

7.5 Results of the Experimental Evaluations and Discussion

This section provides the information regarding the results of the experimental evaluations of the WGBT and includes important discussion regarding the evaluations. The WGBT is explored on standard benchmark sleep stages data named Sleep-EDF dataset (as discoursed in Section 7-2) which is present online. The experiments is used to investigate the different test-problem as presented in Table 7.4.





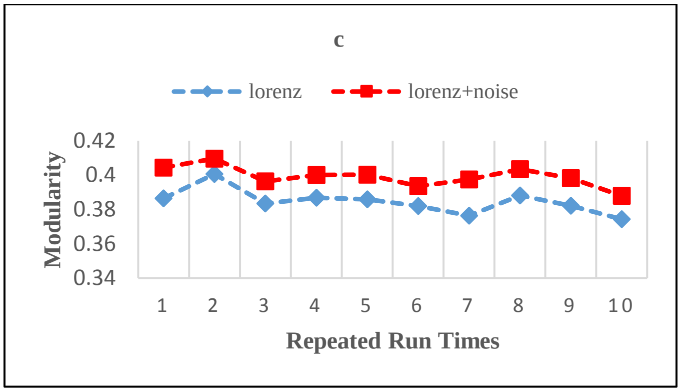
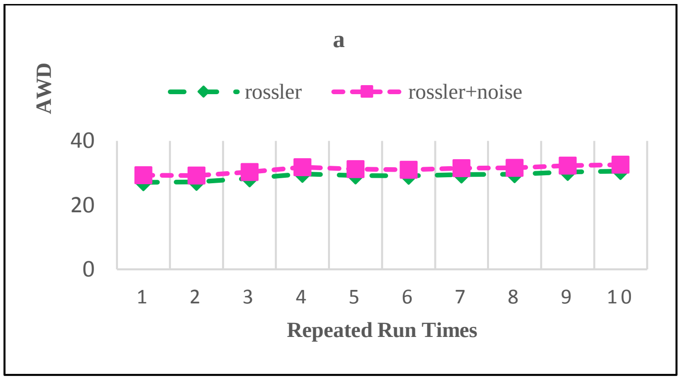
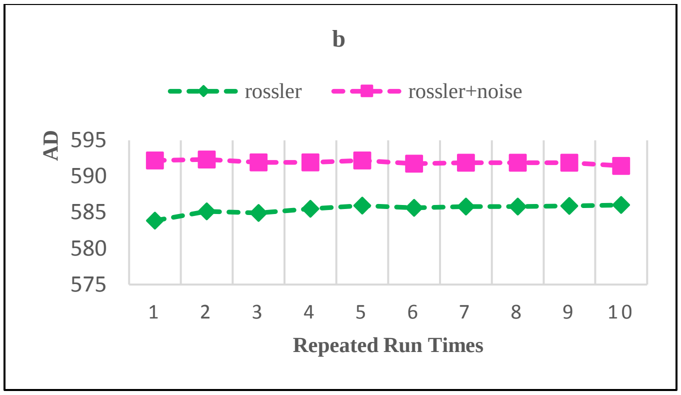


Figure 7-3: Illustration of (a) AWD, (b) AD, and (c) Modularity parameters of the WGBT with Lorenz and Lorenz with noise using 10 repeat run times plus 1200 simulated sample points.





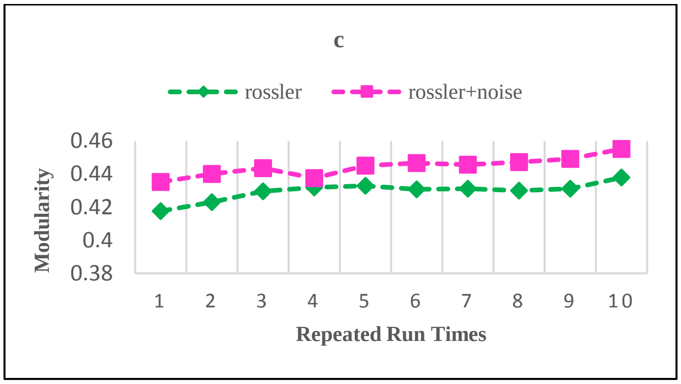


Figure 7-4: Illustration of (a) AWD, (b) AD, and (c) Modularity parameters of the WGBT with Rossler and Rossler with noise using 10 repeat run times plus 1200 simulated sample points.

Before mapping the EEG data to WVN, I have done the segmentation. Each epoch of EEG signals is comprises with 3000 sample points and to achieve the fast computational results, I divided the each epoch into the two parts named segment (i.e., Segment1 includes 1500 sample points and similarly, Segment2 comprises with 1500 sample points). After that, these two segmented parts are utilized as two different independent samples. According to Table 7.3, this database has total 4706 epochs, and after applying the segmentation, the resultant 9412 independent segmentations are achieved. As discussed earlier, the parameter's values located at odd location are utilize for train the classifier and the remaining value is used for the testing. Amid 9412, 50% of the segments are resered for training the classifier and remaining 50% segments are preserved for testing after applying the WGBT. Figure 7-5 illustrates the boxplot diagram of AWD, Figure 7-6 illustrates the boxplot diagram of AD, and Figure 7-7 illustrates the boxplot diagram of the Modularity parameters extracted from the WVN of sleep EEG signals with distinct sleep stages. Figure 7-5, illustrates that the AWD parameter value for REM period is very close to S1and S2 periods of sleep.

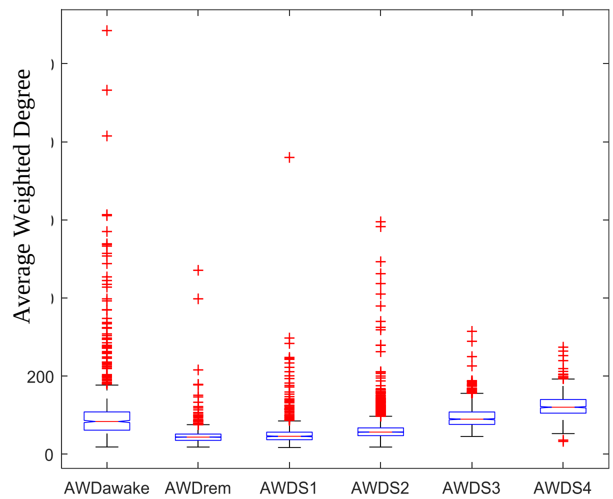


Figure 7-5: Box plot diagram of AWD parameter for the WGBT of different sleep stages.

Whereas, Figure 7-6 as well as Figure 7-7, depict that the AD and Modularity parameters value for the awake stage is more in comparison to other sleep stages. The above experimental investigation, demonstrates that for the duration of sleep, in comparison to awake period, the other sleep states period exhibits less fluctuations. As a result, the edge weight value associated to different parameters of the WGBT for awake state exhibits high value. Hence, our experimental results are consistency with Achermann & Borbély 1997, result for the period of sleep i.e., the EEG signals are dominated via slow wave actions with low-frequency range. For classifying the sleep states, k-NN classifier based on Euclidean-distance is used. The KNN is finalized by considering the various values of *k* parameter. The experiments proved that K=2 accomplished the superlative performance for the classification.

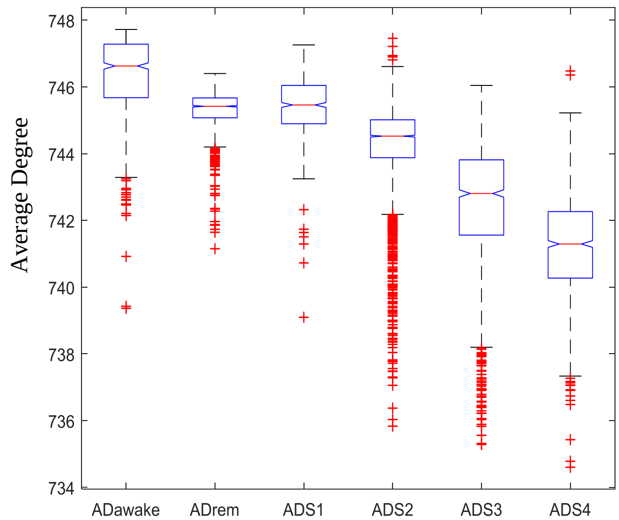


Figure 7-6: Box plot diagram of AD parameter for the WGBT of different sleep stages

To explore the performance of WGBT, I performed different experiments by considering the R & K rule to EEG data. Table 7.5 displays the experimental outcomes of two kinds of trials: (i) Classification without sorting the parameters vector set; (ii) Classification after sorting the parameters vector set.

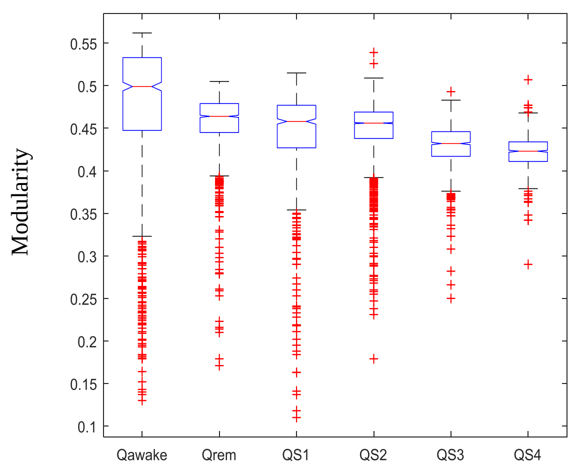


Figure 7-7: Box plot diagram of Modularity parameter for the WGBT of different sleep stages .

Table 7.5 portrayed the experimental outcomes of different parameters with sorting or without sorting the parameter vector sets. Table 7.5 demonstrates that for AWD parameter, the accuracy measure of classification task increases from 39.54% to 55.14%. Similarly, for Average Degree parameter, the accuracy measure of classification task associated to sorted and non-sorted approach are 47.21% and 55.73%. Likewise, for modularity parameter, the accuracy measure of classification task associated with sorted and non-sorted approach are 14.81% and 10.05%. In addition, the performance of classification of distinct sleep states by considering the accuracy measure is also evaluated by applying the sorted and non-sorted approach on the combined parameters vector sets.

Table 7.3: Total epochs associated to the different sleep states used in the experiments

Sleep Stages	Awake	S1	S2	S3	S4	REM
8	352	307	2223	517	478	829

Table 7.4: Test-problem associated to different sleep stages for classification

Test-problems	Classification	Different sleep stages
Test-problem I	Two-State	Awake vs. Sleep
Test-problem II	Three-State	Awake vs. NREM vs. REM
Test-problem III	Four-State	Awake vs. (S1+S2) vs. SWS vs. REM
Test-problem IV	AASM standard (based)	Awake vs. S1 v S2 vs. SWS vs. REM
Test-problem V	R & K standard (based)	Awake vs. S1 v S2 vs. S3 vs. S4 vs. REM

The confusion matrix corresponds to the classification task with unsorted and sorted parameters vector set approach is illustrated in the Table 7.6 and Table 7.7 according to R & K principle.

Table 7.6 and Table 7.7 clearly demonstrate that sorted the parameters vector sets increased the accuracy of the classification task for all the distinct sleep states such as for awake state accuracy increases from 65.9% to 93.4%, for S1 from 13.30% to 87.9%, for S2 from 54.38% to 99.5%, for S3 from 25.72% to 99.61, for S4 from 66.10% to 99.16 and for REM state the accuracy increases from 31.84% to 97.34%. Furthermore, Table 7.5 portrays that S3 exhibit maximum value for classification accuracy i.e. 99.6% whereas, S1 exhibit lowest value for classification accuracy i.e. 87.9% in comparison to other sleep states. While, the overall accuracy in terms of mean value of the complete classification is 97.91% after applying the sorted approach. Different researchers (Zhu, Li & Wen 2014; Alcin et al. 2016) combined the S3 state with S4 state during the experimental evaluation. In addition, to measure the performance of WGBT, some more experiments are conducted by considering the AASM principle on EEG data in which S3 state of sleep and S4 state of sleep data are combined and called as SWS. In the same way, the classification task is executed by considering the AASM principle on the same EEG data in accordance with sorted and non-sorted the parameters approach. And the results are portrayed in Table 7.8. for different parameters. The results of experimentations proves that by combining the parameter sets i.e. AWD + AD + Q along with sorted approach produce higher accuracy results i.e. 97.93%. Table 7.9 depicts the classification outcomes of sleep data in terms of confusion matrix using AASM principle. From the Table 7.9, it can be seen that S2 state of sleep exhibit the maximum value of accuracy i.e. 99.55% and S1 state of sleep exhibit lowest value of accuracy i.e. 87.94% whereas SWS has 99.49% accuracy outcome. The overall performance in terms of mean accuracy of EEG data on the basis of AASM principle is 97.93% which is little higher as compared to R & K principle.

The performance of WGBT is appraised by performing the comparison analysis of the classification accuracy measure of WGBT with existing two eminent techniques as well as with the visibility graph technique that have also utilize the same EEG sleep data for five distinct test-problems that haven't applied by

Table 7.5: The experimental outcomes of different parameters with sorting or without sorting the parameter vector sets, according to R & K principle of EEG sleep data

Parameters	**Classification without sorting**	**Classification with sorting**
	Accuracy (%)	Accuracy (%)
AWD	39.54	55.14
AD	47.21	55.73
Q	14.81	10.05
AWD + AD + Q	46.64	97.91

Table 7.6: The confusion matrix corresponds to the classification accuracy with unsorted parameters vector set approach, according to R & K principle

Sleep Stages	Awake	REM	S4	S1	S3	S2
Awake	232	99	3	65	21	128
REM	7	264	1	70	5	318
S4	48	4	316	9	213	153
S1	34	101	1	41	7	149
S3	3	16	135	15	133	266
S2	28	345	22	107	138	1209
Accuracy (%)	65.90	31.84	66.10	13.3	25.72	54.38

Table 7.7: The confusion matrix corresponds to the classification accuracy with sorted parameters vector set approach, according to R & K principle.

Sleep Stages	Awake	S1	S2	S3	S4	REM
Awake	329	14	4	1	3	12
S1	8	270	2	0	0	2
S2	3	7	2213	1	0	6
S3	1	0	2	515	1	1
S4	1	0	1	0	474	1
REM	10	16	1	0	0	807
Accuracy (%)	93.4	87.9	99.5	99.61	99.16	97.34

other researchers. Consequently, Table 7.10 presents the comparison analysis of the classification performance in terms of accuracy for two-state to six-state among existing and the WGBT. Table 7.10 clearly revealed that the WGBT provides improved accuracy in comparison to the other three technique for different test-problems with 98.78% accuracy for Test-problem I, 98.21% for Test-problem II, 98.13% for Test-problem III, 97.93% for Test-problem IV, and 97.91% accuracy for Test-problem V.

Additionally, for verifying the classification accuracy of the WGBT, I used only AASM and R & K principle and illustrated in Table 7.11. Table 7.11 illustrates the comparison analysis of accuracy measure of the WGBT with some existing technique present in the state of the art. Table 7.11 clearly illustrates that the WGBT outperforms in comparison to other existing techniques with 97.93% accuracy for AASM principle and 97.91% accuracy for R

& K principle of sleep EEG data.

Table 7.8: The experimental outcomes of different parameters with sorting or without sorting the parameter vector sets, according to AASM principle

Parameters	Classification without sorting	Classification with sorting
	Accuracy (%)	Accuracy (%)
AWD	46.83	59.09
AD	53.86	59.79
Q	15.38	10.05
AWD + AD + Q	54.03	97.93

Table 7.9: The confusion matrix corresponds to the classification accuracy with sorted parameters vector set approach, according to according to AASM principle

Sleep Stages	Awake	S1	S2	SWS(S3+S4)	REM
Awake	329	14	4	4	12
S1	8	270	2	0	2
S2	3	7	2213	1	6
SWS(S3+S4)	2	0	3	990	2
REM	10	16	1	0	807
Accuracy (%)	93.46	87.94	99.55	99.49	97.34

Table 7.10: Representation of the comparison analysis of the classification performance in terms of accuracy for two-state to six-state among existing and the WGBT

Different Test-problems	PSD with ANN (Ronzhina et al. 2012)	The fuzzy logic based system (Berthomier et al. 2007)	Difference Visibility Graph (Zhu, Li & Wen 2014)	The WGBT
Test-problem I	96.9%	95.4%	97.9%	98.78%
Test-problem II	88.97%	88.3%	92.6%	98.21%
Test-problem III	81.42%	74.5%	89.3%	98.13%
Test-problem IV	-	71.2%	88.9%	97.93%
Test-problem V	76.7%	-	87.5%	97.91%

Table 7.11: Illustration of the comparison analysis of accuracy measure of the WGBT with some existing technique present in the state of the art according to AASM and R& K principles

Standards	Researcher	Method	Accuracy
According to AASM standard	Hsu et al. 2013	Energy based features	87.20%
	Bajaj & Pachori 2013	T-F image-based features	92.93%
	Fraiwan et al. 2012	T-F features and Random forest	83%
	Alcin et al. 2016	GLCM + FV	95.17%
	WGBT	WVN	97.93%
According to R & K standard	Doroshenkov, Konyshev & Selishchev 2007	FFT based features and hidden Markov model	61.08%
	Bajaj & Pachori 2013	T-F image-based features	92.93%
	Alcin et al. 2016	GLCM + FV	95.38%
	Diykh & Li 2016	Complex network approach	92.16%
	WGBT	WVN	97.91%

Moreover, the results presented in Table 7.5, Table 7.6, and Table 7.7 also agreed with the conclusions defined by Corsi-Cabrera et al. 2006, that S1 sate of EEG sleep was easily erroneously characterized as any of Awake state, S2 state as well as REM state. The investigation based on experiments also explored that in comparison to individual parameter, the combined parameters vector sets accomplishes more promising and higher accuracy results. Lastly, the experimental analysis divulges that the WGBT based upon WVN helps to discover the hidden dynamics of the distinct states of EEG signals. Further, to analyse the validity of the WGBT, I implemented the k-fold Cross-Validation (with k=5) on the combined parameters (AWD + AD + Q) by considering to R & K principle. The accuracy outcomes for each fold are: fold-1=97.45%, fold-2=97.18%, fold-3=96.94%, fold-4=97.06% and fold-5=97.11%. The overall accuracy for the 5-fold cross-validation is 97.14% and also very close to the results reported in above experimentation i.e. 97.91%. The 5-fold cross-validation outcomes depicts the consistency of the WGBT.

7.6 Summary

In this chapter, an effective technique is developed for analysis as well as identifying distinct sleep states from EEG signals. The WGBT is verified on sleep data associated to EEG signals and in the form of time-series. Firstly, the EEG sleep data is transformed to WVN. After that three statistical parameter are mined form WVN that characterized the behaviors of Sleep pattern. k-NN classifier is used to categorized distinct states of sleep present in the EEG signals. The experimental outcomes prove that the WGBT outperforms as compared to the recent techniques. The extensive experimentation outcomes also validate that the WGBT is effective for classifying the distinct states of sleep present in EEG data (as well as for multi-class classification problem for EEG).

The next chapter present a novel technique for analysis the EEG signal data to evaluate the different types of epilepsy data

CHAPTER 8

AUTOMATED DETECTION OF EPILEPTIC SEIZURE USING COMPLEX NETWORK FEATURES

In the previous chapters, different frameworks were developed such as WCNBF, VGBNBF, and WHVN. They have one major shortcoming that they are based upon some criteria to define or select the links among vertices. If the data points of the EEGs, (vertices) are not able to satisfy the requirement criteria then there is no link between them. Because of this reason some important vertices are missed, whereas, it is important to consider all the data points of EEGs for clinical analysis. By considering this fact, this chapter aims to propose a new algorithm to detect epileptic seizure activity by developing a new complex network approach named as New Weighted Complex Network (NWCN) Technique. In this study, a new method is introduced for the mapping of time series EEG signals to complex network. A new feature is also developed, named as '"Edge Weight Fluctuation (EWF)", which helps to extract sudden fluctuation in EEG signals. The NWCN scheme is tested on two benchmark Epileptic EEG databases (Bern-Barcelona EEG database and Bonn University EEG database). In order to check the validity of the NWCN methodology, the simulation analysis has been performed with two different chaotic signals named as Henon map and Logistic map. The One-Way ANOVA statistical test is also performed. The overall accuracy has achieved 99% for Bern-Barcelona database and 100% for Bonn University database. The experimental results reveals that the NWCNT is more effective to distinguish epileptic seizure signal from between diverse EEG signals.

Without loss of generality, the reaming parts of the chapter is systematized as: Section 8.1 comprises with the introduction. Section 8.2 includes information about the EEG database used. Section 8.3 describes the detailed explanation of the NWCNT with data acquisition. Section 8.4 provides the validation of the NWCNT in terms of statistical analysis by using One-Way ANOVA and simulation analysis with different chaotic signals. Section 8.5

includes the results of the experiment with a detailed discussion about the outcomes. Section 8.6 draws the summary of this chapter.

8.1 Introduction

EPILEPSY has been identified as a critical brain syndrome that is effecting around 65 million population at world-level (Ramgopal et al. 2014). It needs special medical attention as it happens with an incidence of 68.8/100,000 person-years and the age-adjusted incidence because of the epileptic seizure is approximately 44/100,000 person-years (Ramgopal et al. 2014). Epileptic disorder is a neurological condition, which occurs due to some degree of impairment in the electrophysiological portion of the brain and affects the nervous system of the brain. Epilepsy is identified as, at least two seizure attacks without some other medical conditions. Epileptic patients have a higher risk of other complications such as Bleeding into the brain, Brain tumors, Cerebral palsy, Alzheimer's disease (in the later stage of life) and Autism disorder, etc. Epilepsy is diagnosed with the help of an EEG, which tracks the electrical activity in the brain and records the brain wave pattern (Siuly 2012). Despite the fact that numerous anti-epileptic drugs are developed from the last decade, still, one-third of epileptic patients continue to have a seizure attack in spite of treatment. One of the main essential difficulties in the treatment of epilepsy syndrome is the ability to detect clinical seizures rapidly and accurately. Finding traces of epileptic activity from human EEG is not only very crucial for efficient diagnosis and treatment management in the health monitoring applications but also is a very tedious, resource-consuming and exorbitant task. Moreover, SUDEP is the main reason for fatality in epileptic patients. This concern also makes epileptic seizure detection an important and emerging aspect of research currently [200]. EEG has been recognized as the most promising tool for the analysis of Epileptic seizure. Because the fluctuating pattern of the action potentials during seizure activity can be best intelligible with the help of EEG. The ability to detect epileptic seizure rapidly and accurately can enhance its treatment therapy. Therefore, there is continuous research towards the field of automatic detection of an epileptic seizure from Brain EEG signals. The wide-ranging of approaches are available from linear methods to non-linear methods (Chua et al. 2010; Polat & Gunes 2007; Polat & Gunes 2008; Xiang et al. 2015).

Currently, Time series analysis using complex network approach is continuously attaining attention in the neuroscience and other various disciplines (Baggio & Sainaghi 2016; Scarsoglio, Cazzato & Ridolfi 2017; Tanizawa & Nakamura 2014). Complex network-based time series analysis encompasses the underlying complex and irregular structure of traditional signals with the help of graph (Chen et al. 2015). Moreover, this mapping approach helps in analysing the structural properties of time series by quantify the graph features, such as the existence and size of the gigantic component, distribution of module sizes, degree distributions and clique distributions, and specific parameters of node or links, which includes clustering coefficients, path length, diameter, and centrality: betweenness; closeness and Eigenvector centralities (Sandryhaila & Moura 2013). During the mapping of times series EEG signals to the complex network, the different EEG signals acquire different statistical features. In addition, with the help of different network attributes, we can illustrate the multiple behaviors of EEG signals (Tang et al. 2013). Recently, various researchers and clinicians have implemented the complex network-based approaches to detect epilepsy and other brain disorder from EEG signals (Bhaduri & Ghosh 2014; Liu et al. 2016; Ni et al. 2014). Time-series-complex-network (TSCN) (Wang et al 2013) , recurrence plot network (Niknazar et al. 2013), visibility graph (Lacasa et al. 2008) and horizontal visibility graph (Luque et al. 2009) are the names of the method that are commonly used. But there are two major limitations of these cited methods. First, these approaches include the selection of specific parameters like threshold value (ε) and graph equation. Due to which the chances of loss of information are more because the criteria to form the link between the nodes, sometimes ignores the valuables nodes. Secondly, these approaches have not considered the links (edge) strength, whereas edge weight is an essential concept as different nodes linked with each other on the basis of this strength. As a result, addressing the limitations of the above-mentioned approaches, I introduce the new framework for EEG signals analysis. According to NWCNT, EEG time series signals are transformed into the complex network by preserving all the information of EEG signals. The main objectives of this research chapter are:

1) To categorize the focal and non-focal signals of recorded from an epileptic patient;
2) To detect epileptic seizure in term of classifying the epileptic seizure activity from five dissimilar groups of EEG signals;

3) To introduce a new feature "Edge Weight Fluctuation" (EWF) for a weighted network that more suitable. to identify an unforeseen fluctuation in EEG signals and helps for statistical analysis of the complex network.

In this research study, I develop a new framework for automated detection of the epileptic seizure. I present a single framework that works effectively for two different EEG database, i.e., The Bern-Barcelona EEG database and Bonn University Germany, Epilepsy database. In this NWCNT, firstly converted EEG signals into New Weighted Complex Network and then three features Modularity Gain (MG), Average Weighted Degree (AWD) and Edge Weight Fluctuation (EWF) are extracted for classification. SVM classifier with three different kernel functions, KNN classifier, DA classifier with two different discriminant analysis functions are used for to check the performance of three features. The noise robustness validity of NWCNT is checked by performing simulation analysis on two different chaotic signals named: Henon map and Logistic map. To justify the significance of NWCNT, I have also performed the statistical analysis by using One-Way ANOVA test.

The experimental results prove that NWCNT is effectual with 99% accuracy for Barcelona database and 100% of Bonn database. Moreover, the newly developed feature plays a significant role in categorizing the diverse EEG signals and improves the classification performances. As far as, I are aware of, this NWCNT is genuinely new and can be beneficial in the arena of automated detection of epilepsy and other brain abnormalities.

8.2 Experimental Database

This section describes data acquisition. I have used the following two different time series EEG databases for this research study, which are publicly available.

8.2.1 Database 1: The Bern-Barcelona EEG database

This database used is made online available by the neurological department of the Bern University in 2012. This database is collected by the long-term recording of the intracranial EEG of five patient with the epileptic disorder via using10-20 electrode placement system by placing the electrode at the positions: Fz and Pz. The sampling rate of the EEG signals are lies between 512 or 1024 Hz. The EEG recording has been classified into focal and non-focal EEG channels by the judgments of the two expert neurologists. Each recording corresponds to time-window of 20 sec has 10240 data samples points. This research work has used Data_F_50.zip and Data_N_50.zip data recordings. More details about this database are available in R. Andrzejak et al. [183].

8.2.2 Database 2: Bonn University Epileptic EEG database

Bonn University, Germany data, issued by the department of epilepsy. More details about this database are available in Andrzejak, Schindler & Rummel 2012.

8.3 NWCNT

In this research work, I developed a framework named New Weighted Complex Network Technique (NWCNT), which can automatically classify the diverse EEG signals. The overall schematic presentation of the NWCNT is illustrated in Figure 8-1. In this NWCNT, firstly the time series EEG data are transformed into the NWCN. Then, with the help of feature extraction technique, the statistical parameters (features) of the NWCN are extracted. Finally, classification is performed via different classifiers. The classification performance is evaluated with the help of performance measures. Following is the detailed discussion about the NWCNT:

Step I: Transformation of EEG signals to NWCN:

For the construction of the NWCN, I have considered that all the data sample points of EEG time-series signals are the nodes of the complex networks. i.e., if a time series is represented by $\{X(t_i), i=1, 2,\ldots N\}$ with N number of data sampling points. And G= (N, E) represents the complex network with N numbers of nodes and E set of edges. According to NWCNT, if N= $\{n_i\}$, i=1, 2,… N, are the nodes and E =e_i, i=1,2,3,………… N, are the edges then each node n_i corresponds to data sample point x_i. For determine the link (edge) between the nodes, I have considered that all the nodes of the NWCN are connected to each other, i.e., if we are having N number of nodes, then each node is connected with the remaining N-1 number of nodes in the same order. The edge should be directional in nature. E.g., if there is a time series of 10 nodes, then it should have 45 edges and is represented as G (10, 45). Figure 8-4. illustrates the G (10, 45).

Afterward, the edge strength of the links is calculated. It is uncovered from the literature studies in the discipline of the complex network theory that if we preserve the information about the weight of the network, then the more reliable and robust results can be achieved (Polikar 2006). Because the binary network just provides the information regarding the existence of the link between the nodes. Moreover, with the help of edge weight information, it is easy to recognize the strength of different links which will further help in the detection

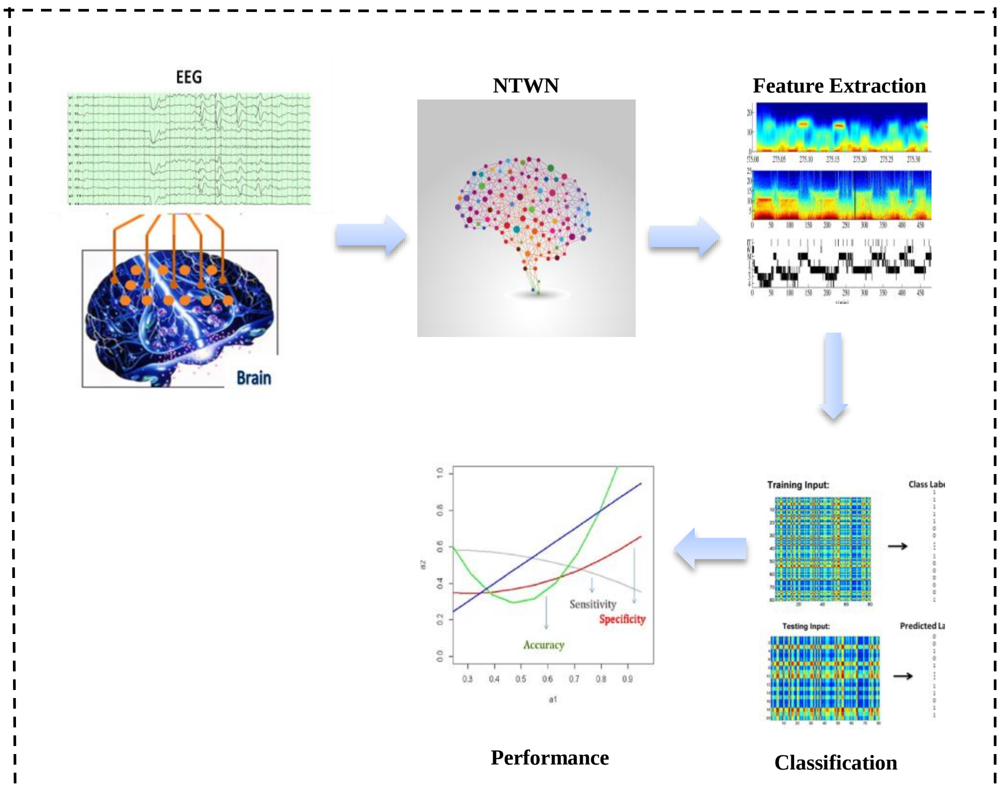


Figure 8-1: The structural diagram of the NWCNT of EEG Signals for Epilepsy Classification.

of potentially strong or more essential links. Fundamentally, weight is any value that is accompanied by the link of a network. The edge strength of NWCN is calculated with the help of equation (1):

$$w_{ij} \quad = \frac{n_j - n_i}{t_j - t_i}, < j \qquad , \tag{1}$$

Where n_i and n_j are the nodes of the complex network and correspond to time series data sample points $x\ (t_i)$ and $x(t_j)$. Also, t_i and t_j represent the time of interval. And w_{ij} represents the edge weight between node n_i and n_j. In this research study, I have considered the absolute value of edge weight. Moreover, I have also considered that all the edges of the network are directional in nature. The Figure 8-2 demonstrates how this equation has been derived and helps to detect sudden fluctuation.

As from Figure 8-2, it is clearly visible that the time interval t_2 and t_6 has the same voltage, i.e., 10v but at t_7 there is a sudden fluctuation, i.e., =60 v. The edge weight of sample point $x\ (t_2)$ and $x(t_7)$ is denoted as w_1. Whereas, the w_2 symbolizes the edge weight between (t_6) and $x(t_7)$. With the help of equation (1), the $w_1 = 10$ and $w_2 = 50$. Therefore, Figure 8.2 illustrates that when there is a sudden fluctuation in the EEG signal, then there is change (increase or decrease) in the edge weight value. Figure 8-3. Illustrates the idea of presenting the edge weight between different nodes. The main advantage of this edge weight equation is that it will help to detect sudden fluctuations in EEG signals, as different nodes of the complex network will connect with each other via their strengths (edge weight).

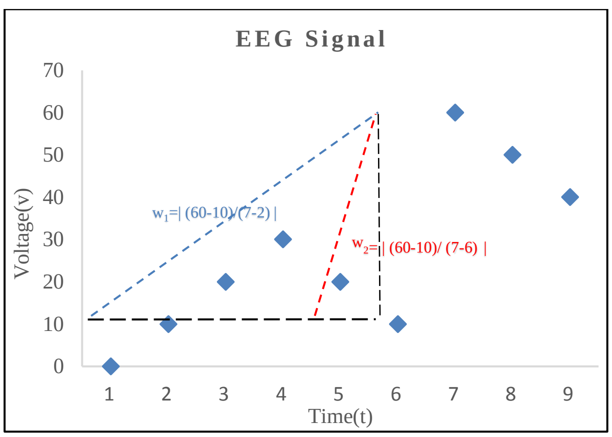


Figure 8-2: Illustration of using edge weight in order to find the effect of sudden fluctuation between two different data points of EEG signals.

Figure 8-4. illustrates the NWCN of X. Where, X ={22.62, 26.55, 28.43, 30.10, 30.03, 27.86, 27.28, 30.01, 34.58, 39.98}is a small EEG time series with ten data sample points taken from the segment of Focal EEG signals (of Bern-Barcelona EEG database). The main advantage of this NWCN from visibility graph or horizontal visibility graph is that Lacasa's graphs used the equation to find the edges between the nodes which is basically a decision tree statement to find the links. If the nodes satisfied the equation then there are links between them, otherwise not. Thus, with the aim of, to find the links between the nodes, the algorithm has to execute the decision tree statement every time, which is basically, takes more computation or execution time. Whereas in this research study, I have not used any decision tree statement to find the edge links; therefore, the NWCNT takes less execution time and reduces the complexity of the algorithm.

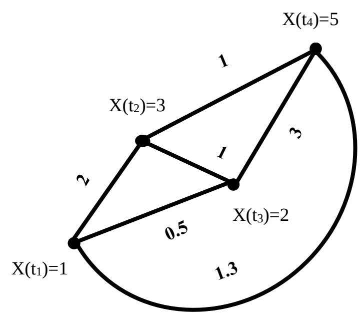


Figure 8-3: Illustration of the edge weights between different data points

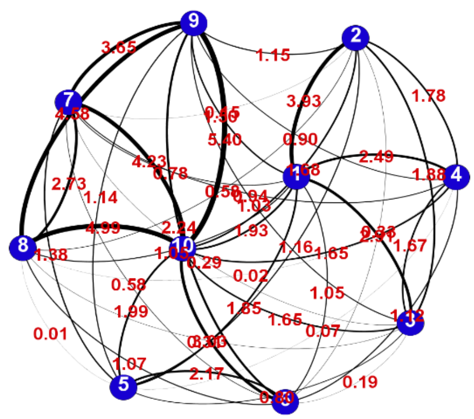


Figure 8-4: Illustration of NWCN of small EEG segment

Step II: Feature Extraction

Features are a small number of derived variables or identifiable measurement used to represent the larger set of data by preserving most of the information on the cost of least loss of information. The feature extraction process not only helps to reduce the computation cost but also play a significant role to enhance the classification accuracy. In this research work, I have extracted the following three features from the NWCN of EEG signals:

1) Community Finding Approach;
2) Average Weighted Degree;
3) Edge Weight Fluctuation.

Community Finding Approach: Newman was the first to introduce the community finding approach in the complex network for measuring the strength of partition of network (Newman 2004). In this research study, I have used the Louvain community finding approach, as it is an easy and efficient method for the large complex network. When group *i* combined into group *j*, then, according to Louvain (Blondel et al. 2008):

$$\Delta \mathrm{MG}_{ij} = \left[\frac{\sum_{jn} + k_{i,jn}}{2m} - \left(\frac{\sum_{tot} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{jn}}{2m} - \left(\frac{\sum_{tot}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right], \qquad (2)$$

where $\sum_{jn}$ symbolises the total weights associated with all the edges that come under group *j;* $\sum_{tot}$ represents the total weights of the links that are incident to the nodes in the group*;* $k_{i,jn}$ symbolizes the total weight of the edges from the group *i* to group *j;* k_i is the total weights of the links incident to node *i; m* represents the total weight of all the links in the network and ΔMG_{ij} symbolizes modularity gain. The modularity is a complex network feature which is used to measure the quality of the division of the complex network into clusters (Newman 2004). Louvain modularity comprises of two stages. Firstly, identify the small clusters with the help of optimization of modularity in a local manner. Secondly, in order to rebuild the new network, the nodes fit into the same clusters are combined together and named as the communities. These two steps repeated iteratively until the maximum value of modularity is attained.

Average Weighted Degree (AWD): The weighted degree of the node *i* is the total weight of all the links connected to a node *i* and denoted by (Antoniou & Tsompa 2008):

$$wd_i = \sum_{j \in B(i)} w_{ij} \,, \tag{3}$$

Where *B (i)* is the neighborhood of node *i*. and w_{ij} signifies the edge weight between nodes *i* and *j*. Thus, the Average Weighted Degree of a complex network is defined as the average mean of the total weights of the incident links on all the nodes in the network.

Edge Weight Fluctuation (EWF): In this chapter, we have developed this new feature and the first time going to use this feature for classifying different EEG signals. To the best of my knowledge, this feature has not been developed and used before. EWF of a single channel EEG signals is measured by:

$$EWF = (w_{max} - w_{min}) \quad , \tag{4}$$

where w_{max} represents the maximum edge weight value of a channel or maximum fluctuation, occur in EEG signals, and w_{min} is the minimum edge weight value of the same channel. The EWF will be higher in case of an epileptic seizure as in case of seizure activity, there is a huge fluctuation in EEG signals. The advantage of introducing EWF is clearly disclosed in the result and discussion section, where I had explained the effect of using EWF on the classification performance.

Step III: Classification

In order to evaluate the performance of the above-mentioned three features, I have used the following binary supervised machine-learning classifiers:

a. SVM classifier with different kernel function Cristianini & Shawe-Taylor 2014;
b. KNN classifier (Cover & Hart 1967);
c. DA classifier with different discriminant functions (Tharwat 2016).

Step IV: Performance Evaluation

The performance of the introduced framework is assessed by employing the defined standard measuring parameters (Siuly 2012) named as sensitivity, specificity and accuracy.

8.4 Analysis of the NWCNT

This section includes the Simulation Analysis and Statistical Analysis, for the NWCNT and feature sets.

8.4.1 Simulation Analysis with Chaotic Signals

The stability and robustness to noise of the NWCNT are very crucial aspects in pattern classification. I considered two different chaotic signals named Henon map and Logistic map to investigate the potential of NWCNT. The Henon map is generated from the following equations with parameters values a=1.3 and b=0.3 (Hénon 1976):

$$x_{i+1} = y_i + 1 - ax_i^2 \tag{5}$$

$$y_{i+1} = bx_i \tag{6}$$

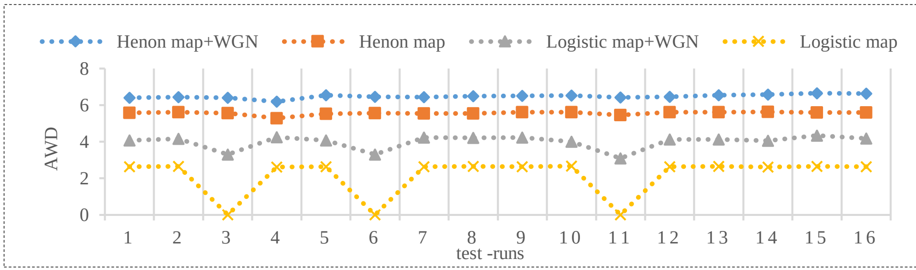
The Logistic map is generated from the following equation with parameter value a= 4 (Vapnik 1998):

$$x_{i+1} = ax_i(1 - x_i) \tag{7}$$

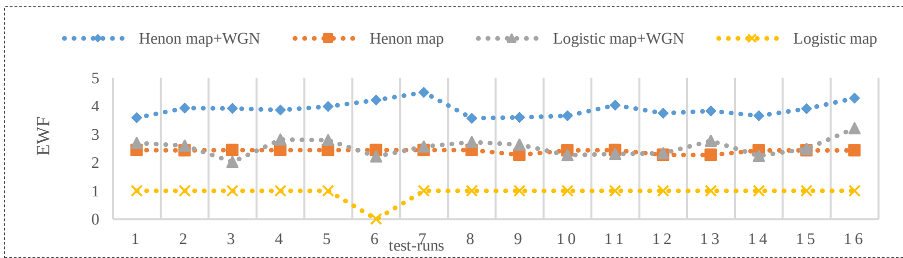
To evaluate the performance of the robustness to noise, I have added the similar Gaussian white noise (GWN) with variance = 0.2 in the two chaotic signals. I have conducted 16 test-runs for the initial value of x_0 and y_0 , by randomly assigned value between (0,1). I have taken the size of each chaotic signals as 1000 data samples.

Figure 8-5 illustrates the three features, i.e. AWD, EWF, and MG that are extracted from two chaotic time series (Henon map and Logistic map) with and without Gaussian white noise. From Figure 8-5(b) it is clear that the newly developed feature EWF is robust against noise. Based on the distance between chaotic signals and chaotic signals with noise, it is also noticed that the AWD and EWF features are more robust against noise as compared to Q.

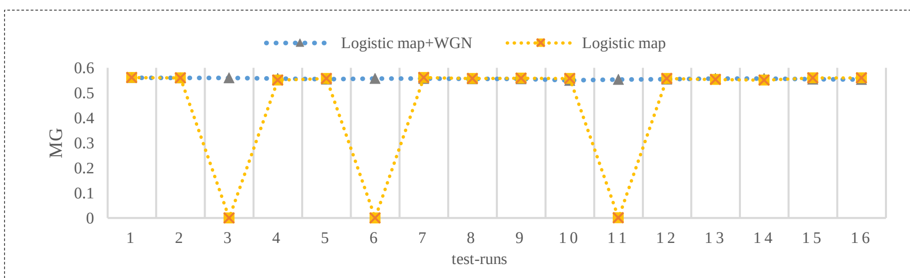
(a)



(b)



(c)



(d)

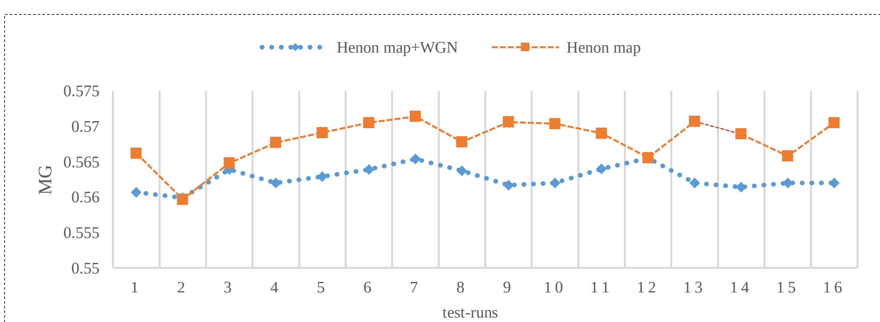


Figure 8-5: Illustration of Average Weighted Degree(a), Edge Weight Fluctuation (b) and Modularity Gain(c,d) feature of the chaotic time series of Henon map and Logistic map.

8.4.2 Statistical Analysis

I have performed one statistical analysis test named: One-Way ANOVA with the help of Matlab toolbox, to prove the statistical significance of NWCNT (May 1976).

As I can see from Table 8.1 that the p-value results of the three feature (Q, EWF, and AWD) for both the databases lies between < 0.005 and < 0.0001, which not only justifying the statistical significance of this newly developed feature EWF but also for other two features.

Table 8.1: One-Way ANOVA test results

Data Set	Feature	p-value test
Bonn University EEG Data	AWD	3.1173e-118 < 0.0001
	EWF	2.1031e-71 < 0.0001
	MG	9.9810e-95 < 0.0001
Bern-Barcelona EEG database	AWD	0.0013 < 0.005
	EWF	4.1973e-05 < 0.0001
	MG	1.6595e-15 < 0.0001

8.5 Results and Discussion

In order, to investigate the validation and consistency of the NWCNT, different experiments are performed with the help of MATLAB. This section presents the experimental outcomes of the NWCNT on the two different benchmark EEG databases: Bonn university epileptic EEG data and the Bern-Barcelona EEG database. This section also covers the comparative analysis of the NWCNT outcomes with the existing state of the art. The experimental results are discussed below:

8.5.1 Database1: The Bern-Barcelona EEG database

In order, to investigate the performance of NWCNT, firstly, I employed the NWCNT to first benchmark epilepsy EEG database known as The Bern-Barcelona EEG database. As mentioned earlier, I have used the subset of this database, i.e., Data_F_50.zip and

Data_N_50.zip, which contains only the first 50 signals (channels). Because each channel is equivalent to 10240 data samples of 20 seconds, therefore, to make the computation task faster, I divided each channel into four segments of 5 sec each (i.e., Seg1=2560, Seg2=2560, Seg3=2560, Seg4=2560 data sample points). And these four segments are further considered as four independent channels. According to the NWCNT, each segment is first transformed into the NWCN. Afterward, the three features: MG, AWD, and EWF are extracted for classification. Following Figure 8-6, Figure 8-7 and Figure 8-8 represent the box-plot diagram of the feature sets of Bern-Barcelona EEG database with focal and non-focal EEG signals.

Figure 8-6 illustrates the box-plot diagram of the MG feature set of Bern-Barcelona EEG database. MG feature values of the non-focal EEG signals are more as compared to focal EEG signals. This signifies that the non-focal EEG signals have strong community structure as compared to focal, i.e. in case of non-focal EEG signals; the nodes are denser connecting inside the groups as compared to focal. In addition, it also depicts that the non-focal EEG signals have a better partition of the network as compared to the focal.

Figure 8-7 represents the box-plot diagram of the Average Weighted Degree feature set of Bern-Barcelona EEG database. As I can see from Figure 8-7 that, AWD of the focal complex network is more as compared to non-focal. The reason behind is that during focal-epileptic seizure attacks the EEG signals starts showing fluctuation. In addition, because of this fluctuation, the edge weight values will show great change and increases the AWD feature. The AWD feature is directly proportionate to the values of edge weights.

Figure 8-8. illustrates the boxplot diagram of the Edge Weight Fluctuation feature set of Bern-Barcelona EEG database. The diagram shows that EWF of the focal complex network is more as compared to non-focal. Because during focal-seizure activity, the sudden fluctuation increases the maximum edge weight, due to which EWF also increases.

As discussed earlier, after feature extraction the next step is classification. I have implemented the sorting of the feature sets before classification in my previous study of Sleep stages analysis (Supriya et al. 2018). In this study, I also want to investigate the effect of sorting the feature set before classification on the Epileptic EEG database. After applying the sorting the feature set approach, I divided 50% data for training and the remaining 50% for testing. In order to explore the performance of the feature sets, I have used six classifiers named as SVM Linear, SVM Rbf, SVM Polynomial, KNN, LDA, and QDA classifier. In the case of KNN classifier, different values of K has been analyzed, and it is evaluated that k=1, 2 gives better significant and same performances as compared to k=3, 4, 5, 6, 7, 8, 9, 10. Therefore, k=2 has been used to represent the experimentation in tabular form.

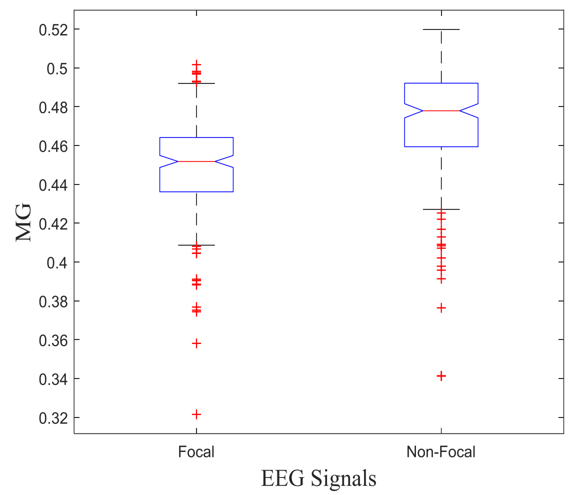


Figure 8-6: Illustration of box-plot diagram of MG feature set for the Bern-Barcelona EEG database.

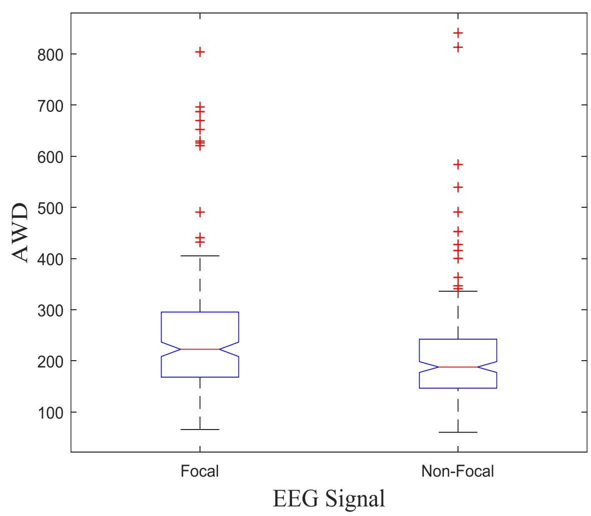


Figure 8-7: Illustration of box-plot diagram of AWD feature set for the Bern-Barcelona EEG database.

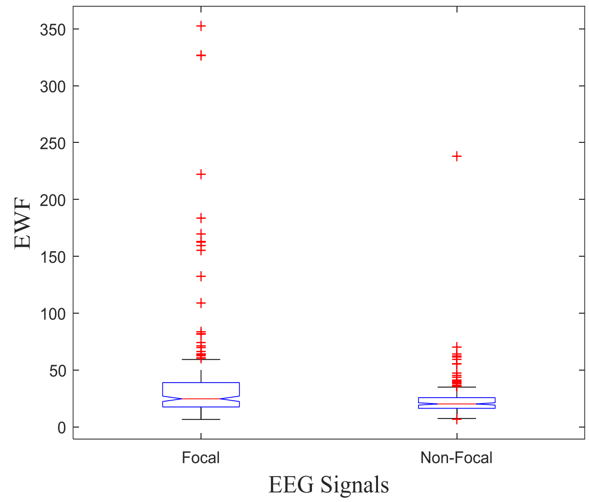


Figure 8-8: Illustration of box-plot diagram of EWF feature set for the Bern-Barcelona EEG database.

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Table 8.2 illustrate the classification accuracy of each feature set individually as well as by combining the feature set. From Table 8.2, it is clearly visible that the classification accuracy increases by combining all of the feature sets for each classifier as compared to the individual feature set. Table 8.2 also validates that LDA classifier performs better as compared to QDA and SVM Poly classifier is best among the six classifiers. Based on the experimental results of Table 8.2, I can demonstrate that SVM poly is more appropriate and provide significant results for this database.

Table 8.2: The classification accuracy results of the Bern-Barcelona EEG database.

Data Group	Classifiers	Classification Accuracy of the individual feature set (Accuracy in %)			Classification Accuracy of the combined feature sets (Accuracy in %)
		AWD	EWF	MG	AWD + EWF + MG
Focal Vs. Non-Focal	KNN=2	64	63	72	83
	LDA	57.5	62	71.5	92.5
	QDA	60	58.5	73.5	69.5
	SVM Linear	57.5	60	71.5	91
	SVM RBF	58.5	61	73	95.5
	SVM Poly	59.5	58.5	73	99

Table 8.3 demonstrates the overall classification results with sensitivity, specificity and accuracy performance of different classifiers. The accuracy performance of KNN is 83%, for LDA is 92.5%, for QDA is 69.5%, SVM with Linear Kernel is 91%, for SVM with RBF is 95.5%, and SVM with the polynomial kernel function reported highest with 99%. Similarly, the sensitivity performance of different classifiers is reported as 83% for KNN, 100% for LDA, 42% for QDA, 100% for SVM Linear, RBF and polynomial kernel function. Likewise, the specificity performance of different classifiers is reported as 83% for KNN, 85% for LDA, 97% for QDA, 82% for SVM Linear, 91% for RBF and 98% for the polynomial kernel function.

Table 8.4 signifies the comparison of NWCNT with the existing state-of-the-art for this Bern-Barcelona EEG database. Table 7.4 also demonstrates that NWCNT provides significant outcomes with 100% sensitivity, 98% specificity, and 99% accuracy as compared to the state-of-the-art. Moreover, the specificity of NWCNT is 98%, which is also very much closer to 98.68% of (Eswaramoorthy, Sivakumaran & Sundarajan 2014). Therefore, I can say that NWCNT is one of the most promising technique for this database and research in this area.

Table 8.3: The overall classification results of the Bern-Barcelona EEG database.

Data Group	Classifiers	Overall classification performance AWD + EWF + Q (%)		
		Sensitivity (%)	Specificity (%)	Accuracy (%)
Focal Vs. Non-Focal	KNN=2	83	83	83
	LDA	100	85	92.5
	QDA	42	97	69.5
	SVM Linear	100	82	91
	SVM RBF	100	91	95.5
	SVM Poly	100	98	99

Table 8.4: Comparative analysis of the accuracy of the NWCNT with existing techniques that used the Bern-Barcelona EEG database for their experimentation.

Authors	Sensitivity (%)	Specificity (%)	Accuracy (%)
Eswaramoorthy, Sivakumaran & Sundarajan 2014	98.7	98.68	98.2

Sharma, Pachori & Acharya 2015	90	84	87
Das & Bhuiyan 2016	90.7	88.1	89.4
Zhao et al. 2018	-	-	77.3
Dalal Tanveer & Pachori 2018	-	-	90.2
NWCNT	100	98	99

8.5.2 Database 2: Bonn University Epileptic EEG Database

To further explore the efficiency of NWCNT, I employed it again on a second benchmark database known as Bonn University Epileptic EEG data. In this case, EEG signals are divided into four test cases (Data Group), where each test case corresponds to the pairs of two-classes of EEG signals. Table 8.5 represents the different test cases or groups.

Table 8.5: Different test group along with a description of the different set problem

Group	Data set	Classification Problem Description
1	Set Z vs. Set S	Healthy persons EEG Vs. seizure activity
2	Set O vs. Set S	Healthy persons EEG Vs. seizure activity
3	Set N vs. Set S	Epileptic patients without seizure Vs. seizure activity
4	Set F vs. Set S	Epileptic patients without seizure Vs. seizure activity

In this case, the data sample value of each channel is 4097, which is very less as compared to the Barcelona EEG database; therefore I have not performed the segmentation of the channel. As a result, each channel is used as an independent sample. According to NWCNT, each channel is first transformed into the NWCN. Afterward, the feature extraction part is progressed by extracting three features: MG, AWD, and EWF. Following Figure 8-9, Figure 8-10 and Figure 8-11 represent the box-plot diagram of the feature sets of all the five classes (Z, O, N, F, and S) of Bonn University Epileptic EEG database.

From Figure 8-9, Figure 8-10, and Figure 8-11, a clear significant difference is visible in the feature sets of all the three feature vectors of different kind of EEG signals. Figure 8-9 illustrates the boxplot diagram of MG feature set. From Figure 8-9, I can see that seizure activity value shows a clear difference as compared to others. This Figure 8-9 also depicts how much strong connection exists among the nodes inside the modules of different EEG signals. Whereas, the boxplot diagram of Average Weighted Degree feature set in Figure 8-

10 represents that Set S (seizure activity) has the highest value as compared to others. The reason behind is the same as mentioned previously that during seizure activity, the EEG signal is extravagantly fluctuating. Due to this fluctuation in the EEG, the edge weight increases, which in turn increase the AWD value. Likewise, in the case of the Edge Weight

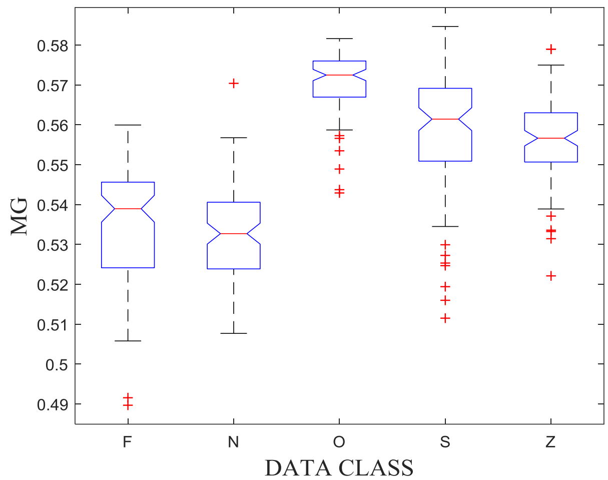

Figure 8-9: Illustration of box-plot diagram of MG feature set for the Bonn University Epileptic EEG database.

Fluctuation feature, as we can see from Figure 8-11 that during seizure activity, the maximum edge weight value of NWCN starts changing which in turn increased the value of EWF feature. However, in the case of a healthy person, the EEG signals are not too much fluctuating which in turn does not effect the EWF feature.

Table 8.6. illustrates the classification accuracy performance of different classifiers based upon individual feature sets as well as by combining the feature sets. Table 8.6 depicts that the classification accuracy of different classifiers increases by combining the feature set as compared to the individual feature set. On the combined feature sets, the classification accuracy for the group 1 has the value 100% for KNN, QDA, and of SVM classifiers with different kernels except for LDA with 99%. For Group 2, the combined feature sets provide classification accuracy of 100% for KNN, and different class of SVM classifiers, whereas QDA and LDA provide 99%. Similarly, for Group 3, the collective feature sets have classification accuracy of 100% for all the three SVM classifiers whereas 99% for KNN and

QDA and for LDA is 89%. Likewise, the classification performance of the Group 4 for the combined feature sets achieved the accuracy of 100% for KNN, 98% for KNN, SVM linear as well as Rbf and 99% for SVM polynomial. We can also notice from this Table 8.6 that the accuracy performance of the combined feature sets for the different classifiers is also very close to each other. The closer accuracy results also validate the performance of newly developed feature EWF as well as the NWCNT.

Table 8.7 illustrates the classification performance in terms of sensitivity, specificity and accuracy parameters of the NWCNT for the different classifiers. For Group 1, all of the six classifiers achieved 100% sensitivity performance whereas except LDA remaining five classifiers attained 100% specificity and accuracy. Likewise, in the case of Group 2, except QDA all the remaining classifiers achieved 100% sensitivity. Whereas, except LDA the remaining five classifiers attained 100% specificity performance. The accuracy performance of KNN, as well as different classes of SVM classifiers, are 100% while 99% for the two-discriminant analysis classifiers. For Group 3, the LDA and SVM class of classifiers achieved 100% sensitivity and 98% for the KNN and QDA. The specificity performance for the same group is 100 % for all the five classifiers except LDA with 78%. The accuracy performance for the similar group is 99% for KNN and QDA, 89% for LDA and 100% for all the SVM classifiers. In the case of Group 4, the sensitivity performance is 96% for the QDA and SVM linear, 98% for SVM Rbf and 100% for KNN, LDA and SVM

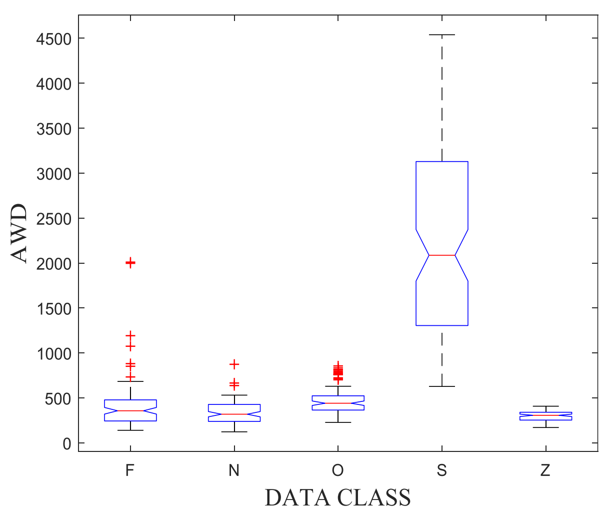

Figure 8-10: Illustration of box-plot diagram of AWD feature set for the Bonn University Epileptic EEG database.

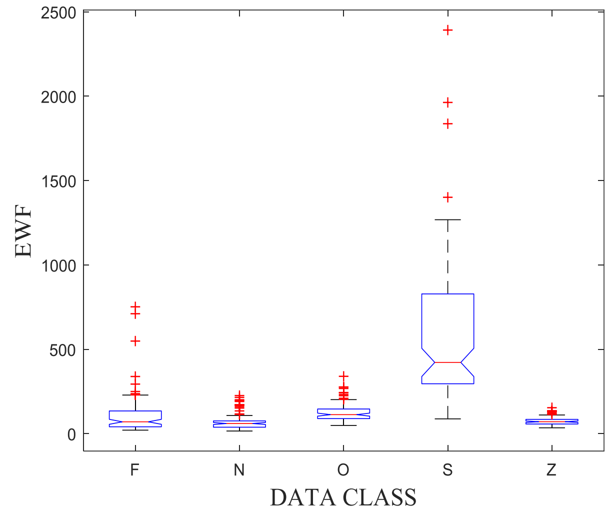

Figure 8-11: Illustration of box-plot diagram of EWF feature set for the Bonn University Epileptic EEG database.

Polynomial. The specificity performance of the same group is 76% for LDA, 98% for SVM Polynomial and 100% for KNN, QDA, SVM with linear and RBF kernel function. The accuracy performance for the similar group is 88% for LDA, 98% for QDA, SVM with linear and RBF kernel function, 99% for SVM Poly and 100% for KNN. The classification performance results are very close to each other for all the different classifiers, which demonstrate the validation of NWCNT. Table 8.7 also predicts that the SVM with polynomial kernel function is the most suitable classifier with NWCNT as compared to the remaining five classifiers. Table 8.8 demonstrates the comparison of the accuracy performance of NWCNT with the existing techniques in which the authors used the Bonn same database. As it is clearly portrayed from Table 8.8 that NWCNT outperforms as compared to the other's methodology with 100% accuracy to set Z VS. S, set O VS. S, set N VS. S and 99% for set F VS. S.

However, Chen, Wan & Bao 2017, implemented the same Bonn University and Bern-Barcelona EEG database for their proposed framework. The accuracy performance of their framework was 83.07% for Bern-Barcelona database and 88% for the Bonn University

Table 8.6: The classification accuracy results of a different test group of the Bonn University Epileptic EEG database

Data Group	Classifiers	Classification Accuracy of the individual feature set (Accuracy in %)			Classification Accuracy of the combined feature sets (Accuracy in %)
		AWD	EWF	MG	AWD + EWF + MG
Group 1	KNN=2	100	95	64	100
	LDA	88	86	57	99
	QDA	100	97	61	100
	SVM Linear	100	95	57	100
	SVM RBF	100	97	63	100
	SVM Poly	100	97	60	100
Group 2	KNN=2	95	90	75	100
	LDA	88	84	71	99
	QDA	95	88	70	99
	SVM Linear	94	88	73	100
	SVM RBF	95	88	73	100
	SVM Poly	94	88	73	100
Group 3	KNN=2	98	92	85	99
	LDA	88	87	86	89
	QDA	99	94	86	99
	SVM Linear	96	93	86	100
	SVM RBF	98	93	86	100
	SVM Poly	99	93	86	100
Group 4	KNN=2	94	87	80	100
	LDA	87	83	79	88
	QDA	90	85	79	98
	SVM Linear	92	87	83	98
	SVM RBF	94	87	83	98
	SVM Poly	96	87	83	99

Table 8.7: The classification performance of different test groups of the Bonn University Epileptic EEG database

Data Group	Classifiers	Overall classification performance AWD + EWF + Q (%)		
		Sensitivity (%)	Specificity (%)	Accuracy (%)
Group 1	KNN=2	100	100	100
	LDA	100	98	99
	QDA	100	100	100
	SVM Linear	100	100	100
	SVM RBF	100	100	100
	SVM Poly	100	100	100
Group 2	KNN=2	100	100	100
	LDA	100	98	99
	QDA	98	100	99
	SVM Linear	100	100	100
	SVM RBF	100	100	100
	SVM Poly	100	100	100
Group 3	KNN=2	98	100	99
	LDA	100	78	89
	QDA	98	100	99
	SVM Linear	100	100	100
	SVM RBF	100	100	100
	SVM Poly	100	100	100
Group 4	KNN=2	100	100	100
	LDA	100	76	88
	QDA	96	100	98
	SVM Linear	96	100	98
	SVM RBF	98	100	98
	SVM Poly	100	98	99

Table 8.8. Comparison of the accuracy performance of the NWCNT with existing techniques that used the Bonn University Epileptic EEG database for their experimentation

Authors	Data Group	Accuracy (%)
Srinivasan, Eswaran & Sriraam 2005	Z vs S	99.6
Siuly, Li & Wen 2011	Z vs. S	99.9
	O vs. S	93.6
	N vs. S	96.20
	F vs. S	93.60
Nicolaou & Georgiou 2012	Z vs S	93.42
	F vs S	83.13
Samiee, Kovacs & Gabbouj 2015	Z vs S	99.8
	O vs S	99.3
	N vs S	98.5
	F vs S	94.9
Siuly et al. 2018	Z vs S	99.5
	O vs S	99
	N vs S	98.5
	F vs S	97.5
Kabir et al. 2018	Z vs S	99
	O vs S	99.25
	N vs S	99.38
	F vs S	93.13
Wang, Gong & Li 2019	Z vs. S	100
	O vs. S	100
	N vs. S	98.4
	F vs. S	98.1
NWCNT	Z vs. S	100
	O vs. S	100
	N vs. S	100
	F vs. S	99

Epileptic EEG database, which is less as compared to NWCNT. As NWCNT achieved 99% accuracy for Bern-Barcelona database and 100 % for the Bonn University database.

In summary, on the basis of all of the above experimentations, I conclude that the innovation of new feature EWF helps to improve the EEG signals classification performance for different classifiers. Furthermore, the investigation results also indicate that NWCNT with SVM Polynomial kernel function is a prominent approach for classifying different types of EEG signals and promising to detect epileptic seizure activity. The NWCNT has the following four main advantages as compared to other complex network technique for epilepsy detection:

1. First, NWCNT does not rely on a threshold value for edge detection. As a result, taking less computation time in the transformation of EEG signals to the complex network or graph;
2. Secondly, the projected framework considered all the nodes (all the data points of EEG time series) for the construction of the network. Thus, there is no loss of information during the transformation of EEG time-series signals to a weighted network;
3. Third, the introduced framework is compatible with different EEG recording or different nature of EEG signals (the Bern-Barcelona EEG database and Bonn University Epilepsy database);
4. For the Bern-Barcelona database, NWCNT attained 99% accuracy, which is the highest classification performance results achieved till now.

I believed that NWCNT can be a helpful resource to the expert's neurologist and researchers for acquiring information in the field of epileptic seizure detection. In addition, this research study will pave a way to assist the technicians in developing a software system for EEG signals classification and improves the presently available technology. It is my belief that this innovative framework can also be applied to identify other brain disorders from EEG signals and applies to other databases of time series signals.

8.6 Summary

During the epileptic seizure attack, a sudden fluctuation can be catastrophic if not detected early enough. This chapter presents a framework to classify epileptic seizures from different EEG signals. The NWCNT focus on the extraction of vital information in the form of a newly developed feature from EEG signals for epileptic abnormality detection. For this purpose, firstly the time series EEG signals are transformed into the NWCN. Afterward, three features MG, EWF and AWD are extracted from the NWCN. Six machine-learning classifiers named SVM Linear, SVM Rbf, SVM Polynomial, LDA, KNN, and QDA assessed the obtained feature sets. NWCNT outperformed with 99% classification results for Barcelona database and 100% for Bonn database. Moreover, experimental results also suggested that the newly developed feature is commendable to increasing the classification performance. The experimental study in this chapter has explored that the NWCNT is suitable to distinguish between two distinct EEG signals. The future step in this research study is to implement the NWCNT for multi-class EEG signals with the help of deep learning classifiers and also to detect other brain disorders from EEG signals.

CHAPTER 9

CONCLUSION

The application of graph-theory in the neuroscience discipline for the analysis of brain anatomy discloses a different qualitative view of brain-activities as well as brain-behavior mapping. The graph approaches provide effective techniques for the subjects such as discovery and exploration of hierarchical structure, assessment of efficacy as well as vulnerability, plus structure-function relations in healthy brains and brain abnormalities. The way nodes (or vertices) and edges are allied are related with an abundant number of dynamical as well as topological properties at all different scales, i.e., from that of the vertex to that of the whole complex network, that ultimately allows the neuroscientists to divulge several hitherto unaddressed matters.

By considering above-mentioned information, this dissertation developed techniques for EEG signals analysis and classification by mapping the EEG signals to network using network theory. This research project aims to develop different innovative techniques that investigate the three issues specifically: Epilepsy detection from EEG, EEG sleep staging, and classifying alcohol use disorder from EEG.

This Ph.D. project introduces different weighted network techniques for the analysis and classification of the nonlinear EEG signals. In this research project, different frameworks have been developed using three types of EEG signals: alcoholics, Epilepsy, and sleep. The first framework introduces the weight in the edges of the visibility graph for identifying the epileptic seizures activity from EEG signals. The promising results were achieved with the help of the Average weighted degree parameter that is extracted from the WCN. The other objective of the first framework is to evaluate the effect of segmentation on EEG signal analysis. The experimental results prove that the proposed framework is not affected by the segmentation and un-segmentation of EEG signals.

The second framework introduces an innovative technique for identifying or classifying the epileptic seizure using weighted visibility graph-based network. The WVGBN is developed by introducing the arctan function as the weight allied to different links in the visibility graph-based network. The reason behind introducing the weight associated with links is to find the underlying dynamics of EEG signals, which is best defined by evaluating the strength amongst the nodes of the network. In addition, the modularity feature of community detection has been the first time used in the analysis of WVGBN. The 100% accuracy results for classifying the EEG signals of seizure activity and healthy subjects, proves that the proposed framework is significant for epilepsy detection.

The third framework introduces a weighted horizontal visibility network for analyzing the distinct EEG databases. Two parameters correspond to the coherence characteristics of WHVN are mined: Average Weighted Degree, and Average degree. The proposed framework is tested on distinct EEG databases: Epileptic database and Alcoholic database. 10-fold cross validation applied for the classification proves the importance of the framework for characterizing the underlying dynamical properties of the WHVN of EEG signals.

The fourth framework applied WVGN for automated classification of distinct sleep states using three parameters: AWD, modularity, and AD. This framework achieves higher classification outcomes for two different criteria of sleep data evaluation (named: R&Ks and AASM). The analysis explored Lorenz and Rossler series based simulation proved the validity of the proposed framework against noises. The aim of developing this framework was to investigate the effect of weight allied to links of the network for categorizing the problem domain of multi-class EEG classification. All the three parameters were first time tested for the analysis of EEG data of sleep states. This research discovered that the combined parameter sets provide more pertinent outcomes in comparison to separable feature.

The fifth framework proposes a new algorithm to detect epileptic seizure activity by developing a new complex network approach named as New Weighted Complex Network (NWCN) Technique. A new feature is also developed, named as 'Edge Weight Fluctuation" (EWF), which helps to extract sudden fluctuation in EEG signals. This research work has evaluated the significance of the proposed framework by applying it on two dissimilar benchmarks Epileptic database, i.e. Bern-Barcelona EEG database and Bonn University EEG database. The simulation analysis has been performed with two different chaotic signals named Henon map and Logistic map to evaluate the validity of the proposed framework. The main aims of this research study were to categorize the focal and non-focal signals of recorded from an epileptic patient; classifying the distinct types of EEG signals and to develop a new feature for detecting the sudden fluctuation in the EEG signals. The 99% accuracy for Barcelona database and 100% of Bonn database proves the effectiveness of the proposed framework.

9.1 Contributions to Four Research Field

This research project has a major contribution in the following fields:

- **In the network theory:** Three different methods techniques are developed for analyzing the network: Weighted visibility graph-based network (WVGBN), weighted horizontal visibility network (WHVN) and new weighted complex network (NWCN) Technique. Moreover, the idea of introducing the two new weight methods in the links of the network also plays a significant role in the analysis of time series based network.
- **In the analysis of non-linear time series:** This study explores the nonlinear time series analyses from different aspects. Firstly, the noise-robustness of the complex networks was evaluated. Unlike the conventional feature measuring methods, this study designed a new feature named Edge Weight Fluctuation for characterizing the underlying dynamical properties of the non-linear time-series.
- **EEG diagnosing:** Three different types of EEG databases: alcoholic, epileptic, and sleep EEGs were used for analysis. Sleep scoring based on a single-channel EEG signal is challenging for biomedical engineers and experts. This study applied weighted complex networks to extract features from sleep EEGs.
- **Pattern recognition:** EEG patterns are complex and time-variant. For example, EEG signals from one subject are significantly different from those of another subject. Effectively performing supervised classifiers are difficult to obtain in these cases because the training set from one subject is significantly different from that of others. This research study provides the sorting of the feature set technique for effectively classifying the different types of EEG signals.

9.2 Future Work

Currently, clinical diagnosis of brain abnormalities is generating Multimodel database such as: EEG-fMRI data, DEAP database, MAHNOB-HCI database, etc. This research project is based upon EEG database analysis. In future, I have planned to develop weighed complex network-based framework for Multimodel database.

Feature selection approaches are applied for removing the redundant or extraneous features to evade the issue of overfitting of the data. By developing a different generalized feature set from the main feature sets, it improves the accuracy of the classification process and also reduces computational efforts as well as data storage. I have planned to develop new feature selection techniques for all the proposed frameworks in this research study.

This Ph.D. project developed different frameworks based on the offline system for analysis of EEG while the clinical diagnosis desire a real-time online system for EEG analysis. In the future, I would like to extend my research project for the development of a real-time online based system for EEG analysis and classification.

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