Secure communications in wireless networks for biomedical EEG sensor networks applications.

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Thèse de Doctorat

école doctorale sciences pour l'ingénieur et microtechniques

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SECURE COMMUNICATIONS IN WIRELESS NETWORKS APPLICATIONS FOR BIOMEDICAL EEG SENSOR NETWORKS

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Abstract

The framework of this thesis concerns the use of sensor networks and wireless communications in regards to the implementation of reliable healthcare systems. More precisely, it offers an innovative method for biomedical Wireless Sensor Network (WSN) monitoring systems as a predictor as well as advances sensitive portable electroencephalogram (EEG).

An EEG wireless sensor network is used to monitor spontaneous brain waves, including both normal and abnormal waves, for patients suffering from different types of epilepsy. The biomedical epilepsy Wireless Sensor Network monitoring system (WSN-EEG) reads signals from a wireless sensor network from the patient's scalp and filters these signals to run parallel data processing for brain waves. The predicting procedure for the severity of a forthcoming epileptic attack depends on a proposed algorithm and the FeedForward Neural Network (FFNN) learning machine model that analyses the abnormality in the brainwaves by alert signals for the upcoming attack.

This method can help to save lives by predicting a seizure before it occurs, and in turn, different injuries and serious behaviours arising during an epilepsy attack. In addition, the data collected from this proposed method may be used for further medical diagnosis measures.

This research focuses on developing a prediction algorithm using FFNN and the implementation for IEEE802.11n communication features. The research investigates the security performance and privacy for data transfer.

The measured results show that the implementation of security protocols plays an important role in the data transmission and seizure prediction, which can significantly reduce prediction time and delay the alert signals, affecting patients with epilepsy.

Keywords: Sensor Networks, Brain Waves, Electroencephalography, Quality Performance, Algorithms, Feed Forward Neural Network, Quality of Service, IEEE802.11n, Security Protocols, Epilepsy Diagnosis, Seizure Detection.

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Contents

Chapter 1: General Introduction

1.1 Research domain

General context: healthcare monitoring systems over wireless sensor networks.

Specific context: EEG system and sensors, predictive approaches.

1.2 Background

During recent years, wireless communications has grown rapidly, and wireless technology has taken a significant place in people's lives[1]. The new technology has evolved Wireless Sensor Networks (WSNs) implementation and applications latterly; meanwhile the challenge for selecting WSN appropriate technologies (IEEE802.11x, Bluetooth, ZigBee, PAN and WLAN etc.) is high especially with certain level efficiency and effectiveness [1], [2]. Many applications for sensor networks request certain level of Quality of Service (QoS), high data rates and network capacity, energy consumptions, memory constraints, and reliability for short ranges, such as medical and healthcare services, Smart Technologies, online streaming and others. Specifically, applications in neurology and cardiology domains which impose stringent requirements on system consistency, high quality of service, and a certain level of privacy and security [3].

Moreover, advances in wireless sensor networking have led to the emergence and opportunities of WSNs in healthcare systems. The development and improvement of the Sensor-based technology has invaded medical equipment's and replaced large number of cables and devices interconnections found in medical centres and hospitals. This technology has improved the requirement for providing capability and reliability for many patients with enhanced mobility. In the future, the integration of wireless networks will exist and will be specialize in many medical technology devices [1][2].

Wireless Sensor networks are becoming increasingly important for healthcare implementations such as continuous monitoring health condition for patients in homes and hospitals, and share the medical information with remote care providers or hospitals. The demand to the technology is an overwhelming need for more physiological functions study and monitoring in a hospital and clinical setting [1][3].

Today wireless sensor networks are effective relevance tools in health measuring and recording of various physiological functions diseases, where many sensors are working simultaneously on an individual patient. The need creates new implementations for personal wireless biomedical sensor wireless networks with a specific architecture and capacity to handle different body signals, according to the requirements. The wireless sensor networks type and numbers should be configured according to monitoring needs related to the diseases, treatment, and the patient life style [1][3][4].

In this work, a wireless sensor network healthcare monitoring system for Electroencephalography (EEG) utilizing IEEE802.11n technology and FFNN will be proposed for epileptic patients developed by taking inspiration from EEG system and advanced WSNs technology to monitor brain waves and predict abnormal waves, to improve and save patients life. This proposed development to wireless EEG and added predations functions is seen as an effective method of providing immediate care as it allows for continuous monitoring process for brain activities and, alerts the epileptic patients as well as save the patient information in a storage memory for further diagnoses by medical doctors or healthcare providers. This proposed technique will not only redefine patient monitoring system in hospital care but also work, home, and recreational activities. These development EEG WSN technologies enable us to monitor patients on a regular basis, enhance the need to frequently medical consulting and visit the local doctor and save patents life [5].

1.3 Motivation

The growing demand of WSN applications in medical care can play crucial roles to improve the quality and increase the efficiency in epilepsy healthcare service. This demand of applications can be categorized into six types: monitoring of patients, system reliability, quality of service, privacy and security, safety, data collection for medical diagnoses and treatments [6]. The monitoring process deals with patient needs and medications on a regular basis. The reliability of the system deals with comfort use and patients complexities care requirements. The aim of this demand is to enhance safety of patients by triggering alerts in acute situations for abnormal brain activities and improvements in precautions steps. Application as WSN for EEG monitoring process required a high level for quality of service, a specific demand on privacy and security for patents. As well as deals with continuous data transmission, system capacity, latency restrictions, jitter and perform a real-time data analysis by adopting or adapting the methods and paradigms of healthcare noted for high reliability and relevance system requirements [6][7] . The thesis will investigate the application of sensor networks in healthcare systems and will address how WSN concepts will be integrated into a proposed EEG wireless epileptic prediction systems.

The thesis investigate the stringent requirements on system reliability, quality of service, and particularly privacy and security data transfer approaches in wireless sensor network utilizing IEEE 802.11n for Electroencephalography (EEG) health care application, to measure the service time as part of quality of service and improving efficiency and effectiveness in epileptic healthcare service [6].

1.4 Problem Statement

Wireless sensor networks technology is integrated in many applications, particularly in areas requiring extensive information and development such as healthcare and safety applications, monitoring of patients in clinical settings, monitoring of chronic illness or elderly patients in nursing homes or houses, and for long-term clinical databases collection [5][8].

Wireless sensor applications use different data transmission techniques, such as Bluetooth, IEEE802.11, ZigBee PAN, etc. which might be a challenge for application requirements such as reliability, quality of service, and security and privacy [4][5]. The Epileptic healthcare Electroencephalogram EEG monitoring system is one of the applications that demand such as requirements with respect to healthcare value and matrix quality standard [6][8][9].

The techniques used in network sensor technology data transmission for monitoring systems can be a challenge and reliable factor for any sustainable system. Specifically, EEG network sensor technology monitoring system used to detect abnormal brainwaves for epileptic patients. In the recent years, several EEG systems were developed to use wireless sensor network technology, **however, it should be noted that these** systems are mainly used for medical analysis and diagnosis but not for real-time prediction of epilepsy attack.

Therefore, new approaches are required, where the wireless EEG system can be improved with more functional parameters using patient emends such as epileptic **predictions**, safety information in surrounding environment, with respect to QoS parameters and **data privacy**.

More precisely, to develop wireless sensor network EEG systems with prediction capabilities, implementing IEEE802.11n data transmission technique's with high quality of service parameters (such as, service time, bandwidth, delay, jitter etc.). This system should be considered together with neurology medical knowledge for epileptic patients, abnormal brainwave activities, seizure type and attack duration for prediction algorithms tuning to figure out the best fit for a reliable EEG wireless sensor systems epileptic predictor.

1.5 Contribution

Biomedical equipment for healthcare is the intersection between medical science, information science, implementing new information technology and healthcare principles It deals with information sources, equipment, concepts and clinical methods required to improve acquisition, data storage and information recovery in health and biomedicine. This includes not only medical equipment but also clinical guidelines, current medical terminology, and information and communication systems. Research and Development efforts within the health care industry and information technology have made significant advances in the quality of patient medical services [10].

For these reasons, it is important to study the sensor networks design, wireless sensor applications, and health care matrix to provide a reliable and stable level of performance with respect to QoS parameters and data privacy transmitted using sensor networks [1][5]. This research focuses on health care services and systems for patients with epilepsy medical history and implementing secure wireless sensor network to monitor the brainwaves, and predict the abnormality in the brain activities to improve the quality of life in Patients with epilepsy history [3].

The thesis work deals with wireless sensor network utilizing IEEE802.11n for EEG biomedical application system, particularly, targeted to measure WSN service time performance, and to propose a predictor Wireless Sensor Network EEG Systems for epilepsy.

Particularly, within the scope of the thesis the following contributions have been made:

- Measurements and evaluation for performance of WSN service time delay, and examined the effect of User Data Protocol (UDP) packet size and bit rate on the performance of the network when security is enabled/disabled for IEEE802.11n security protocols.
- A new wearable Biomedical Sensor Network (WSN-EEG) concept development not only to monitor but also to predict irregular brain waves as advanced sensitive portable for an electroencephalogram (EEG) analysis device.
- An analytical model and algorithms developed to describe and control abnormality detection in the brain waves as a core for the proposed wearable Biomedical Sensor Network (WSN-EEG).
- A learning-based approach for prediction using Feed Forward Neural Network (FFNN) for abnormal brainwaves and seizure attack as a base for the predictor the alert system.

1.5.1 Measurement and evaluation.

This research evaluated an adaptive, scalable and effective information transmission and communication, in the context of IEEE802.11n as Ad hoc sensor networks. In this approach, measured the transmission time, data packet using UDP as data transmission for information between nodes with and without security protocol scenarios, to evaluate the service time, delay impacts and data congestion. The details will be provided in the Chapter 4 and 5

1.5.2 WSN-EEG device.

This research developed a WSN EEG network concept approach by taking inspiration from sensor network implementation for complex systems and communication principles, to provide the analyser with information about each brain wave and assist the patients to be aware of irregular activities for the brain. The details are provided in the Chapter 4.

1.5.3 Data flow Algorithm.

The thesis introduced a novel data flow algorithm and FFNN model based on the experiment results to predict irregular brain waves behaviour. The model use a tolerance point to predict the time slot for immergence support for patients and alert process before the attack or during the irregular brain waves. The approaches can be use as communication process to share information about irregular brain signals to support patients in severe conditions or provide medical reports about the brain activities in certain conations for medications. The details will be provided in the Chapter 5

1.6 Related works

Currently, the related research on wireless networks is focused on the computationally efficient protocols and algorithms and on the energy design whereas the application domain is limited to the areas of simple application reporting and data-oriented monitoring activities (Labrador et. al. 2009) [11].

Other researchers also highlighted relay nodes deploying issue in case of heterogeneous WSNs to give fault tolerance in higher network connectivity wherein a different type of transmission radii is possessed by the sensor nodes (Han et al., 2010). Owing to the latest advancements in technology, the heterogeneous devices in new network architectures go beyond the current limitations which set the expansion of WSNs for possible applications to significant degree, which also make rapid changes all along the line) [11].

Others have done research on predication Algorithms for EEG without using sensor networks technology, the main research results are:

- EEG seizure detection and prediction algorithms: A survey. They presented an overview of seizure detection and prediction problem and provide insights on the challenges in this area. They cover some of the state-of-the-art seizure detection and prediction algorithms and provide comparison between these algorithms [12] .

- EEG signal processing for epileptic seizure prediction and Employed computational intelligence techniques to predict epileptic seizures using multichannel EEG data and novel methodologies to identify seizure precursors.[13].
- Seizure Prediction. Epilepsy presented a research in automated seizure prediction algorithms[14].

1.7 Organization of the Dissertation

1.7.1 General presentation

The dissertation is structured in six chapters, including a general introduction, literature study for wireless sensor networks, comparative study for EEG and epilepsy, prediction system, results, conclusions and perspectives. The first chapter provides General introduction and information about the problem statement, the objectives and the contributions. The second chapter overviews the main concepts of Wireless Communication standards, Security Protocols in WLAN, Ad hoc Networks, Wireless Sensor Networks and medical applications. The third chapter overviews EEG system, brain waves epilepsy diagnosis, Seizure detection. The fourth chapter proposes an adaptive wirelesses sensor networks EEG (WSN-EEG) system design, protocol layer, data flow concept. The fifth chapter illustrated different simulation testbed for IEEE802.11n, microcontroller for brainwaves, algorithm and Feed Forward Neural Network (FFNN) model as a learning-based approach to predict epilepsy attack based on the simulation results and prediction algorithm. The conclusions and perspectives are presented in the sixth chapter.

1.7.2 Global view

- Chapter 1: General Introduction
- Chapter 2: IEEE802.11 transmission and security protocols
- Chapter 3: Wireless sensor networks and EEG in brief
- Chapter 4: Wireless Sensor Network EEG approach
- Chapter 5: Prediction system and Results
- Chapter 6: Conclusions & Perspectives

1.7.3 Chapter Contents

A. Chapter 1: General Introduction

The General introduction chapter provides information about background and motivation, problem statement, the objectives and contributions of the dissertation.

B. Chapter 2: State of the art

This chapter presents the main concepts of wireless sensor networks, applications and implementation, IEEE802.11n transmission techniques and security protocols

C. Chapter 3:

This chapter describe EEG and epilepsy medical part information.

D. *Chapter 4: Wireless Sensor Network EEG and IEEE802.11n approach*

This chapter introduce a novel biomedical Wireless Sensor Network monitoring system, as a predictor and advances sensitive portable electroencephalogram

E. Chapter 5: WSN model and Feed Forward Neural Network prediction system

In this chapter, describe WSN-EEG prediction procedure, simulations, results f or learning based FFNN that analyses the abnormality in the brain signals, and detect the steady abnormal waves for the device alert system.

F. Chapter 6: Conclusions and perspectives

This part of the thesis present the summary of the research and proposed future work.

Chapter 2: State of the Art

The major contribution of this chapter is a comprehensive introduction for communication for wireless networks, security protocols, sensor networks and implementation. First, the wireless and sensor network classification, communication mechanisms, security protocol implementations and applications, followed by classification of information dissemination approaches in wireless sensor networks.

2.1 Introduction

During recent years, wireless communications has grown rapidly, and wireless technology has taken a significant place in people’s lives. The benefits of wireless networks such as mobility and flexibility offer advantages over wired networks, which require physical connectivity to a wired backbone in order to have service. The advantages of wireless networks over the wired ones help users to access to information from many locations. [15]:

Wireless personal area network coverage area is limited to approximately 10-meter radius, such as system are used for ad hoc communications between computers, cell phones, and Personal Digital Assistants (PDAs). The Bluetooth wireless standard is a prevalent WPAN, it uses the 2.4GHz frequency band based on low power signalling and provides a data rate up to 1Mbps. In the coming three years, many applications of WPAN will be used for higher data rates. With new technologies that are under development by IEEE and industrial working groups. This new technology is called Ultra WideBand technology (UWB) and can provide data rates up to 100 Mbps [16] [17].

Wireless Networks provide a high data transmission rates among wireless devices using electromagnetic waves rather than wired media. It covers a range to 100 meter i.e. (between the access point and the client).

In 1997, IEEE, as later IEEE 802.11n which was delivered to the market, standardized wireless LAN and it uses the 2.4 -5 GHz frequency band. The maximum bit rate achievable is currently 600Mbps. In the recent years, many standards have been introduced with higher data transmission rates using different signal modulation techniques and bands. The data rate was increased to 600MbpsMbps with IEEE802.11n and IEEE802.11a standards. Other standards have been introduced by IEEE such as Wi-Fi Protected Access (WPA) and IEEE 802.11i (WPA2) to provide security and authentication for data [17] [18].

2.2 Wireless Sensor Network

When it comes to defining Wireless Sensor Networks (WSNs), they are referred as infrastructure-less and self-configured wireless networks with the purpose of monitoring environmental and physical conditions like motion, pollutants, pressure, vibration, sound, temperature, and they are used to pass their data through the network cooperatively to the sink or main site where the data can be examined and observed. Between the network and the users, the base or sink station performs as a middle interface. By gathering results and injecting queries from the sink, the desired information from the network can be retrieved. Generally, there are hundreds and thousands of nodes in a wireless sensor network. Through the radio signals, the communication among the sensor nodes take place. Computing and sensing devices alongside other power components and radio transceivers are attached with a wireless sensor node. There happens to be resource constraints in WSN individual nodes as they have limited communication bandwidth, storage capacity, and processing speed [11].

After the deployment of sensor nodes, they hold the responsibility for self-organizing a suitable infrastructure of network, often times with the idea of multi-hop communication. After that, the information of interest is gathered with the aid of on board sensors. Those queries which are sent by the “control site” are also answered by the wireless sensor devices in a bid to provide sensing samples and to execute particular instructions. It is noted here that the sensor nodes working mode might be either event driven or continuous. The positioning information and the location can be obtained by the local positioning algorithms and the Global Positioning System (GPS). In order to act upon specific conditions, the wireless sensor devices can also hold actuators. According to Akkaya et al. (2005), these networks are at times called by the name “wireless sensor and actuator networks”.

Because of numerous restrictions Wireless sensor networks (WSNs) also need protocol design related non-conventional paradigms and also enable the new applications. There is a great need to obtain a proper balance between signal/data processing and communication for the reason that networks have long lifetime and there is a great need of consuming low energy and less complexity of device. Hence, this triggers more efforts from the researchers, and in the last decade they’ve come up with more industrial investments in the field alongside standardization of processes (Chiara et. al. 2009) [11].

2.2.1 Network Characteristics

Generally, a WSN network is composed of a large number of multifunctional sensor nodes which are low power and low cost that are deployed in the desired region. Despite their small sizes, these sensor nodes are tagged with embedded radio transceivers and microprocessors. Hence, their capabilities are not only limited to sensing, but they also perform well in communication and data processing scenarios. They use a wireless medium to communicate over a short distance and accomplish a common goal through collaboration. For instance, they are utilized in industrial process control, surveillance of battlefield, and in the monitoring of environment scenarios [11][19] [20].

WSN is utilized these days in unattended real-world physical environments. Hence, when it comes to analyzing the attributes for networks efficient deployment, the WSN characteristics must be taken into consideration. Their key characteristics are as below[11][19][20][21][22][23].

- Low cost: in a bid to measure any physical environment, generally the WSN deployment entails hundreds and thousands of sensor nodes. It is suggested to cut down the cost of the sensor nodes as much as possible in a bid to lessen the total cost of the entire WSN network.

- Energy efficient: there are different types of purposes for which the WSN energy is used such as storage, communication, or computation etc. When it comes to examining the energy consumption scenarios with any other communication, sensor nodes come on the top since they consume more energy than the others. They frequently turn into invalid provided that they run out of power for the reason that charging them is next to impossible due to no options for recharging them. Hence, the design phase wherein the algorithms and protocols are developed must consider the power consumption scenarios.

- Computational power: generally, the computational capabilities of node are very limited because the energy and cost needs to be taken into consideration.
- Communication Capabilities: Using a wireless channel, generally WSN make use of the radio waves for communication. They can communicate in short-range distance, with dynamic and narrow bandwidth. The communication channel could be either unidirectional or bidirectional. To run WNS smoothly is still a big question due to hostile and unattended operational environment. Hence, the resiliency, security, and robustness highly depend on the software and hardware for communication.

- Security and Privacy: adequate security mechanisms should be in place for each sensor node so that the unintentional information damage, attacks, and unauthorized access could be inhibited. Moreover, there should also be added privacy mechanisms in place.

- Distributed sensing and processing: the sensor nodes are either distributed randomly or uniformly in a large number. It is to be noted here that each and every node has certain capabilities such as collecting, processing, sorting, aggregating, and sending data to the sink. Hence, the system's robustness is provided by the distributed sensing.

- Self-organization: it is imperative for the sensor nodes to organize themselves since their deployment is executed in an unattended hostile environment and in an unknown fashion as well. They need to collaborate so that they organize themselves according to the distributed algorithm in a bid to obtain automatic formation of network.

- Multi-hop communication: the WSN entails a large number of sensor nodes deployment. Hence, it is feasible to take aid from an intermediate node via a routing path in order to communicate with base station or sinker. If there is a requirement to communication with base station or other node, which lies across its radio frequency, the intermediate node must go through the multi-hop route to make it possible.

- Application oriented: there is difference between conventional network and WSN in the sense that their nature differs from each other. WSN type of network is highly reliant on the application ranges from the health, environmental, and military sectors. It randomly deploys the nodes and depending on the requirement, they're spanned accordingly.

- Robust Operations: as discussed earlier that the sensors are likely to be deployed in a hostile environment, the sensor nodes should be tolerant towards errors and faults. Hence, the sensor nodes should be equipped with the abilities like self-repairing, self-calibrating, and self-test.

- Small physical size: the size of the sensor nodes is generally small and with a restricted type of range that's why they have limited energy which lowers the capability of communication.

- Dynamic Network Topology: most of the time, the deployment of sensor nodes is conducted in an infrastructure-less area because of which the new nodes are added, creates occurrences of failure nodes and mobility, which in turn changes the network topology likewise. Hence, maintaining the sensor networks topology becomes extremely difficult and challenging. Hence, the topology accounts for putting an impact on the sensor network properties like data processing, complexity, robustness, capacity, and latency.

- Node Types: There are two kinds of groups or sets of nodes on the grounds of sensing range i.e. subsisting homogenous or heterogenous group of nodes. It is to be noted here that where all nodes bear the same capability and are identical is referred as a homogeneous group of nodes. Layered architecture is the superb example in this case. While on the flip side, a group in which all nodes are tagged with dissimilar capabilities and are not identical for instance, some nodes are weaker than the others, is referred as a heterogeneous group. The Cluster architecture is an example in this case wherein a cluster head is formed by the node and the gathering of data is performed by the node though a less powerful node.

2.2.2 Wireless Sensor Network Applications

- Based on the system's characteristics and requirements, there exist a broad range of applications in which the continuous detection of particular events and monitoring is needed [11][19-23-[24].
- Military Applications: When it comes to deploying sensor networks, military sensing comes on the top slot. They can be used as an integral component of military command, military situation awareness, nuclear and biological chemical attack detection reconnaissance, detection of enemy

movement and detection of explosion and mass destruction, reconnaissance and targeting systems, surveillance, intelligence, computing, and communications.

- Environmental Applications: The sensor nodes are widely being utilized in various environmental applications such as ocean and fish monitoring, traffic control monitoring, flood detection and forest fire, animal's habitat exploration, ph. levels, soil moisture, agricultural research etc.

- Structural Health Monitoring: There is no denying the fact that both for academia and industry, the health monitoring is one of the hottest research topics. The order of 1-10 Mbps constitutes the amount of raw data which could be collected and transported for those applications. Hence, the transmission of information is limited to only limited information through the aid of sophisticated algorithms such as auto regressive module, wavelet transmission etc.

- Heavy Industrial Monitoring. In harsh and hostile environments, there is a great need for the industrial applications to rely on the highly dependable operations such as factor process control, industrial automation, monitoring of manufacturing, warehousing etc.

- Health or Medical Applications: Healthcare is one of the important sectors wherein sensor networks are broadly used. For example, they are being utilized in the healthcare settings like physiological data monitoring of patient's as their hearth rate and blood pressure, administration of controlling the drugs, detection of unconsciousness, non-invasive monitoring of health, and monitoring of exercising activities.

- Home Application. There are many uses of sensor nodes in home application scenarios such as they can be integrated into home appliances and furniture for monitoring and managing inventory systems, products quality, and automatically controlling the airflow and temperature of the room.

2.2.3 Architecture Design Objectives

The following are the architecture Design Objectives. [11] [21-24][25][26].

- Identifying Requirements for Typical Sensor Node Application: There is a possibility of developing new architecture on the basis of target application. Its vital to figure out the future sensor node applications nature in case of sensor networks, but the precise and accurate design objectives highly rely on the qualitative analysis of an application.

- Identifying Relevant Technological Trends: It’s vitally important to understand the complexity and heterogeneous nature of WSN systems. Hence, proper evaluation of costs bottlenecks and design complexity should be performed because of changing and progressing technological environments. In order to maximize the power optimization, it is important to evaluate the technological trends during the architecture design phase. It is believed that WSN would hold many different types of algorithms based on the future technology related communication and storage costs and the future competition ratios.

- Balanced Design: To utilize sensor nodes to their maximum, its important that every component of sensor node is optimized to a significant degree.

- Techniques for Design and Usage of the Components**:** Depending on their maturity, there are two categories in which the sensor node components can be grouped. An example of mature technology is power supplies i.e. specially storage and power supply. On the flip side, those technologies which are awaiting key revolutions are like ultra-low power wireless communication, actuators, and sensors. It’s vital to figure out that which tools, architectures, and techniques are reusable and what are the aspects where efforts are needed for new design.

- Survey of Technology, Components and Sensor Nodes: There is strong need to focus on sensor node architecture to provide the quantitative and qualitative analysis. To make it possible, one needs to take sensor nodes state, components and technology into consideration and then the decision regarding architecture designing should be made.

2.3 Wi-Fi Protected Access

Wi-Fi Alliance created a certification program called by the name PA (Wi-Fi Protected Access) in a bid to highlight few WEB related security problems, such as the weakness in its IV headers, mentioned as before. For wireless communication, a latest encryption technology suggested for the security of wireless networks despite that WPA or WPA2 might not be supported by the older hardware. These technologies are called by the name WPA-PSK and WPA2-PSK as far as the home users are concerned since they make use of the Pre-Shared key so that they don't need the dedicated authentication mechanisms as required in the business or corporate environment scenarios [17] [27].

An enhancement on WEP is provided by the WPA-PSK using the mechanisms as below:

- IV Length – a 48-bit Initialization Vector is provided in WPA which increases the encrypted data's cryptographic complexity.

- Dedicated authentication methods – the capability of using 802.1x servers was introduced in WPA. Users use these as dedicated authentication mechanisms i.e. RADIUS

Cipher Block Chaining Message Authentication Code Protocol (CCMP) is also supported by WPA2. Although an increased processing power is required because it makes use of the Advanced Encryption Standard (AES) algorithm. As the wireless networks shown growth all around the globe, it becomes vital to enable the secure communication all along the line. When WPA is used (recommended AES algorithm with WPA2), it is believed to be the best method for wireless network encryption. However, WPA can get attacks from some forces by utilizing the TKIP algorithm wherein a strong, randomized key is employed succeeding a layered security approach along few secondary methods for wireless security rather than depending only on encryption, and it is highly likely to low the risks to a significant degree[17] [28].

2.3.1 Wi-Fi Protected Access 2 (WPA2)

An amendment is made in the 802.11 standard which is referred as Wi-Fi Protected Access 2 (WPA2) or IEEE 802.11i standard which lays down the wireless networks related security mechanisms. It was June 24, 2004 when the ratification of the draft standard was made which replaced past security specifications. It was observed that there were many security weaknesses in the Wired Equivalent Privacy (WEP), and to provide an intermediate solution to WEP related insecurities, WPA was introduced which employs only a subset of IEEE 802.11i. A specific mode of Advanced Encryption Standard (AES) was used by WPA2 which is also referred as the Counter Mode Cipher Block Chaining-Message Authentication Code (CBC-MAC) protocol (CCMP). It gives both data integrity as well as the data confidentiality (encryption). WEP and WPA2 use the RC4 stream cipher whereas their best alternative is AES. There are two components of WPA2 standard i.e. encryption and authentication, and there is no denying their importance in securing wireless LAN. The use of AES is mandated by the encryption piece of WPA2 but for maintaining the existing WAP hardware's backward compatibility, TKIP is available [29][30][31].

When it comes analyzing the modes of authentication piece of WPA2, one can see two modes which are named as Personal mode and Enterprize mode. There is no need to separately authenticate the users in the personal mode which uses the Pre-Shared Key (PSK). On the other hand, the users are separately authenticated in the Enterprize mode depending upon the IEEE 802.1X authentication standard. This mode makes use of the Extended EAP (Extensible Authentication Protocol) wherein 5 EAP standards are provided to choose from as below[30][31]:

a) EAP-Transport Layer Security (EAP-TLS)
b) EAP-Tunneled Transport Layer Security (EAP-TTLS)

c) Protected EAP vo/EAPMicrosoft's Challenge Handshake Authentication Protocol v2 (PEAP vo/EAP-MSCHAPv2)

d) Protected EAP v1/EAP-Generic Token Card (PEAPv1/EAPGTC)

e) EAP-Subscriber Identity Module of the Global System of Mobile Communications (EAPSIM)

The software/hardware implementation requirements in the Enterprise mode are as follows [30] [31]:

1) The EAP types selection which would be supported on stations, authentication servers and APs (Access Point)
2) Choosing and deploying the authentication servers, generally these authentication servers are Remote Authentication Dial-in User Service (RADIUS) based.
3) For clients and Aps, the software upgrades of WPA2. It is to be noted here that there are 4 phases in which a secure communication context is established by the WPA2 server. The first phase is where the AP, the client, and the parties would agree on the security policy which includes the protocol for multicast traffic and pre-authentication method, protocol for unicast traffic, and the method of authentication. This security policy will be supported both by the client and the AP. The 2^{nd} phase is only applicable to Enterprize mode in which the initiation of 802.1X authentication takes place between the client and the AP based on the preferred authentication method for the

purpose of generating a Common Master Key (MK). Then comes the third phase in which the creation of successful authentication alongside temporary key generation takes place which are updated on a regular basis. The key generation and exchange is the overall objective of this phase. Then comes the 4th phase in which CCMP protocol will make use of the all previously generated keys in a bid to provide data integrity and data confidentiality all along the line [30] [31].

2.3.2 WPA2 Authentication

By enforcing the message integrity and privacy through separating the user authentication is believed to be one of the key changes introduced in WPA2 standard, hence, it provides with the robust security and more scalable standard of security architecture which is appropriate both for corporate and home networks. There is no authentication server needed in the WPA2 personal mode that is executed between the AP and the client thus producing a 256-bit PSK through a plain text pass phrase which includes characters length from range 8 to 63. Afterwards later in the process of key generation part, the PSK creates the mathematical basis for the Pair-wise Master Key (PMK) with the cooperation of SSID length and Service Set Identifier. It is the IEEE 802.1X authentication standard on which WPA2 Enterprize mode authentication depends upon wherein the key components are like the supplicant i.e. the clients which join the network as well as the authenticator such as AP which helps in making decisions through the aid of authentication server (RADIUS) and access control alike. every virtual port is subdivided into 2 logical ports with the help of authenticator (AP) wherein one port is for the service while the other serves the purpose of authentication, both of them makes the Port Access Entity (PAE) [17] [18]. To permit the passing of authentication frames, the authentication PAE remains open at all times. On the other hand, the opening of Service PAE is bound to the RADIUS server related successful authentication. The communication between the supplicant and the authenticator takes place by utilizing the Layer 2 EAPoL (EAP over LAN). The EAPoL messages are converted into RADIUS messages by the authenticator and then forwards them towards the RADIUS Server. There must be compatibility between the authentication server (RADIUS) and the supplicant's EAP types in a bid to successfully receive and process the authentication request [30][31]. Once, the process of authentication successfully completes, both the authenticator and the supplicant possess a Master Key (MK), which is also shown in the below:

2.3.3 WPA2 Key Generation

With the aid of two handshakes, the WPA2 key generation is obtained. The two handshakes involve the a 4-Way Handshake for Pairwise Transient Key (PTK) and the Group Transient Key (GTK), and it also involves a GTK renewal related Group Key handshake. See Figure 1. The 4-way handshake between the

AP and the client through 4 EAPoL-Key messages is commenced by the access point and executes the tasks below [17][28] [30][31]:

- The client's knowledge about the PMK needs to be confirmed. The main requirement to generate the PTK is the PMK derivation purely relies on the authentication method employed. On the other hand, the authentication PSK derives the PMK in WPA2 personal mode while the authentication MK derives the PMK in case of WPA2 Enterprise mode.

- Then a fresh PTK is derived which is composed of 3 kinds of keys as follows: Key Confirmation Key – 128 bits (KCK) which is employed to confirm the integrity of EAPoL-Key frames. Then comes the Key Encryption Key – 128 bits (KEK) which is employed to encrypt the Temporal Keys – 128 bits (TK) and the GTK to impose data traffic security.

- The installation of integrity keys and encryption needs to be performed.

- The confirmation of cipher suite selection should be done.

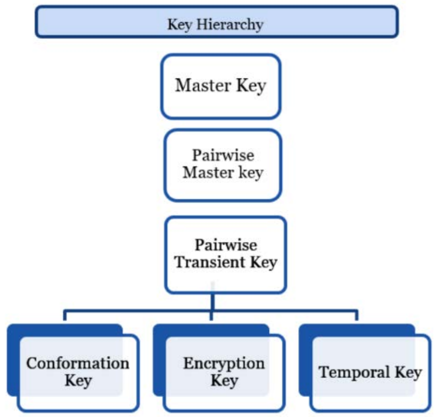

Figure 1 MK hierarchy

The Group Key Handshake is only employed to renew the GTK or to disassociate a host, and it makes use of the KEK generated during the 4-way handshake for GTK encryption see Figure 2.

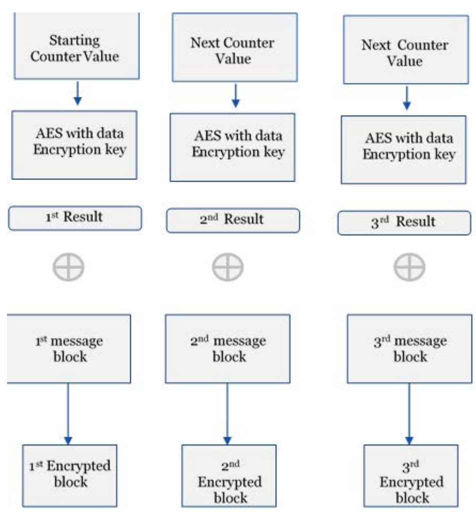

Figure 2 AES Counter Mode

2.3.4 WPA2 Encryption

WPA2 uses the AES which “is a block cypher that is a kind of symmetric key cipher that makes use of the groups of bits with a fixed type of length known as blocks [32]. A symmetric key cipher is a set of algorithm or instruction which employs the same key for decryption and encryption. By using a 128 bit key length in blocks of plaintext, bits are encrypted in the case of WPA2/802.11.i implementation of AES wherein independent calculation of bits is performed rather than a keystream executing across a plaintext data input stream. There are four stages in AES encryption, which make one round, and the iteration of every round is done 10 times. The Counter-Mode/CBC-Mac Protocol (CCMP) is employed in AES. It is to be noted here that for a block cipher, CCM is a new mode of operation that allows a single key usage for both authentication (with different initialization vectors) and encryption. These two modes are also referred as Counter Mode (CTR) which are employed in CCM, also shown in the Figure 3 which serves the purpose of data encryption, and data integrity through Cipher Block Chaining Message Authentication Code (CBC-MAC). An authentication component is generated through CBC-MAC in the wake of encryption. This is not similar to the previous Message Integrity Code (MIC) implementations wherein there is a requirement of a separate algorithm for the purpose of integrity check. A 128-bit Initialization Vector (IV) is used by AES to further enhance its advanced encryption capabilities [33][34].

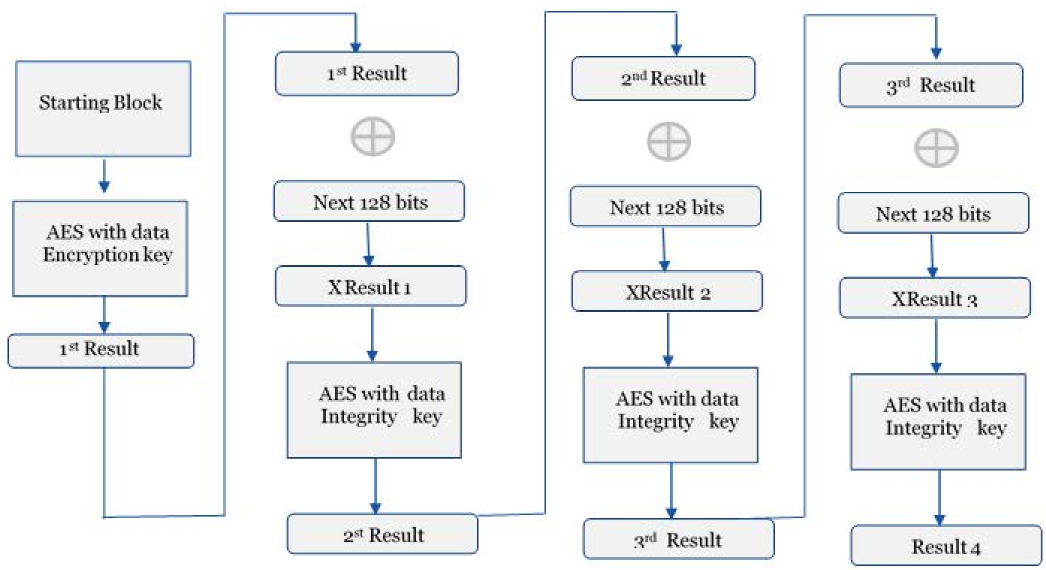

Figure 3 AES CBC-MAC

2.3.4.1 WPA2 Encryption Steps

WPA2 IEEE 802.11i standard introduced the Counter Mode with the Cipher Block Chaining Message Authentication Code Protocol (CCMP) [35] and message integrity code (MIC) with Advanced Encryption Standard (AES) as an encryption mode for the added headers to the MAC frame [36][37]. These modifications provided sufficient security and authentication processes to improve the vulnerability in previous security protocols such as WEP and WPA. Figure 4 shows the new modifications for WPA2 [38].

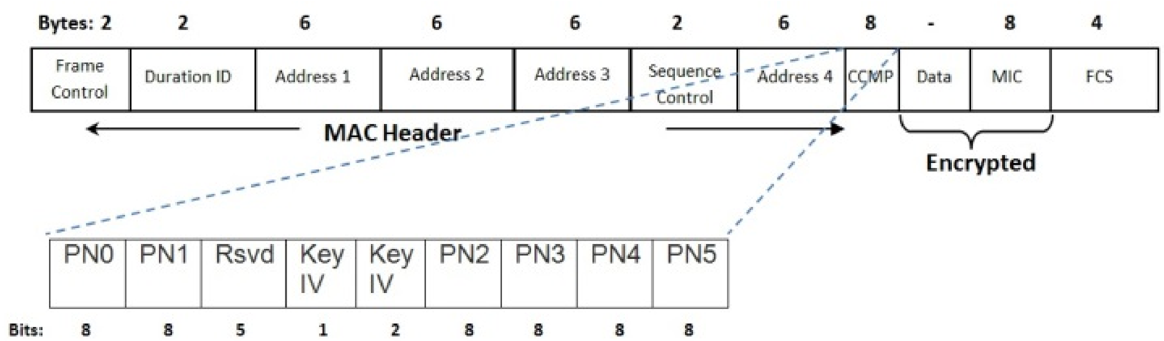

Figure 4 WPA2/CCMP MPDU

The integrity of data in the 802.11 header for the non-changeable fields is provided by MIC (similar to checksum), which is contrary to the WPA and WEP in which packet replay is prohibited from being exploited to compromise cryptographic information or to decrypt the package. A 128-bit IV is used to calculate the MIC as below see Figure 5 [39][40][41][42][43].

1) AES and TK is used to encrypt IV to produce a result of 128-bit.
2) With the next 128 bits data, the result obtained in 128-bit is XOR
3) Then the XOR result is passed through steps one and two till such time full blocks of 128 are exhausted in the 802.11 payload.

4) Finally, MIC is produced by using the first 64 bits. The data and the MIC (calculated using the CBC-MAC) are encrypted with the aid of Counter Mode algorithm. Beginning with a 128-bit counter preload, the Counter Mode algorithm initiates identical to the MIC IV, but it is different in the sense that it holds a counter value initialized to 1 rather than the resulting data length in a dissimilar counter employed to encrypt every packet.

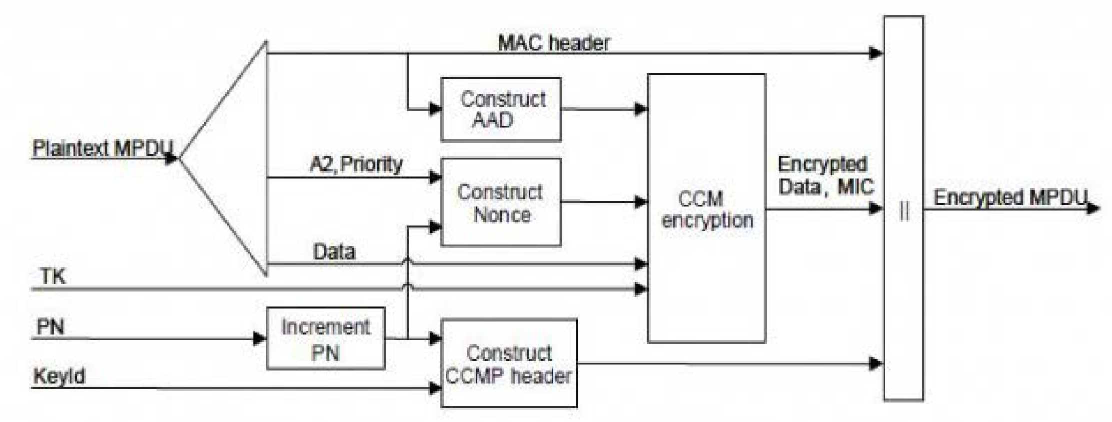

Figure 5 MPDU Encryption

The MIC and the data are encrypted as below see Figure 6 [39-43]:

1) If it is the first time, then the counter needs to be initialized; and if not, then increment counter.

2) The TK and AES are used to produce a 128-bit result by encrypting the first 128 bits.

3) The result of step 1 is subjected to an XOR

4) The first 128-bit encrypted block is produced by the first 1285 bits of data

5) The steps 1-4 should be repeated till such time encryption is made to all 128-bit blocks.

6) The counter is to be set at zero and AES and XOR with MIC should be used for encryption joining the encrypted frame result.

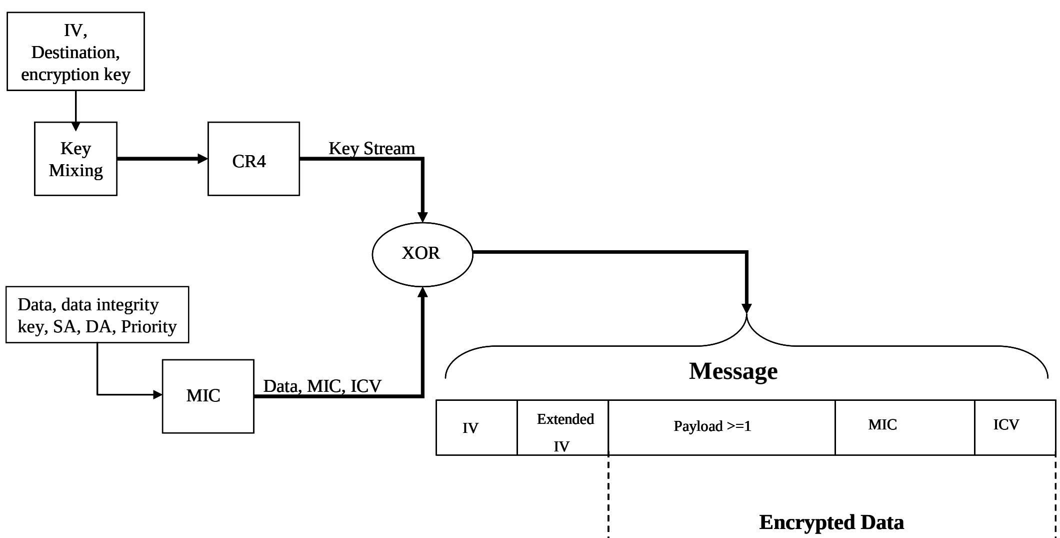

Figure 6 Message Encryption

2.3.4.2 WPA2 Decryption Steps

The process of decryption operates in the opposite direction. Below is the summarization of steps involved see Figure 7 [39-43].

1) The counter value is derived by utilizing the same algorithm for encryption
2) The encrypted segment of the 802.11 payload and the value obtained from step 1 are decrypted through the use of TK and Counter Mode algorithm. The resulting data is composed of decrypted data and the MIC.
3) Then the CBC-MAC algorithm is used to process the data in a bid to perform the recalculation of MIC, and if dropped, the values from step 2 and 3 would not match. Or else the decrypted data is passed to the network stack and to the client as well.

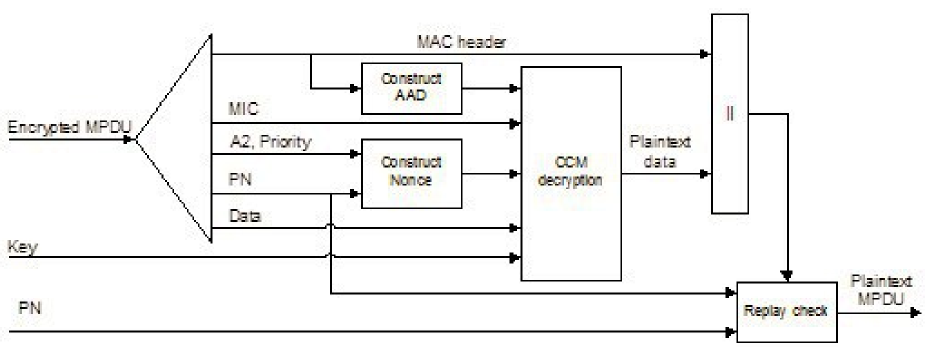

Figure 7 CCMP Decryption block diagram

Chapter 3: Electroencephalography EEG

The major contribution of this chapter is a comprehensive introduction for EEG system, brain wave classifications, detailed information about epilepsy and clarification for different epileptic seizures.

3.1 EEG History

When it comes to analysing the historical information about EEG, it all started by a physician who happened to work in the Liverpool called by the name Swartz Richard Caton (1842-1926), who published his findings in the year 1875 in a British Medical Journal based on the cerebral hemispheres related electrical phenomena conducted on monkeys and rabbits. Afterward, the process of oscillating oscillations of light was performed on the dogs and rabbits during an investigation into their electrical brain related spontaneity by Polish physicist Adolf Beck in the year 1890. In the next step, the first planning of brain diseases (EEG) was published by Vladimirovich Pravdich-Niminski in the year 1912 who was a Russian physiologist. Two years later, the photographic recordings of EEG in the context of experimentally induced seizures were performed by Gillenska Maxisna and Napoleon Sibolski in the year 1914[44][45].

In the year 1920, the study of human EEG was conducted by a psychiatrist and physiologist named Hans Berger (1873-1941) who was from Germany. Though other scientists also put their share in terms of conducting similar experiments, yet Hans Berger is named after its invention and also the device was given its name as well[44][45].

The epileptic mutations were first aired by Winnipack and Fischer in 1934. The very next year, the field of clinical electrophysiology started through the contribution of Gibbs, Davis, and Lenox who explained the episodes of clinical absence and their three patterns in a bid to describe the waves of sharp elevations. Then the axial signature of epilepsy was reported as a sign of rise of radiation by Gibbs and Jasper in the year 1936. It was also the year 1936 when the Massachusetts General Hospital inaugurated the very first EEG laboratory. Afterward, the first international EEG conference was held in 1947 after the establishment of American EEG Association in the same year. All of this is still regarded as a primary research tool per se [44][45].

3.1.1 *What is EEG*

The area wherein the recording and interpretation takes place is called as Electroencephalogram. When the mutual work of brain cells produces an electrical signal or to be more accurate, due to their cooperative action, the extracellular field potential's time course produces an electrical signal, then its record is termed as EEG. The two Greek words i.e. graphein (for writing) and enkephalo (for brain) forms the "electric photographer". The measurement of EEG can be performed by either placing the electrodes on the cortex directly or on the scalp.

In the former method, the procedure is at times referred to as electrocardiogram (ECoG). The local field capabilities (LFP) were measured through the intracortical measurement of electrical fields. If there is no spontaneous external simulation, then the recorded EEG is called accoringly. The response to the internal event related potential (ERP) or to the response to the external stimulus generates the EEG in return. 10-100 mV scalp electrodes in the observed state in the normal subject is termed as the EEG expansion. The capacity of EEG might increase in case of epilepsy by approx. one percent whereas the variation of capacities from 500 to 1500 m is observed in the cortex[46] .

On the flip side, the brain's generated recorded electrical activity is termed as EEG (electroencephalograph). Generally, the electrodes are placed on a scalp with the application of a conductive gel so as to obtain the EEG. The brain holds millions of neurons, and small electrical fields are generated by every neuron. An electrical reading is created by groups of these electrical fields and the scalp electrodes are capable to detect and record that electrical reading. Hence, the overlapping of several simplest signals is termed as EEG. In a normal adult, the range of EEG signal level is from 1 to 100 uV, and when they are measured by using the needle electrodes that are termed as underground electrodes, then the range varies from approx. 10 to 20 mV [47].

The EEG is also termed as a test wherein the electrical activity inside the brain is documented. If any disease puts a negative impact on brain cells performance, then that defect could be exposed through this type of EEG test. It is to be noted here that the brain damaging diseases are constrained in the affected zone in shape of slow waves. While those diseases which trigger extensive brain damage (such as the degenerative cases of poisoning, metabolic ailments, and encephalitis) exhibit the signs of widespread slow waves. Because this test involves the direct electrical activity measurement inside the brain, EEG is helpful in diagnosing the cases of epilepsy wherein the brain exhibits abnormal and severe electrical activity. This activity appears as tortuous or sharp waves. Also, a section of epilepsy patients might exhibit spasmodic activity amongst different epileptic seizures when they are subjected to a brain electroencephalogram, which occurs in a particular brain area, or it can also surround all of the brain zones [46][48].

3.1.2 Source of EEG activity

The brain's electrical activity inside the dendritic spine or inside the currents spatial scales can be referred to as the scalp EEG recorded relative total potential which is same as in the case when the level of the individual person could be used to study the economy on a larger scale. The primary brain function is dependent on the electrical activity cells which are called neurons. They carry out many tasks such as creating the work potentials, separating those electrical signals which move to axons thereby triggering the chemical neurotransmitters release activity in the synapse which is a nearby area to the contact between two neurons [44-47].

This neurotransmitter triggers the activation of a receptor inside the post-synaptic nerve which is a nerve cell situated on the other side of the neurotransmitter or inside the synapse. When joined with the receiver, an electrical signal is triggered by the neurotransmitter inside the neuron of the neuron cell or synapse. Hence, the post synaptic neurotransmitter currents are generated in thousands and the work potential is generated by the neurons through the summarization of the body. This activity continues as this neuron activates on the other neurons, and the process continues further. The post entanglement potential of the cortical neurons generates a synaptic activity which denotes the EEG [44-47].

In a great variety of frequencies, the oscillations are shown by the EEG scalp activity. Many of the oscillations exhibited are tagged with separate spatial distributions and frequency bands, and they are related to diverse functions of the brain such as diverse sleep stages and waking up etc. On a minute scale, these oscillations show concurrent and synchronized activity across a neurons network. When it comes to measuring the neuronal loss and brain layout, the research discovers the association between the two complexities wherein the surface strength of EEG is shown in two parts of delta and gamma that are associated with the dental nerve activity [44-47].

3.1.3 Brain waves classification

Normally, while performing the brain waves classification to gauge the individual's basic patterns of brain, instructions are given to the people that they relax by closing their eyes. The waveforms formed by the brain patterns are common to the sinus. When it comes to measuring them, the peak to peak values are generally measured in amplitude volts that ranges between 0.5 to 100. Of note that the ECG signals are 100 times higher than the said amplitudes. Very apparent is the contribution of sine waves with diverse frequencies in making the energy spectrum. Though it exhibits a continuous spectrum which ranges between zero Hz and half of the sampling frequency, more dominant frequencies could be created by the individual brain state as well. The below figure 8 shows the classification of brain waves into four main groups such as beta (> 13 Hz), alpha (8-13 Hz), - theta (4-8 Hz), - Delta (0.5-4 Hz) [45-47].

Normally, the frequency range is used to describe the EEG. There is a great deal of variation shown in the EEG amplitude which depends on the internal mental states as well as on the external simulation alike. The different names given to the EEG frequency are alpha, beta, delta, gamma, and theta which are associated with diverse types of brain cycles [45-47].

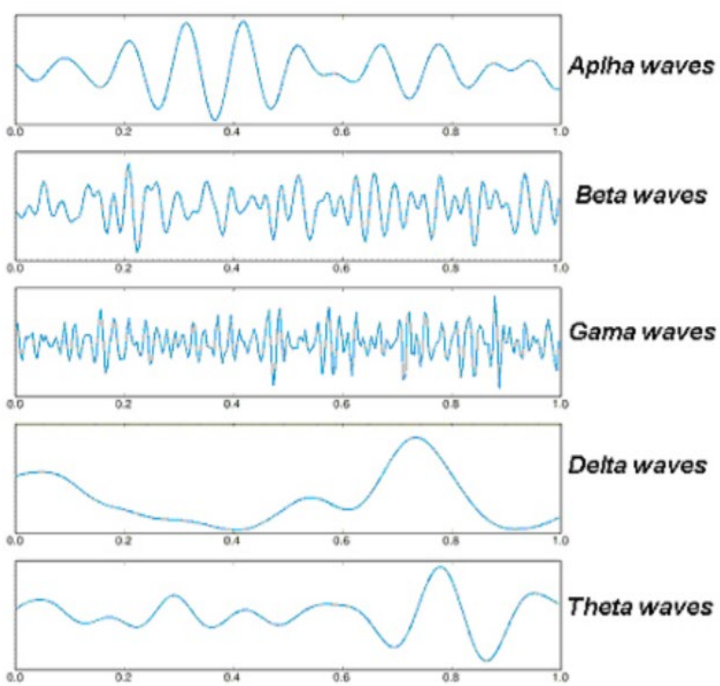

Figure 8 Brain Waves[47]

The following table 1 shows the frequency of mental states and cases. [45-47].

Table 1 Brain waves Frequency Ranges

Brainwave	Frequency range in Hz	The mental states and conditions
Delta	0.1 – 3	Deep, Dreamless sleep, non-REM sleep, unconscious
Theta	4-7	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha	8-12	Relaxed, but not drowsy, tranquil, tranquil, conscious
Low Beta	12-15	Formerly SMR, relaxed yet focused, integrated
Midrange Beta	16-20	Thinking, aware of self &surroundings
High Beta	21-30	Alertness, agitation
Gamma	30-100	Motor Function, higher mental activity

It was also revealed that while determining the different areas of brain activity, an association is found between the electrical activity and the performance as well as with various consciousness stages. This was revealed during the course of EEG recording by careful observation of those elements which put their share in performance like when the brain is used to solve mathematical problems. The 13 Hz illustrates the usage of more frequency bands alongside their wave activity. The 31Hz and above frequency band holds the Gamma waves. According to Rangaswamy et al. (2002), the perception and attention are linked with gamma and beta waves respectively that are also believed as the awareness mechanism. The frequency band between 12 and 30 Hz holds the beta waves, but in a bid to attain a more accurate and particular range, they are divided into β1 and β2. The waves are fast and smaller in size and for the purpose of better definition and more focused approach, they're associated in the front and the central areas [45][47].

Researchers Lucas et al. (1995) have highlighted that the marijuana smoking considerably increase the strength of alpha waves. The frequency band range from 3.5 to 7.5 Hz is associated with the theta waves which are associated with daydreaming and inefficiency. The theta waves are those waves which exhibit the thinnest thread between sleeping or waking up. The researchers Zhang et al. (2005) explain that the theta waves are generated in the occurrence of emotional tension, particularly disappointment or frustration. The theta waves are also associated with the process of profound reflection, creative inspiration, and with the access to unconscious material [45][47].

In adults, theta waves with high levels are termed as abnormal, for instance, Heinrich et al. (2007) explain that the high levels are linked with the diseases such as AD/HD. The frequency band between 0.5 to 3.5 Hz is specific to the delta waves, and according to Hammond (2006), these waves originate during the sleeping process and they are termed as slower waves. If a person exhibits these waves while they are awake, then it could point toward brain side physical defect. Of note that artificial delta waves could be created due to movement, but it could be verified by immediate analysis whether they've occurred due to movement or not. The kinetic activities are generally linked with MU, and it also exists in the frequency band reserved for alpha waves, but on the section where maximum amplitude is recorded on the motor cortex. Bernier et al. (2007) highlight that primarily it happens when the person exhibits a movement intention or when he actually moves. The different parts of the brain hold these wave groups which occur in diverse degrees [49].

3.2 Normal EEG

The inherent electrical physiological attributes of the nervous system signify on which the source of brain potential is based on. In a bid to identify the electro technical patterns which principally exhibit the “brain waves” expression either abnormally or naturally, the field (s) of the diffusion and the source (s) of the generator are taken as the basis of identification. Most of the routine electromagnetic cells that are recorded on the scalp surface show the collective electrical activity that is generated by a wide variety of neurons. When the electrical charges move within the central nervous system, electrical signals are created in response [50][51][52].

The ionic gradients formed by the neural membranes normally maintains the neural function. Adequate length and duration of small amounts of brain related electrical activity (in microvolt's) is required to broaden the display in a bid to perform the interpretation. Normally, the flow of positively charged ions (potassium) forms the membrane potential which sustains the -75 mV electrochemical balance. When the brain undergoes the process of polarization, the occurrence of sodium ions with positive charge takes place which go beyond the natural electrochemical resting state. It is the voltage which forms the basis of opening the channel within the lipid layer while it is the time which forms the basis of the closing that channel likewise [50-52].

When the nearby parts of the neuromuscular membranes are touched then there could be a possible action wherein the de-polarization threshold exceeds the level. But, when it comes to analysing the critical source of extracellular stream flow which produces the EEG potential, the most important source is the synaptic potential. The direction of flow of the post-clamping potential (EPPs) is internal i.e. from extracellular to intracellular side), and through calcium ions or sodium, it moves into the other cell parts (sinks). On the other hand, the direction of flow of post-entanglement potential (IPPs) is in the opposite direction (source) i.e. from intracellular to extracellular outwardly which holds potassium ions or chloride in particular. Most of the EEG waveforms are due to the combined potential and its duration when compared with the work potential is longer. Inside the cerebral cortex, the synchronization of groups of modern neurons takes place by the mulch and brain function beneath the cortex. Of note that it occurs in case of the abnormal conditions such as wave and generalized complex waves, and it also occurs in case of the natural elements such as sleep elements as well [50-52].

The electrode register and the brain generator's current flow process is described as the sound volume. The key sources of EEG are the layers of cortical neurons. EEG is formed by the hierarchical cells which also make the key contributions to the synaptic potentials. Right on the cortical surface of the 3rd, 4th, and the 6th layers, the arrangement of neurones takes place in a vertical direction. There is no hinderance in terms of measuring the scalp areas of size 6 cm 2 because the sizes are reasonably large, yet for most of the IEDs which exhibit on the EEG scalp might need the size 10 cm 2 because of the skull related dilute properties. There is a negative and a positive pole on all generators which plays the key role of a double pole. On diverse scalp locations, the EEG exhibits both variable and continuous fields with variable voltage [50-52].

The recording of EEG scalp exhibits the electrical position difference between the two different positions on the cerebral cortex top nearer to the recording pole. During the course of normal usage, indirect accomplishment of electrical potential is obtained from the scalp surface and both of the systems observe the waveforms for terrain, morphology, voltage, and frequency. Nevertheless, it is under the scalp surface wherein most of the human cortex lies, and furthermore, it exhibits a three-dimensional source in shape of a two-dimensional projection which is an issue when it comes to localizing the generators inside the scalp. Moreover, a simultaneous activity is shown from the scalp recorded wavelength which comprises of large number of neuron groups which might not exhibit micro or radioactive sources, but they happen to create the cortical capacities indeed [50-52].

There are two ways in which the normal EEG pole position systems operate i.e. they either use an average fusion system with a 10-10 mode (white and black circles) or they use a 10-20 system that is composed of a black circuit only. In order to help in the process of sleep mode (with eye monitors) or to help in the process of differentiation of artefacts, the other electrophysiological electrodes might include the external electrodes, electromyogram (EMG), eye movement control, or EKG (suggested with EEG). If the patient exhibits respiratory problems, then the respiratory monitors could be used. In normal routine clinical usage, the combination of 10-20 system along with the 10-10 system's electrodes might be used as a more practical option because the situation might need an extra electrode. During the course of long recording methods, electrodes are secured by using colloid ion compound, for instance, during the mobile observation or during the process of EEG. A temporary paste is normally used for routine recordings. If the other recordings are not deemed as beneficial when compared with the ICU or operating room, then the ground electrodes are utilized below [50-52].

When the eyes are opened and return to close, the normal alpha-Hz 10 rhythm is blocked and immediately near the eye, a fastest frequency is noticed ("creak"). In the process of the clinical EEG analysis, the very starting point remains the Alpha rhythm. Furthermore, during the routine EEG analysis, the areas at the back of the head show the rear dominant rhythm and the band range is within 8 to 13 Hz that shows the alpha frequency. It is called as Alpha rhythm when this rhythm is weakened due to opening of eyes. At 3 years age, the alpha frequency is shown at 8 Hz during normal development. A constant alpha rhythm is observed between 8 and 12 Hz even when it is measured during the normal aging process till such time the person is enjoying their last years. There is a poor visibility of alpha rhythm in those cases wherein almost ordinary adults are involved. In cases where the size of the right side is smaller than the left, the EEG would be seen as 50% abnormal. It is best seen during the process wherein sedative vigilance is observed and there is 50% to side difference of wakeup in which the bandwidth range is between 14-16 Hz. When it comes to analysing the mental stimulation, mild sleep, and drowsiness, an increased beta activity is normally observed. If a low voltage is observed then it would point towards the cortical gray matter defect of more than 50% with low amplitude inside the hemisphere; nevertheless, the normal skull incompatibility is shown in shape of a less steady inconsistency [50-52].

Of note that this is considered as a normal thing except if it is accompanied with focal delay or mutations. When it comes to analyzing the normal theta rhythm before an awakened patient of 18 years age, the frequencies of theta rhythms with different configurations and amplitude fall in the range between 4-7 Hz. In case of 1/3rd of the elderly patient, if the right theta rhythms show irregular width between 6-7 Hz in normal waking, then it is termed as normal and symptomatic. Research shows that in a patient of 28 years age with dizziness, the lampeta waves are bioccipital [47][48][49].

Initially, the Lambda waves were also called as positive theta waves which occur in the occipital area bilaterally bearing sharply positive edges. This is the potential which spans it duration from 160-250 milliseconds, and they are also at times, called as asymmetric, and their amplitude is greater than the remaining dominant rear rhythm. Confusion with epileptic seizures might arise if they occur inconsistently, and it might also contribute to the confusion due to the EEG misinterpretation as well. Though it is more common in children, but it is best observed in grown up young adults at large. In case when the patient scans the compound or complex visual image of fast eye movements, the best recommendation is to get the lambda waves. The visual inputs that are essentially required for its growth would be eliminated when the patient is exposed to a white sheet in front of him [50-52].

3.3 The Abnormal EEG

3.3.1 Focal and Generalized Slowing and Significance

The evidence of a focal brain or a diffuse brain dysfunction is revealed through the EEG by exhibiting the background sluggishness. The general slowdowns and the focal slowdowns are the two key types of deceleration. As discussed above, when some young people, adolescents, or children experience a slowdown in growth or they undergo the activity of drowsiness and sleep, then the natural brain planning results in the general slowdown in the delta and theta frequency ranges accordingly. On the other hand, if a particular single head region experiences a discontinuous or persistent focal delay, or an adult patient is exposed to a slow moving, non-reacting, non-variable, continuous, or a slow activity, then this is a normal satisfactory slow activity which is associated with the corresponding generalized or focal coordination of either cerebral dysfunction or both of them [49-52].

3.3.2 Focal Slowing

When the brain's layout is a slow focal wave activity then this is termed as a sign of primary brain's region focal brain foci. It might show either a permanent or a sporadic deceleration and if the brain has more severe brain dysfunction, then it would show either a slow deceleration or a more stable activity. There are a wide variety of triggers/causes behind the condition of focal cerebral palsy. An accurate focal myocardial defect might be indicated when unsteady/intermittent focal deceleration is observed which might befall due to the hypnotic or sedative drugs though by nature, normally the drug slow down process is generalized. The underlying white matter or the cortex region or even both of them slow down on focusing for a number of reasons due to focal brain lesions. There could be a number of complex causes behind this but primarily the key causes are like focal point caused by viral encephalitis or bacterial encephalitis, anomalies related to venous artery, focal involvement of the cortex due to neurodegeneration, focal epilepsy related non-structural focal brain disorders, malformations of cortical development, traumatic injuries, tumours, brain haemorrhage, stroke related permanent or temporary ischemia. The temporal deceleration is exhibited in the figure 9 wherein "rip rhythm" is shown with a high photographic background capacity due to either past surgery in the said area or due to skull dysfunction [52].

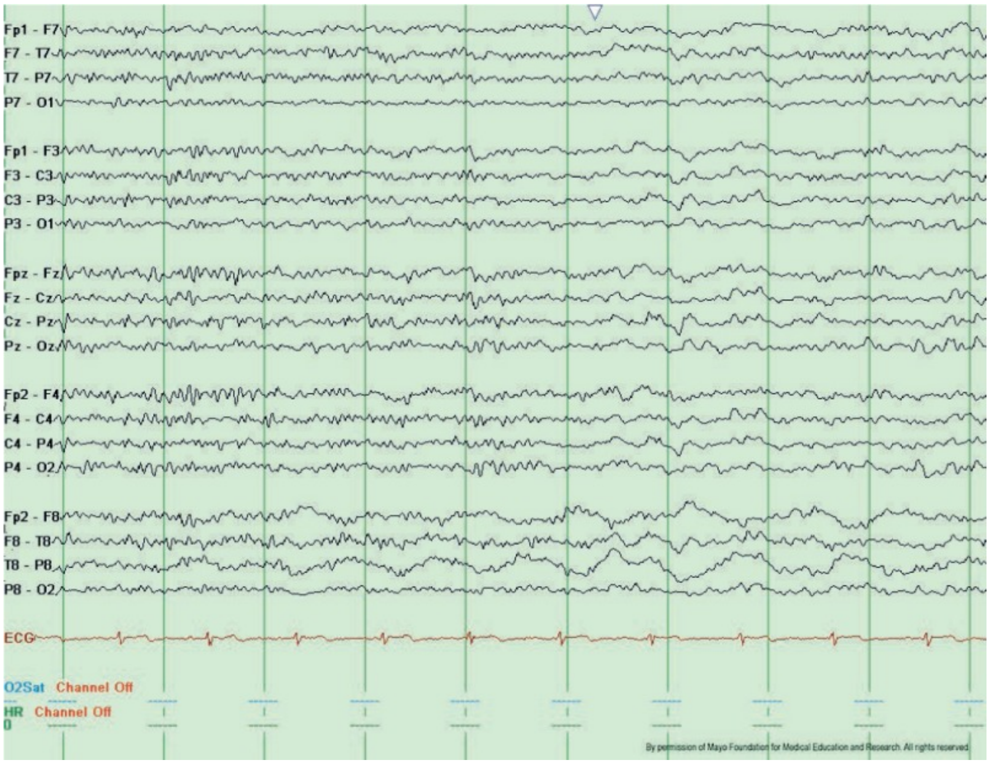

Figure 9 example of temporal deceleration[52]

3.3.3 Generalized Slowing

A diffuse brain dysfunction is indicated by a general background slowdown, which is not specific as in the case of focal deceleration. The general background might be slow down by a number of different causes which includes the middle structure sinus lesion which include the ding flex structures or the deep midline brain stem, or even both, central nervous system related infectious disorders like brain meningitis, toxic or metabolic brain dysfunction, hydrocephalus, widespread neurodevelopmental growth, neurological disorders, and sedative central anaesthetics effects. An example is shown in the figure 10 wherein an encephalopathy triggered generalized EEG slowing is shown[52].

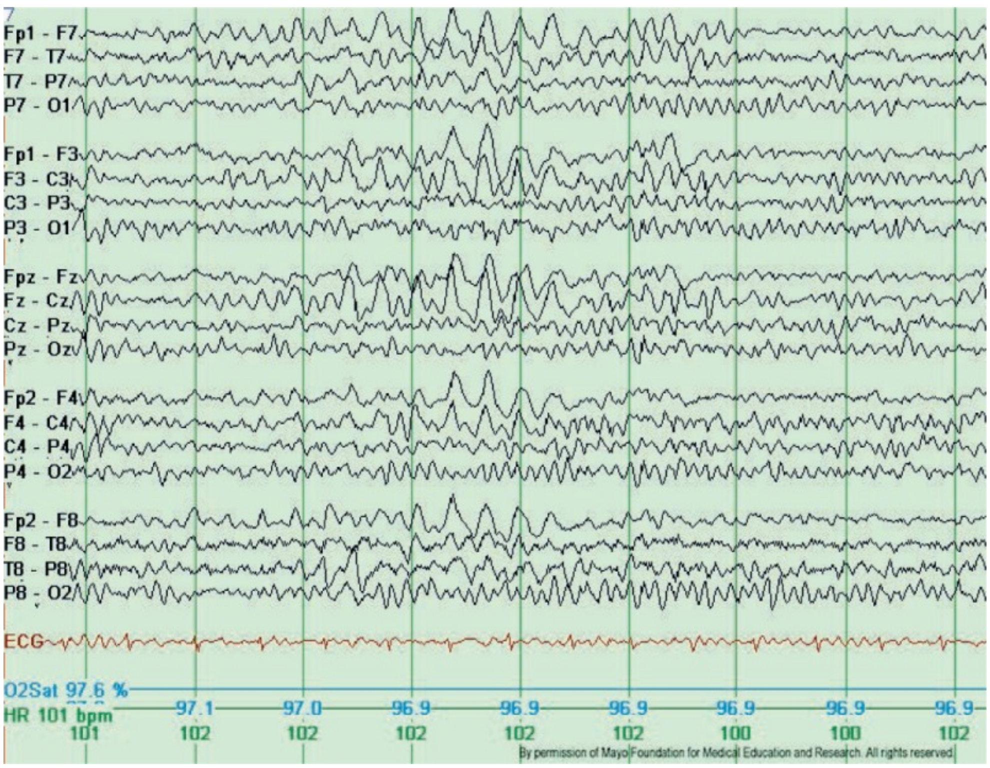

Figure 10 example of generalized EEG slowing due to encephalopathy[52]

The generalized cerebral pacing related particular examples are exhibited below:

3.3.3.1 Encephalopathy/Delirium

Another name of Delirium is encephalopathy, which is regarded as a general genetic ailment and systemic order can reverse it. It includes the conditions such as muscular dystrophy or unusual movements, less vigilance related stoniness, subconscious stare with lack of attention and confusion. Severe episodes might be experienced by the patients with encephalopathy, which can also result in diagnostic confusion. The patient with brain delirium might exhibit a non-specific or non-diffused background deceleration through the electroencephalogram. These patients might also depict the patterns of epilepsy such as 3-phase wavelength forms as depicted in the figure 11. Mostly, these are shown in patients with renal impairment conjunctivitis or hepatic impairment or both, however, drug poisoning can also trigger similar patterns as well, and the same goes true for other non-physical triggers of severe generalized cerebral dysfunction or other relevant adverse effects [52].

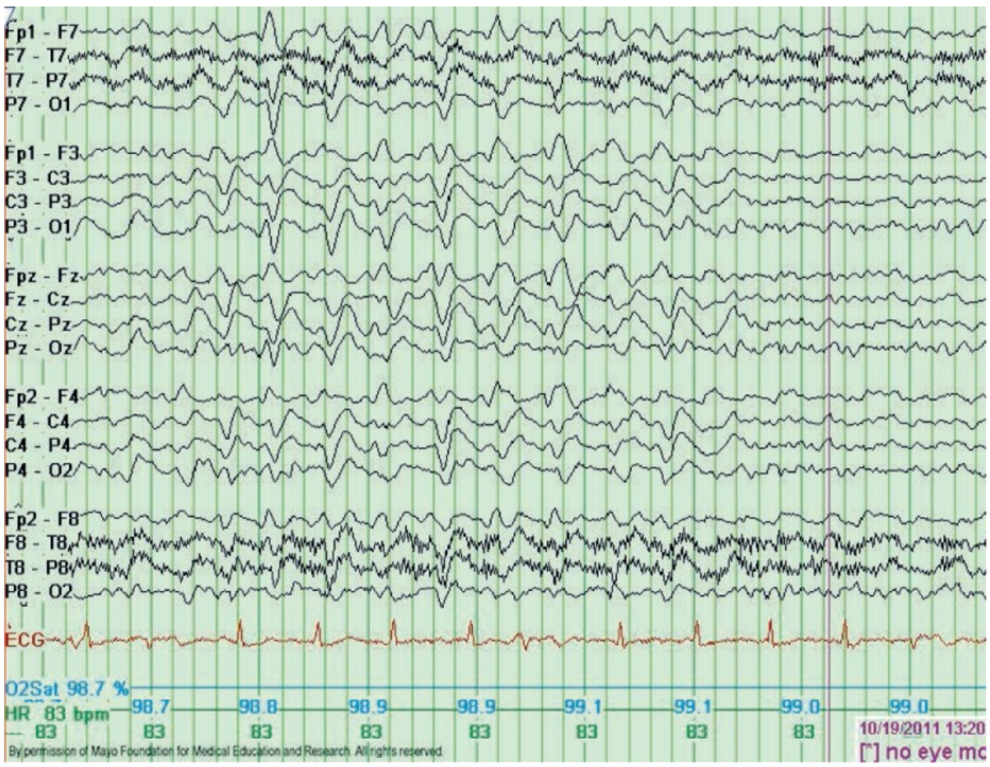

Figure 11 the three-phase wave pattern[52]

3.3.3.2 Dementia

In case of diseases like Alzheimer's disease which fall in the category of progressive neurodegenerative dementia, normal EEG results are shown both during the sleep and wakefulness. Later on, during the progression of the disease, the moderate circulation commonly reveals a slow background along with the signs of focal deceleration [52].

3.3.3.3 Coma

Coma is a condition wherein no irreversible response is seen with the closed eye, opposite to the sleeping stage wherein waking up reflects the easily reversible state from the unresponsive sleeping state. The coma patterns are associated with lack of interaction and variability alike. There are plenty of commonly described coma patterns in general. The recovery after ischemia is considered as one of the worst recovery conditions whereas coma suppression and alpha suppression also fall in the same category. The moderate or even favourable patterns are also there such as thyroid coma. At the same time, alone EEG prediction should not be fully trusted because integration of results is to be made using the secondary tests like neuroscience and the clinical tests alike [52].

3.3.3.4 Anesthesia patterns

When it comes to following the anaesthetic depth during the course of surgery, EEG is commonly beneficial, and when it comes to performing neurovascular surgeries which involves the blood clots related risk and also involves the cerebral ischemia related inactivity such as in the carotid endotracheal surgery, EEG is also useful. A predominant dominant activity is exhibited with a typical anaesthesia pattern as depicted in the figure 12. Adjustment of the duration of the extrusion mode or pickup could be usefully obtained if there is a suppression, a voltage reduction, or a background related increased slowdown from one side[52].

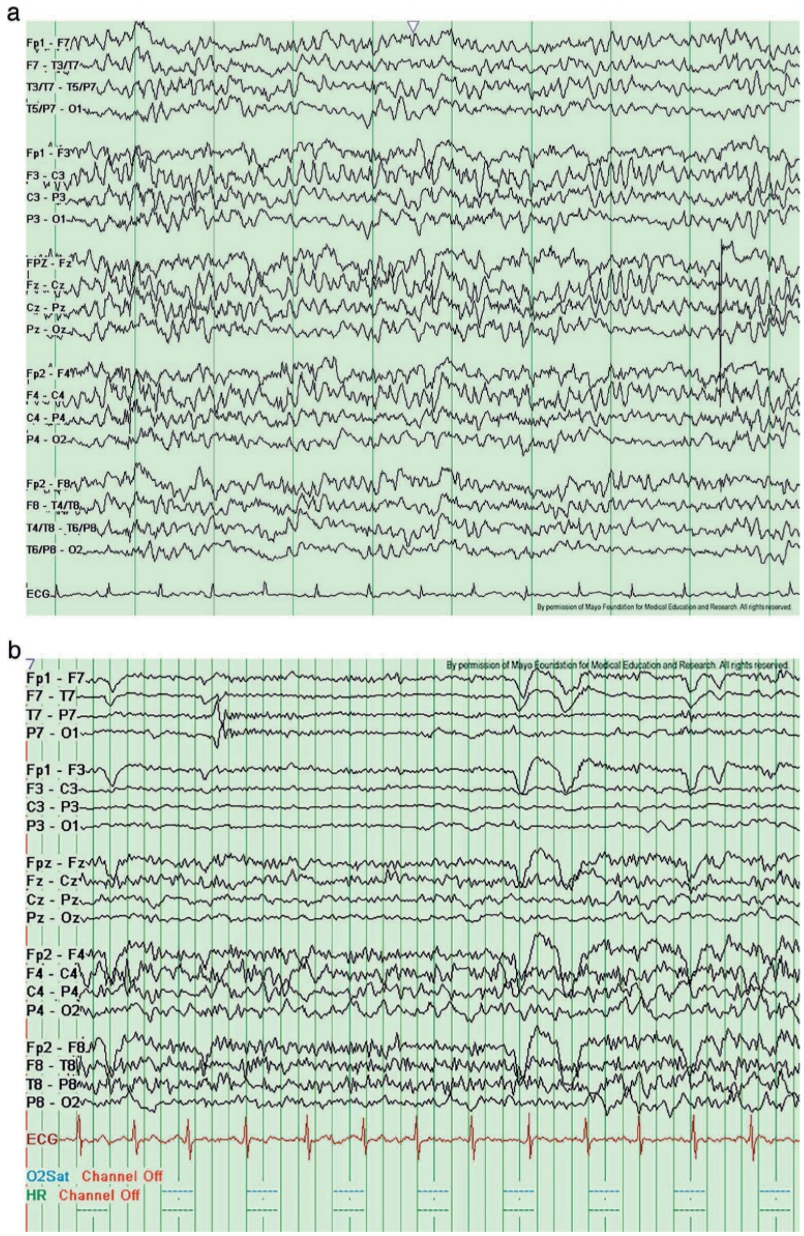

Figure 12 a pattern of typical anesthesia, characterized by predominant predominant dominant activity[52]

3.3.4 EEG Clinical use and Applications

In the case of the clinical conditions below, Routine EEG is also utilized [44][46]:

To make differentiation between the other types of seizures and the epileptic seizures. Of note that the other types of seizures include migraines, subcortical movement disorders, fainting, and the neural seizures.

When distinction is to be made between delirium or encephalopathy from primary psychological syndromes.

The routine EEG doesn't serve the purpose of determining whether antiepileptic drugs are to be stopped in some cases, particularly, when during an epileptic seizure, it becomes essential to register a patient.

When the EEG recordings are performed continuously in the cases when the patient is admitted to the hospital for a long time such as for days or weeks.

EEG is used to control non-convulsive epilepsy/non-convulsive seizures.

The patients who are tagged with medically induced coma, EEG is used for monitoring the anaesthesia/sedative effect.

EEG is also used for monitoring the brain secondary damage such as if the patient falls prey to angular haemorrhage while the patient is also affected with epilepsy, then most commonly, it becomes essentially important to figure out the source from where the epileptic brain activity comes from. The reason being, the EEG recorded electrical potential comes under distortion due to the scalp, the skull, and the cerebrospinal fluid.

Normally, the EEG in clinical settings involves scalp electrodes recording and it consumes around 20 to 30 minutes.

3.4 Epilepsy

One of the common brain disorders is epilepsy, and it is reported by World Health Organization that there are around 60 million people on this planet who fall prey to this disorder. At some point, every one individual out of hundred would undergo a seizure. The propensity to experience seizures on a frequent basis is normally defined as epilepsy. This word is derived from Greek and Latin words. This reflects that this disorder is an old one, indeed, its roots can be traced back to medical records in almost all the civilizations. In fact, all mammalian species can fall prey to the epilepsy disorder which might be due to the reason that brains are becoming more complex than ever [52][53].

The datasets used were associated with 3 thematic groups such as the physical EEGs, the interracial EEG related epilepsy occurrences, and lastly, the epilepsy subjects in seizure ECT. The EEG signals classification and the seizures detection problems are formulated as three groups related classification issue which can put considerable impact in terms of clinical importance. In order to make an accurate distinction between the internal EEG signals and the natural signals, an automated system could be utilized which is beneficial in terms of diagnosing the epilepsy. In order to make an accurate distinction between the positive signals and the EEG radiation, a system could be utilized to diagnose seizures in the clinical settings. Hence, it is a requirement that the classification of three groups must be accurately performed by the classification algorithm and also, it should be strong enough to detect the changes in EEG signals across diverse mental subjects and varying situations [52] [54].

The electrical disturbances inside the brain and the neurotransmitters which are momentary and unexpected are termed as seizures. Hence, when it comes to analysing the three states of brain and detecting the epileptic seizures through optical scanning of data, EEG signal comes on the top slot in the clinical settings. The data of EEG is normally gathered over a period of few days which takes a bit of a time. Furthermore, the complete EEG recordings are to be observed by an expert clinician so as to effectively and accurately realize the epileptic activity inside the brain [52] [54].

These non-conclusive and short span event surrounds the complete brain and normally children fall prey to such disease. These kinds of seizures show an individual's weakness response and their awareness wherein the patient simply starts gazing with their eyes fluttering or flinching. It might be difficult to differentiate between daydreaming and absenteeism, but the process starts with instant and uninterrupted fits of absence for a few seconds, and then the same way it started, it instantly stops as well. Afterward, the person starts doing their job in a normal way. As a matter of fact, these seizures consume only 10 seconds, but they can occur repeatedly many times in a single day thereby disturbing the learning process [52][53].

These muscular short seizures are solid in the sense that at times, even a single occurrence might create overmuch disturbance in a short span of time. The tone of the muscle undergoes an instant increase or decrease due to automatic seizures. It is worth mentioning here that fits do not last more than 15 seconds. In case of fatal seizures, the patient is suggested to wear a woven headwear for protection so as to avoid injuries to the face or head [52][53].

In case of spasmodic seizures, the sudden movements of the legs, body, or natural muscles harden and as a result, the seizure undergo significant alterations. Most commonly, these types of seizures occur during rapid service while sleeping, or while the individual is trying to get off, he might experience a sudden fall thereby hurting himself in response. The time period of fits doesn't last longer than 20 seconds [52][53].

3.4.1 Epilepsy basics

When it comes to analysing the origin of epilepsy, it came from a Greek word which translates as “a state of feeling defeated or attacked”. Most of the people have faith in the belief that sprites formed the origination of Nubia and epilepsy is nothing shorter than a holy ailment due to various types of fears and myths associated with the said disease. An individual who fall prey to epilepsy is highly unlikely to achieve their normal life goals. Another meaning of epilepsy is the vulnerability of the individual to repeated or recurring seizures [53] [55]

3.4.2 What are seizures

There are no two opinions about the sensitivity and complexity of the organ i.e. brain. It is the key source which is responsible for regulating, controlling, and directing all our actions, and it also controls our emotions, thoughts, feelings, and movements. The brain is the memory’s headquarter which is termed as a regulatory authority which controls the body’s internal involuntary actions like lungs and the heart functions. Through the pathway of electrical signals, different cells inside the brain mutually connect and work together. At times, seizures result due to an abnormal discharge of electrical activity within a group of cells, and the brain part wherein this electrical discharge takes place signifies the kind of seizure accordingly [48][52][55].

3.4.3 Historical overview of epilepsy detection

Epilepsy is one of the oldest disorders' humans know as its roots can be traced back to more than two thousand years before the Christ was born. The ancient Greek texts and the Bible also point toward this disorder in particular[48] .

Until the human race reached in the mid 1800's, there were no concrete studies available in the context of epilepsy disorder. The very first painkillers to control seizures were created by Sir Charles Le Coke in the year 1857. Later on, the brain's outer layer was identified by John Hecklungs Jackson in 1870 along with brain's external cortex and identified it as the epilepsy's part. The possibility of recording the human brain's electrical impulses was first coined in the year 1929 by Hans Burgess [7] [48][52][55].

Before the seizures begin, few people experience the "nymph" phenomenon which equates to pre-warning type of feeling. The infected individual might experience the anaphylaxis in adequate time which contributes to preventing the injury during the course of spasticity.

Of note that different people experience different types of anaphylaxis. For instance, few people would sense a body temperature change whereas the others might experience anxiety and tension. Some people would experience a vivid strange smell, taste, or sound. If the patient is able to describe this experience to the clinician, then it would be very helpful for the clinician to identify the tip of the thread inside the brain from where the electrical discharge originates in particular [7][48][52][55].

3.4.4 What Causes Epilepsy

When it comes to figuring out the causes behind epilepsy, it is still an unanswered question, but the epileptic risk of seizure is considerably increased in the occurrence of few cases [48], such as injuries inflicted on the brain, structural changes inside the brain, oncology, blood vessel diseases and stroke. It is also observed that either one or more than one genes trigger changes inside the brain which might contribute to forming seizures in response.

Epilepsy causes and the contributing factors that lead to seizures:

One of the most common external phenomena which signify the epilepsy disorder in humans referred to as epileptic seizures. There are a variety of factors and reasons responsible for stimulating the epileptic seizures in humans as follows [48][52][51]:

When the person remains sleepless beyond the normal limits of sleeping hours based on their age.

• The epileptic seizures also occur if the person undergoes excessive stress and fatigue be it organic or psychological.

• If the person suffers from very high fever or some organic disease related high temperature.

• The general triggers of frequent seizures are like overdoing the substance abuse or alcohol.

• If a woman fall prey to severe reproductive disorders which make them vulnerable to disorders in their menstrual cycle, then this could also cause frequent epileptic seizures in response.

3.4.5 Epilepsy types

Seizures are the most common symptom for all kinds of epilepsies which represents electrical surges inside the brain. One couldn't help saying them as electrical storms inside the brain which disrupt your brain cells to function in a normal manner. Based on the types of seizures, epilepsy can be subdivided into four main types i.e. generalized, focal, generalized and focal, and the last one is called as the unknown if generalized or focal [48][52][55].

3.4.5.1 Generalized Epilepsy

This kind of epilepsy originates on brain's both sides and it is associated with two main types of seizures as follows:

• Generalized motor seizures.

Another name for them is “grand mal” seizures and they put an impact on your body in such a ways that your body becomes uncontrollable, it starts moving without your consent, and at times, it occurs in a dramatic manner.

- Generalized non-motor (or absence) seizures.

They are also named as “petit mal” seizures, and when they occur, the person stops from performing their tasks and starts gazing into space. This might continue again and again in the same way as you smack your lips. Due to their nature, they are also called as “absence” seizures since they show the absence of the person such as if he is not present there.

3.4.5.2 Focal Epilepsy

This is a kind of epilepsy wherein a particular region on brain’s one side gets affected by the seizure. They are also termed as “partial seizures” and they have 4 categories as below:

- Focal aware seizures

The seizure would be termed as an “aware” seizure if the person knows about what’s happening to him; they are also termed as “simple partial seizures”.

- Focal impaired awareness seizures

The seizure would be termed as an “impaired awareness” seizure or “complex partial seizures” if the person has any confusion or he doesn't know about what’s happening.

• Focal motor seizures

This is a kind of seizure wherein the patient would be able to move to some degree such as he might twitch and then experience the spasms, he might start rubbing his hands or he might start walking around. There are a few common kinds of these seizures which the doctor would normally talk about such as tonic, myoclonic, epileptic spasms, clonic, and atonic.

• Focal non-motor seizures.

This is a kind of seizure which does not contribute further to cramping or other movements, rather, it triggers and affects patient's thinking or feeling aspects. The person might suffer from the sensation of cold waves or heat waves passing through, his heart might rhythm like a racing heart, and he might fall prey to intense emotions.

• Generalized and Focal Epilepsy

This is a kind of epilepsy wherein the patient suffers from both generalized and focal seizures.

• Unknown if Generalized or Focal Epilepsy

If the patient has nobody around him and he is all alone when he had seizures, then there would be nobody who would give the description of the seizure. This is highly likely that the doctor would also mark the condition as "unknown if generalized or focal epilepsy" on the score of unclear results of tests.

3.4.6 Diagnosis

It is worth noting that in order to figure out the occurrence, precise position, and quality of the electrical impulses inside the brain, the EEG does not detect the brain's electrical activity because there might be abnormal electrical charge in a percentage of natural children and even ten percent of epilepsy patients with a natural layout. In many of the cases, right after an abnormal outcome, the patient might be subjected to electrotherapy. Many areas of the cortex might be affected due to vigilance. Hence, it becomes next to impossible to precisely perform the diagnosis. This is why the after many weeks of seizure, the specialists expose the patient to the procedure. This implies that EEG cannot be used as a basis for diagnosing epilepsy, it is but the description revealed by the parents and the story of the sickness itself which forms the basis of diagnosis in particular [48][52][55].

3.4.7 Treating Seizures and Epilepsy

The key objective is that without damaging or hurting the child, the treatment is performed so as to stop the epileptic seizures. Below are the descriptions of the key methods of treatment [48][52][55]:

- Medicines

Each type of cramping has its particular type of treatment, and the doctor is the righteous professional who would prescribe the best treatment based on the symptoms and the patient's condition, and in few cases, it is suggested not to take any medicine until the doctor completes the diagnosis process. Few patients even don’t need the medication and treatment or even they might be prescribed to stop using the mediation by the doctor provided if the patient doesn't show signs of seizures for many months.

• Surgery

There are cases wherein seizures couldn’t be controlled through medications and the source of those tumours or seizures are the particular regions of the brain. Also, it might be useful (after discussing with the neurosurgeon) that surgery might favour in terms of controlling the seizures.

• Eating

If a child suffers from spasticity, then there is not any particular diet to be prescribed, but it’s quite possible that if the child is not subjected to blood treatment, the change in weight might contribute to creating spastic episodes. The reason being, the body might react to the blood related shortage of chemical balance which might trigger the seizures in response.

3.4.8 Epilepsy and Quality Care

The patient should be taken away from all those sources which put him in danger of seizures in the first place.

• The patient should be provided details about the nature of the disease especially if the patient happens to be a child, and if the patient asks any questions, appropriately answer them all.

• It’s critically important to give confidence to the patient without being excessively cruel at any point in time.

• The patient should not be given more than enough explanation, so he might not deem epilepsy as a restriction to his freedom, and also, the explanation should not impact his psychological well-being.

• It is not suggested that you hide or take away the patient from other people in anticipation of their negative response etc.

• Inform the patient about the onset of seizures gently, and also tell him not to panic or surprised.

• Mark the dates when the patient needs to take his medications.

• It is suggested that the patient should not be left alone in a closed space such as washroom.

3.4.9 Safety and First Aid in Seizure

Take the patient away from all those sources which bring harm, and don’t try to squeeze his muscle movements, even if the patient is acting violently during the course of seizures.

• It is recommended that the carer put either a piece of cork or a folded cloth or something similar between the jaws of the patient in order to protect him from biting his own tongue. Of note that the piece should be large enough so that the patient might not devour them through their throat.

• In order to make the patient to breathe easily, the carer should unlock their abdomen, chest, and neck from all types of ligaments.

• The saliva of the patient should be wiped so that it doesn't come in the way of airways and contribute to difficult in breathing in response.

• Don’t wake up the patient if he falls asleep.

• Be with the patient until he fully regains the consciousness.

• Don’t given him any drink while he is in the state of seizures or unconscious.

3.4.10 Challenges with Epilepsy

The people with seizures shows specific symptoms and health problems when compared with the people without seizures. These symptoms arise due to the triggers behind epilepsy. For instance, the symptoms might occur due to the reaction of medicines or they could be associated with the seizure moments. Also, the patients might show mood swings since the brain area which is responsible for the onset of seizures might contribute to creating mood issues. The carer or the healthcare team should recognize those factors so as to act upon certain precautions in return. Below are the few conditions which include [48][52][51]:

- The patient might not do well with the friends, work, school, or home
- The patient might show signs of cognitive or learning issues which require special helping hand to these patients at large.
- The patient might show behavioural changes, mood swings, anxiety or depression symptoms.
- The patient might be exposed to sleeping issues.

- The patient is vulnerable to unexplained illnesses, falls, and injuries.
- The patient is vulnerable to osteoporosis or thinning of bones issue.
- The patient might exhibit issued related to reproduction.
- Death risk also exists.

Chapter 4: Adaptive EEG Device

This chapter presents a novel biomedical wireless monitoring system as a predictor and advances sensitive portable electroencephalogram (WSN-EEG). The WSN-EEG is proposed to monitor spontaneous brain waves, including both normal and abnormal waves, for patients suffering from different types of epilepsy. The biomedical epilepsy Wireless Sensor Network monitoring system (WSN-EEG) reads signals from a Wireless Sensor Network from the patient scalp, and filters these signals to run parallel data processing for brain waves[56].

However, the predicting procedure for the severity of the forthcoming epileptic attack is based on a proposed FFNN model which analyses the abnormality in the brain waves and alerts the patient by giving signals to the patient[56]. This method can save many patients by predicting the seizure before it occurs and can help protect them from different injuries and risky behaviours arising during epilepsy attack. In addition, the data collected from this proposed method may be used for further medical diagnosis measures.

The WSN-EEG can detect all normal brain waves. In addition, any abnormal brain waves, especially those found during epilepsy attacks, i.e. diffuse slowing, focal slowing, Triphasic waves, epileptiform discharges (EDs), periodical lateralized epileptiform discharges (PLEDs) and general periodic sharp waves, can also be detected by the WSN-EEG[56].

4.1 Introduction

During recent years, WSN's medical applications have grown rapidly, and sensor technology has taken a significant place in people's lives[1]. In order to provide a certain level of efficiency and effectiveness, greater amounts of research are required, due to the difficulty required in implementing WSN in many applications, such as medical and healthcare services, intelligent transports, smart homes, and army applications. This difficulty arises because these applications are affected by limited network capacity, memory constraints, and power consumptions[57]. In addition, neurology and cardiology applications have imposed stringent requirements, such as reliability, quality of service, and information privacy [58]. However, the healthcare matrix is a standard for WSN for providing reliability and improved mobility[7].

This research focuses on healthcare services for patients with a history of epilepsy. Because of increased prevalence and the high disease burden of epilepsy, this study has considered the patients whom have this disorder as the target focus group[1][56]. Electroencephalogram (EEG) displays the spontaneous brain waves as a continuous graph of voltage and frequency changes occurring over time. The EEG monitors the brain wave activities, while other imaging techniques, such as CT scan and MRI, provide information about brain structure. Both structural and functional studies of the brain are important, as well as the presence of specific signs and symptoms in order to have a definitive diagnosis of an epileptic disorder [59][60]. However, in those cases where no signs and symptoms are visible, and no structural abnormality is found, EEG can help us more than any other method of investigation to reach a definitive diagnosis [61]. For most of the mild cases of epilepsy, where a neurologist cannot find any abnormal waves on the first EEG, they prefer to perform a continuous EEG monitoring for those patients [62].

This research focuses on the development of a scientific model based on a Feed Forward Neural Network prediction algorithm and IEEE802.11n as part of Wireless Sensor Network transmissions for the brain signal clarifications for the new proposed system, in order to recognize all types of normal spontaneous brain waves, including Alpha waves (8 to 12 cps), Beta waves (13 to 25 cps) and Theta waves (4 to 7 cps)[63]. Moreover, this system will also detect all other abnormal electric activity in the brain, i.e. diffuse slowing, focal slowing, Triphasic waves, epileptiform discharges (EDs), periodical lateralized epileptiform discharges (PLEDs), and general periodic sharp waves [64][65][66]. The proposed device will work based on a wireless connection between all eight sensors placed on different lobes of the scalp to record the electric activity of all lobes of the central nervous system, as well as a central, portable novel device consisting of a WSN-EEG processor, data-storage chipset, novel EEG analyser algorithm, and FFNN. After retrieving the signals from all eight sensors placed over the scalp, the algorithm and FFNN will begin analysing these signals based on medical information. FFNN is used in several medical applications as a learning and perdition machine [67], and it produces basic prognoses about the brain classified as follows:

1: Normal brain activity

2: Mild seizure attack

3: Moderate seizure attack

4: Severe seizure attack.

The alarm uses different alert signals and lights to show the attacks during a specific period. Such a new prediction novel method can help the patients to take precautions against continuing attacks and potentially save their lives.

4.2 Seizure Attack

For this section, an epilepsy seizure attack is divided into three distinct types for the simplicity of describing the brain activities and monitoring brain waves in normal and abnormal situations, which have been discussed in the EEG epilepsy literature Chapter 3, so that the device can detect the seizure based on the different, distinct scenarios. The novel device will distinguish between these seizures based on brain waves and the duration of the attack (abnormality in the waves), which is based upon a specific novel logical algorithm using the FFNN epilepsy model. The classifications of a seizure are divided as follows [56]:

4.2.1 Mild seizure attack

A simple, partial seizure will be considered as a mild seizure attack by the device. Because there is no consciousness impairment in this seizure is the reason this study considers it as a mild seizure attack [53-60].

4.2.2 Moderate seizure attack

A complex, partial seizure and secondary generalized seizure are classified as a moderate seizure attack for the device. Because of the significant consciousness impairment and presence of focal neurological sings in this type of seizure, they are classified as moderate seizure attacks [50][51][56].

4.2.2 Severe seizure attack

A generalized seizure, as well as its subtypes, are considered as severe seizure attacks by the device. Due to a total loss of consciousness and different types of tonic colonic phases in this type of seizure, they have been considered as severe seizure attacks [50][51][56].

4.3 WSN-EEG Epilepsy Device

The device presents a multiprocessor WSN-EEG application to handle continuous brain waves, 24-hours a day, seven days a week. In addition, this device will provide a data-storage for medical doctors, to simplify further analyses and write subscriptions accordingly.

The device will consist of eight sensors placed over the scalp of the patients, connected through wireless links to a portable device (WSN-EEG device) as in Figure 13.

The analyser receives the data from the sensors, and analyses them based on the proposed algorithm in Section 4.3.1. Data analysis starts by distributing the received brain waves to the processor, and based on the analysis results, the device proceeds. The analyser contains four alert lights as follows [56]:

1. The green light is for safety or normal brain activities.
2. The blue light is to indicate mild convulsion attacks.
3. The yellow light is to indicate moderate convulsion attacks.
4. The red light is to indicate severe convulsion attacks.
5. The orange light is for the battery power.

These lights work as an alert to the patient to prepare for any abnormal brain waves, allowing the patient to ask for aid or call emergency numbers.

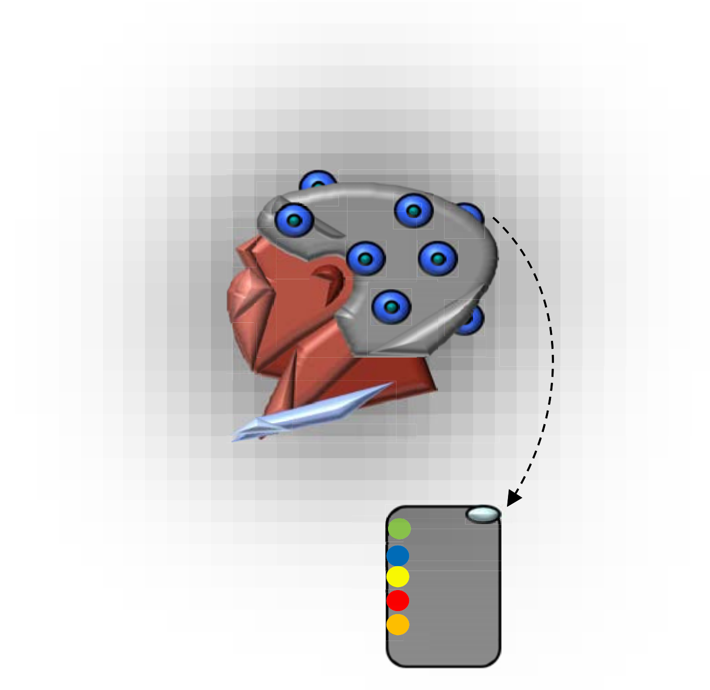

Figure 13 Novel Epilepsy predictor device

4.3.1 WSN-EEG Protocol Layer

The WSN-EEG protocol layers proposed designs based on the transmission techniques and data communications between the sensors on the scalp and the receiving mechanisms, as shown in Figure 14. The proposed design works as a brain wave monitor and analysis system for patients with elliptic history.

The sensors on the patient's scalp represent the communication points between the generated brainwaves and the WSN-EEG receiver device. The receiver is a multiprocessor analyser unit that reads the brain wave output signals and processes the signals based on a proposed analyser algorithm using a learning-based approach for prediction. This is accomplished by using a Feed Forward Neural Network for the alert system. Based on the durations of abnormality in the brain waves and specific symptoms in brain activities, it gives an alert or the safety signal. The system will record all patient data for further medical diagnosis and treatment [56].

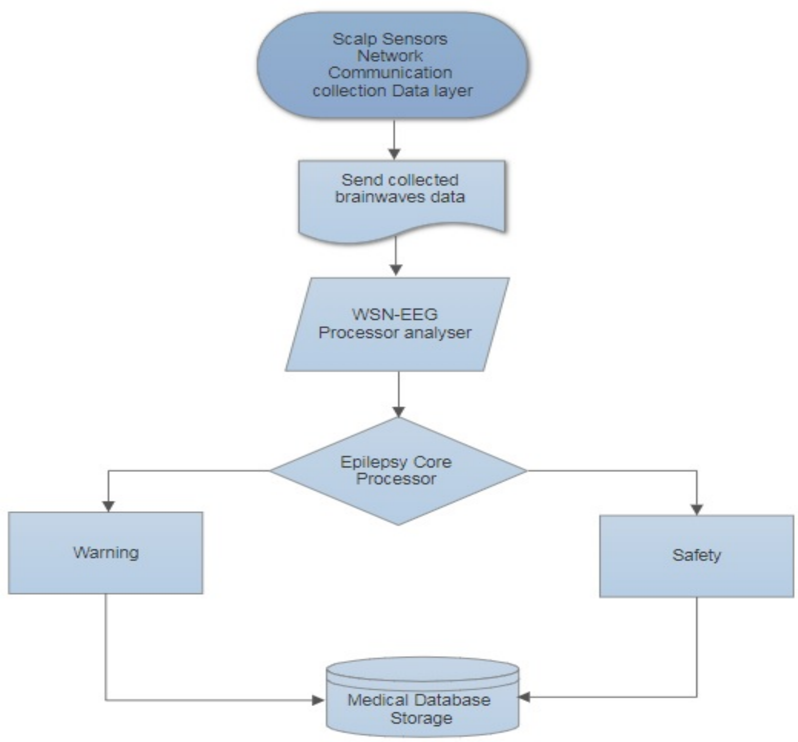

Figure 14 WSN-EEG Protocol layers

4.3.2 WSN-EEG Architecture Design

The WSN-EEG's future chip design proposes a specific feature to handle large amounts of data generated by the nodes on the scalp. As such, high-speed transmission rates between nodes and the receiver using IEEE802.11n wireless communication techniques, high throughput to support a minimum average of steady data transfer, and a reduction in the total latency are critical, due to the fact that the service time is the vital factor to receive data packets with correct sequences in order to avoid deadlock communications and data traffic congestions, as shown in Figure 15 [56].

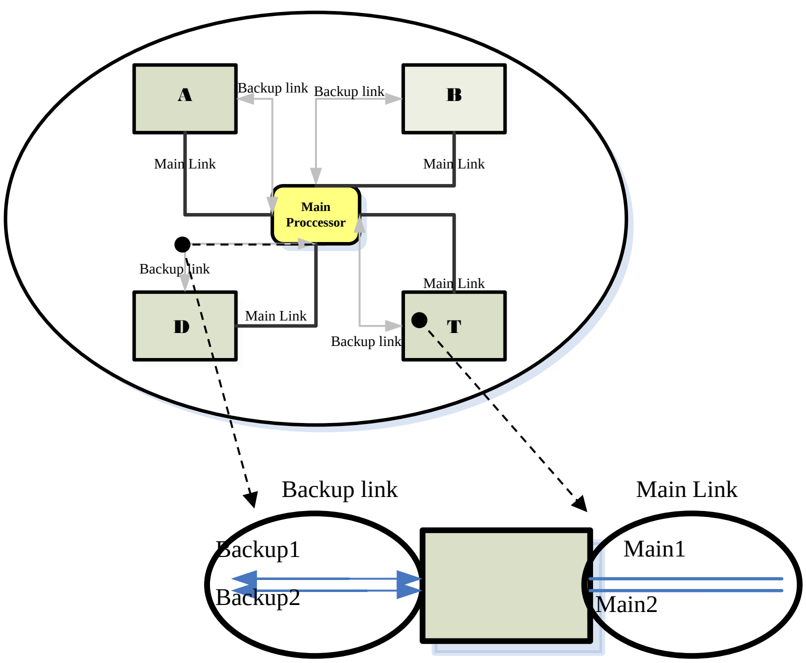

Figure 15 Biomedical WSN-EEG chip proposal Design

The proposed WSN-EEG chip has two communications links to distribute coming data, avoid congestion, and restore communication links. The links are divided into main lines and backup lines. The main lines are the primary links for data communications and the backup lines are used to avoid congestion, overload traffic, and breakdowns in the main links. Adding such improvements will enable the device to handle all brain data mounts according to human physiological attitude and brain instructions.

The communication of the extended links and traffic transmissions in the improved WSN-EEG design implement a generic revolution of data packet transmission that generates improved accuracy and avoids data delaying, as well as flooding.

4.3.3 WSN-EEG Chip Concept

This concept proposes to serve high-performance data transmission between the WSN-EEG, in order to provide a high-speed analysis for brain waves and distribute data traffic between the proposed communication links to avoid congestion and reduce traffic loads during monitoring processes, as follows:

- The algorithm compares the total service time for the transferred brain wave data to the previously recorded total service time activities to estimate the data traffic loads.

  Based on this comparison,

- The algorithm balances the data traffic between the Main1 and Main2 traffic links.

This process reduces the data traffic load from the Main1 link to the Main2 link. In addition, the backup links can be used to recover fault and congestion in the main links [65]. The WSN-EEG data flow concept is shown in Figure 16.

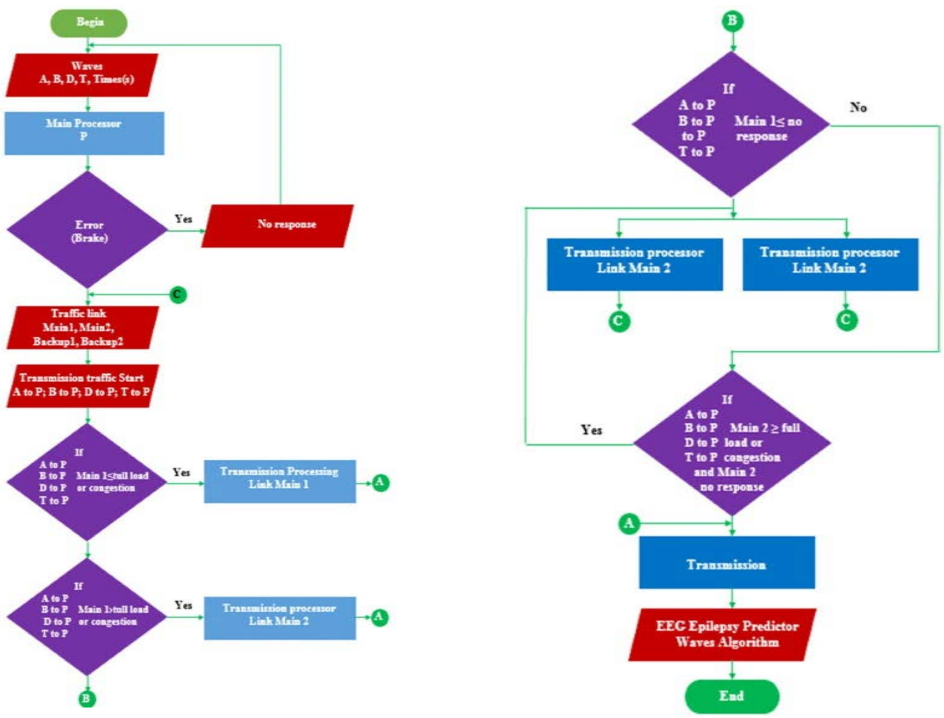

Figure 16 WSN-EEG data flow

4.4.4 WSN-EEG data flow Waves Algorithm

The WSN-EEG algorithm the data flow process, handle data dissemination methods based on an introduced tolerance point as a boundary between normal and abnormal brain waves. These identifications are based on data flow concepts, limitations, and data flow manipulations. The algorithm processes the input signals by the controller in order to study the signal entities using data (brain wave) specifications and weigh them based on the relationships between different variables (frequency, time of data) and retentions to differentiate normal and abnormal waves. The algorithm tracks the existing data flow for abnormal waves using FFNN machine learning for analyses of the seizure attack with consideration to any various effects in the patient's psychological attentions.

The alert process is evaluated based on the results of the algorithm the epileptic attack as it continues in the abnormal brain waves from 5 to 15 seconds or more based on several medical studies [52][53]. The algorithm is shown in Figure 17.

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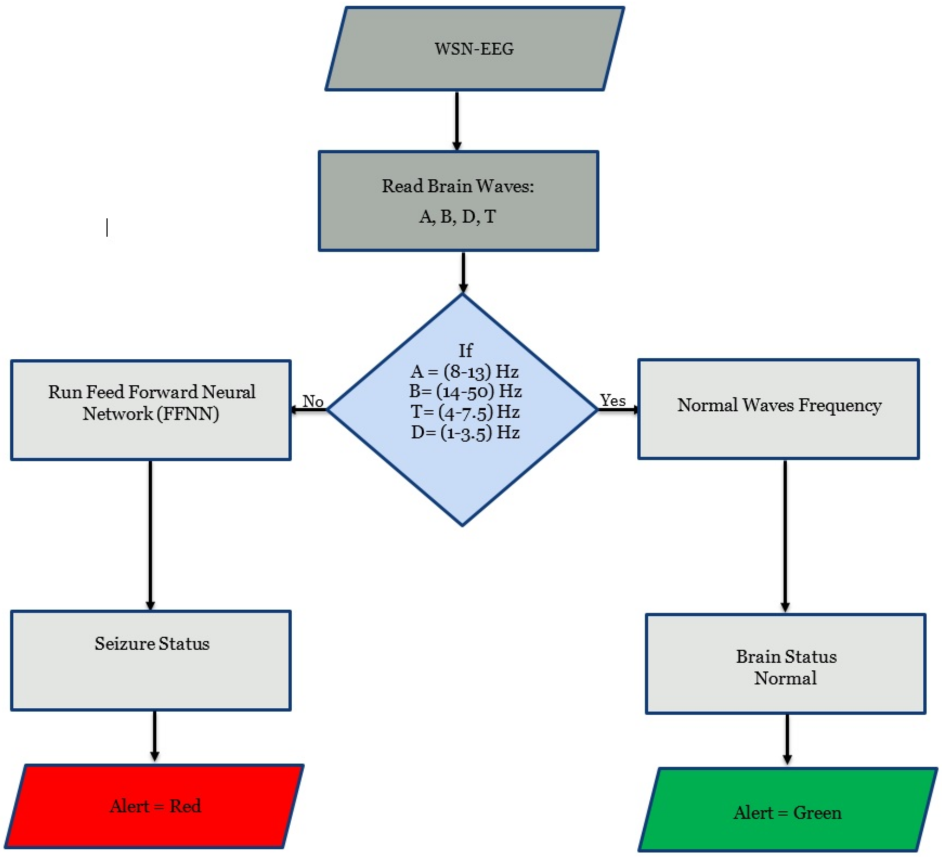


Figure 17 WSN- EEG data flow waves algorithm

Chapter 5: The Prediction System

In this chapter, the WSN-EEG prediction procedure is presented for the severity of the forthcoming epileptic attack based on a proposed algorithm and learning-based FFNN that analyses the abnormality of the brain signals and detects the steady abnormal waves for the device alert system. This method can save many patients by predicting the seizure before it occurs and can help protect them from different injuries and risky behaviors arising during an epilepsy attack. In addition, the proposed method can use the patient data for further medical diagnosis measures.

An overview of the brain signals and IEEE802.11n transmission techniques are provided to implement the proposed prediction system. For this reason, the Proteus 8 Professional 8.4 Model is used as a signal simulator to develop the WSN-EEG model.

The FFNN present in the predicting procedure for the severity of forthcoming epileptic attacks is based on a proposed detection algorithm, which analyses the abnormality in the brain waves and alerts the patient by giving signals to the patient.

The WSN-EEG will detect normal brain waves. In addition, all other forms of abnormal brain waves are detected, especially those found during an epilepsy attack, i.e. diffuse slowing, focal slowing, Triphasic waves, epileptiform discharges (EDs), periodical lateralized epileptiform discharges (PLEDs), and general periodic sharp waves [56].

5.1 Background

EEG plays an important role in diagnosing epilepsy, which causes abnormalities in EEG readings. It is also used to diagnose different diseases related to brain disorders such as sleep disorders, depth of anaesthesia, coma, encephalopathies, and brain death. The majority of EEG's use wired monitoring system, which has a limited advantage in terms of flexibility, mobility, and clinical diagnosis use [68]. On the other hand, the existing wireless EEG's are limited to specific applications to monitor the brain-behavior in different conditions, such as sleep behaviors, simulations, and prediction algorithm concepts as can be seen in Chapter 1, Section 1.5 of related work.

The proposed WSN-EEG wearable device monitors brain activity and alerts patients with epilepsy. The system will implement the prediction algorithm and FFNN model to diagnose epilepsy and enhance activities of daily living of epilepsy patients.

The WSN-EEG consists of three parts:

- WSN- EEG test and model designs
- The brain wave generation
- The FFNN based machine-learning approaches

5.2 WSN-EEG secure communication

A Specific Sensor ad hoc architecture testbed was designed to study the service time with respect to latency and jitter factors for data transmission between the WSN and the EEG receiver. The Testbed consists of a sensor 'Sensor Side' connected to the receiver 'Analyzer Side' by a controlled radio environment (RF cable). This testbed uses specific traffic generator software to generate UDP data (brain waves) and pass these from the sensors to the WSN-EEG receiver, and uses a specific analyzer to monitor network traffic and performance time stamps between the nodes based on IEEE802.11n and security performances in the ad hoc wireless communications [69].

This study conducted the tests with a source and a receiver. The testbed used IEEE802.11n as the transmission technique and security protocol for data privacy. The measurements for data transmission are divided into two subclass tests with both enabled and disabled security. In both tests, the sensor on the patient's scalp is the source of the traffic, and the analyzer is the traffic receiver, as as illustrated in Figure 18.

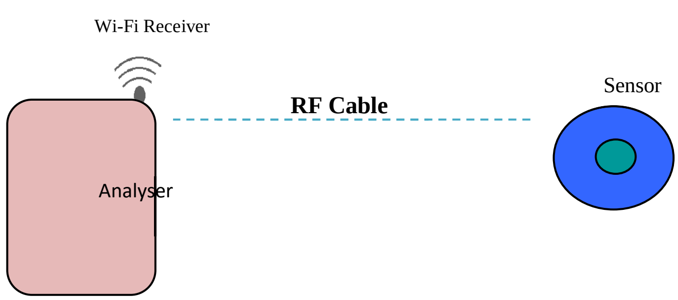


Figure 18 WSN-EEG Ad hoc Sensor Network Connection

In the Test-bed, a set of UDP in different packet sizes are sent from the sensor to the analyser to stress the network with maximum CPU capacity, evaluate the service time, and study the effect of the signal delay and the total service time to diagnose epilepsy and seizure attack predictions in order to alert the patients on time. All tests were repeated four times per test session, and therefore, evaluated four times in total to record the accurate average service time with respect to the data size and security scenarios.

The WSN-EEG deployed IEEE802.11n transmission techniques to estimate and evaluate the total service time and the security protocol impact on sensor networks in a real-time wireless transmission environment. In addition, the data packet delay and packet size relations were evaluated in terms of speed, distortion, and signal-to-noise ratio (SNR). The results showed that the EEG-WSN sensor network performance depends on the design and implementation of security protocols, which adds a significant impact in relation to the data packet delays and the packet size transmitted over the ad hoc sensor network (Figure 19, 20). The total service time showed the time taken for the brain wave signals to be transmitted from the sensors in microseconds, which can be integrated into an FFNN model to predict the seizure attack and alert the patient.

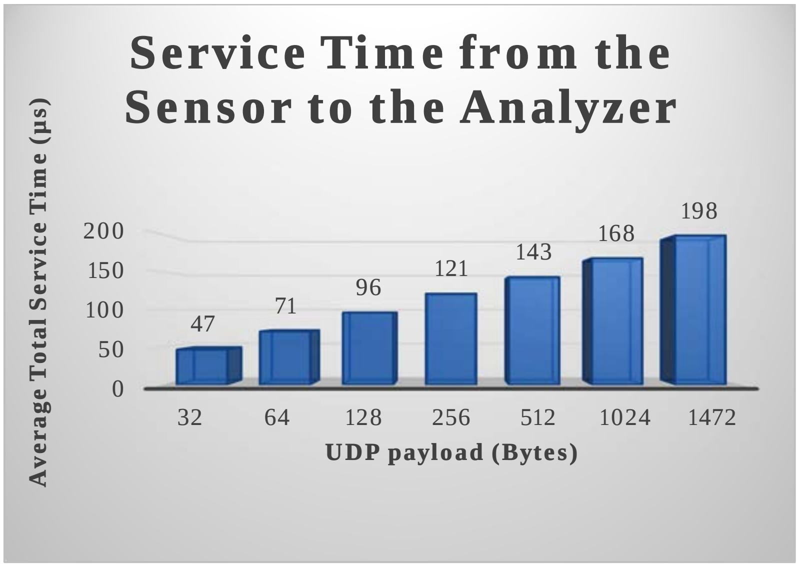


Figure 19 Total service time for data transmission from sensor to receiver side- security disabled

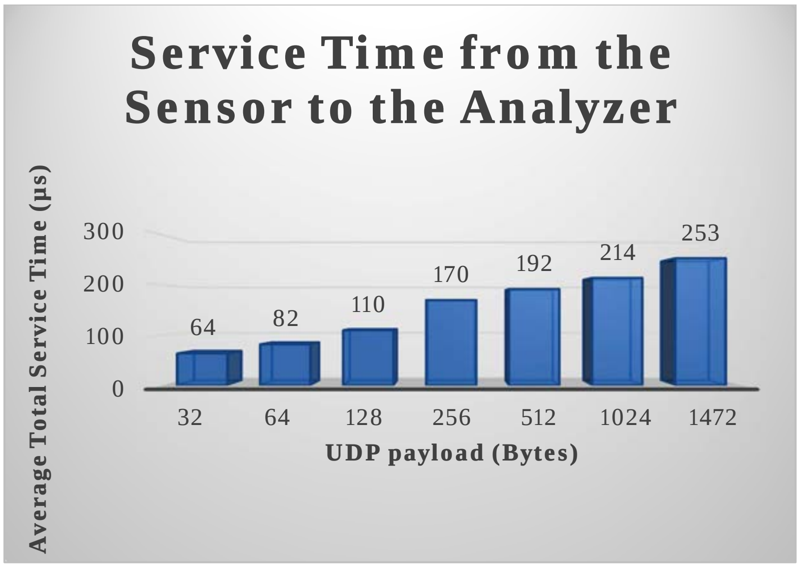


Figure 20 Total service time for data transmission from sensor to the receiver side - security Enabled

5.3 The Brain waves generation

In this section, four brain waves are illustrated using different microcontroller chips, PIC16F877A and Arduino, to evaluate frequency interruption with respect to time differences between the frequency changes. The system illustration of these four brain waves, A, B, T, and D, are on the Proteus 8 professional 8.4 Model microcontroller simulation.

The first test used PIC16F877A. These results were obtained using the microcontroller software imitations on Proteus 8 Professional 8.4 Model. The test used a C compiler for Microchip PIC MCUs coding, and a PIC16F877A chip with a 4MHz crystal. The PIC16F877A has two CCP modules, so one can be used to calculate the frequency of the input signal (brain wave). The brain waves were generated by simulation. First, a frequency value is considered as an identified wave. Then, a change, according to a tolerance point, is described in order to expose the behaviour of each brain signal to a highly changing value. To model a rapid change in frequency, i.e. of the subject's boundary's and numbers, the frequency period is suddenly modified or interrupted. In this case, the CPP module uses Timer1 for reference timing to appropriately set Timer1. This is done through the T1CON register and the pre-scaler of Timer1 is pre-set to 1:4 (T1CON=0x21). Here, the last bit of T1CON means TMR1ON. On the other hand, CCP1 is set to interrupt at an ever-rising edge of input pulse (CCP1CON=5). The system clock is a quarter of that of crystal (fosc/4).

Timer1 was increased with the frequency of a quarter of the system clock so that its frequency is 0.25MHz. If the input frequency is 1Hz, the counter should count 250000 for one cycle and the CCP counter will overflow. Therefore, in this system, at every interrupt of Timer1, another counting variable is increased (tk in code). In this code, to avoid doubles, the interrupt variable, tk, is divided by 2. Every tk is the same of 65536 CCP counter.

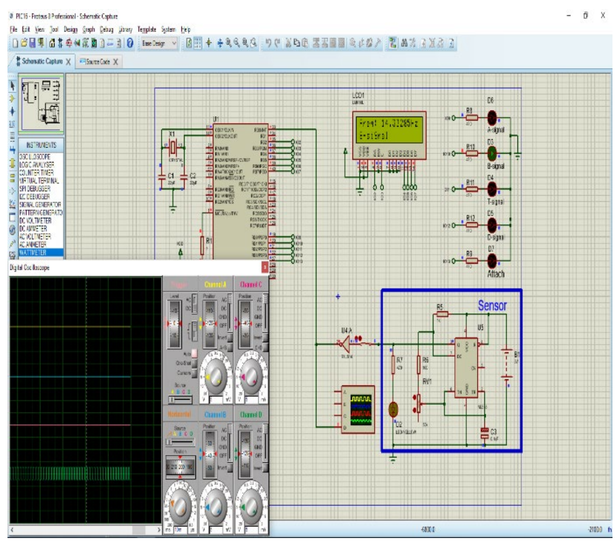
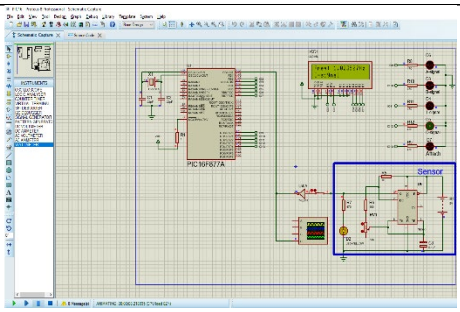
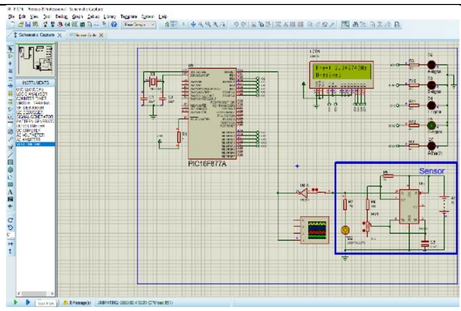
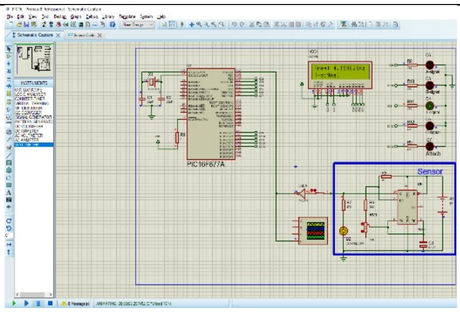
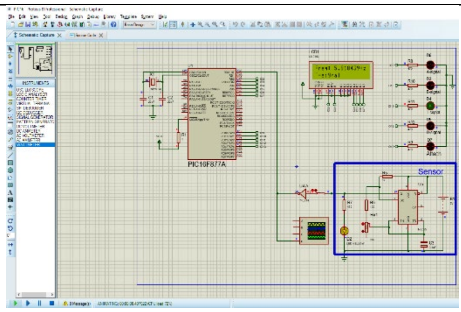
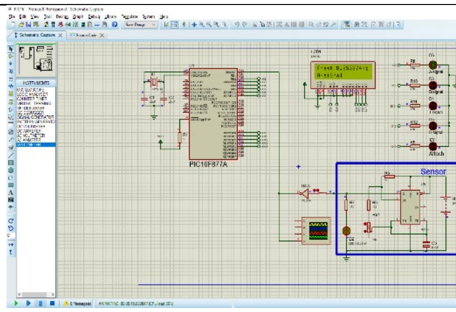
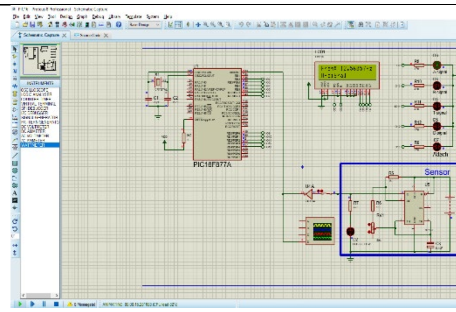
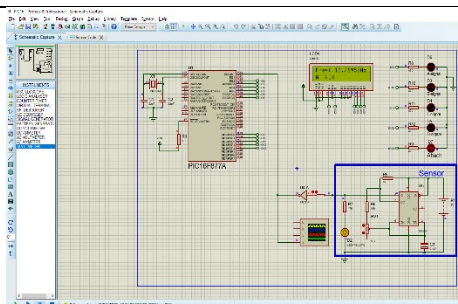
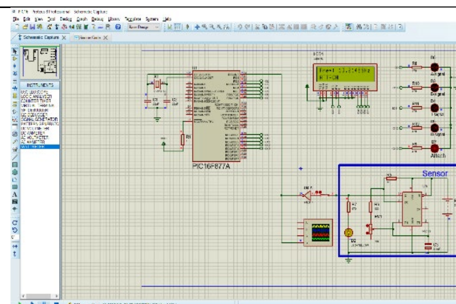


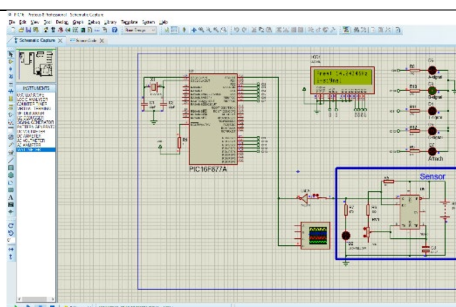
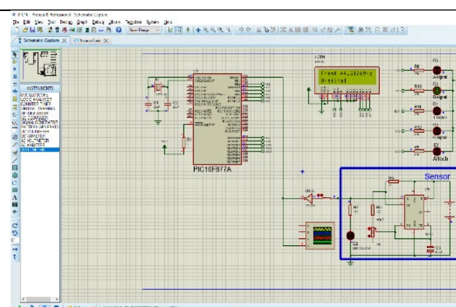
Figure 21 Main research model and results for PIC16F877A when frequency equal to 14.33Hz (B-signal)

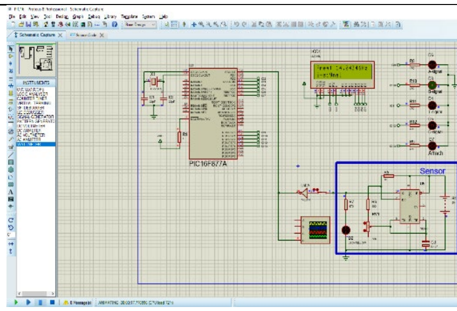
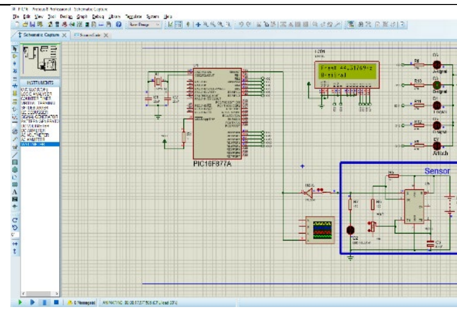
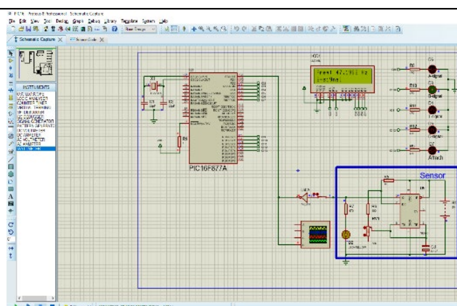
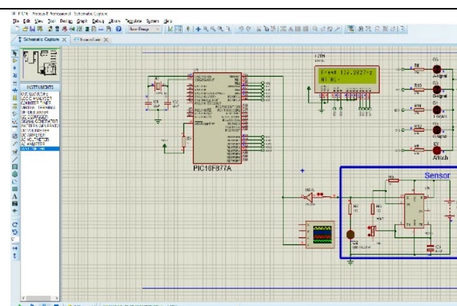
Table 2 Model and results of research-imitations on Proteus 8 PIC16F877A- Processor to measure the time-change between frequencies

	
Result Results of time, when begun changing frequency from 1.02 Hz (D-signal)	**Results of time, when changed frequency to 2.85 Hz (D-signal)**
Difference of frequency: $f_2 - f_1 = 2.85 – 1.02 = 1.83$ Hz **Difference of time:** $t_2 - t_1 = 8.418681 – 8.218935 = 0.199746$ sec.	
	
Results of time, when begun changing frequency from 4.17 Hz	**Results of time, when changed frequency to 5.92 Hz**
Difference of frequency: $f_2 - f_1 = 5.92 - 4.17 = 1.75$ Hz **Difference of time:** $t_2 - t_1 = 8.497922 - 8.297492 = 0.20043$ sec.	

<table>
<tr><td>
</td><td>
</td></tr>
<tr><td>Results of time, when begun changing frequency from 8.05 Hz</td><td>Results of time, when changed frequency to 12.56 Hz</td></tr>
<tr><td colspan="2">Difference of frequency: $f_2 - f_1 = 12.56 – 8.05 = 4.51$ Hz

Difference of time: $t_2 - t_1 = 15.281668 - 15.080847 = 0.200821$ sec.</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Results of time, when begun changing frequency from 13.77 Hz</td><td>Results of time, when changed frequency to 13.01 Hz</td></tr>
<tr><td colspan="2">Difference of frequency: $f_2 - f_1 = 13.77 – 13.01 = 0.76$ Hz

Difference of time: $t_2 - t_1 = 7.573044 – 7.374556 = 0.198488$ sec.</td></tr>
<tr><td>
</td><td>
</td></tr>
</table>

<table>
<tr><td>Results of time, when begun changing frequency from 14.04 Hz</td><td>Results of time, when changed frequency to 44.32 Hz</td></tr>
<tr><td colspan="2">Difference of frequency: $f_2 - f_1 = 44.32 – 14.04 = 30.28$ Hz
Difference of time: $t_2 - t_1$=17.971505 – 17.776596 = 0.194909 sec.</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Results of time, when begun changing frequency from 14.04 Hz</td><td>Results of time, when changed frequency to 44.32 Hz</td></tr>
<tr><td colspan="2">Difference of frequency: $f_2 - f_1 = 44.32 – 14.04 = 30.28$ Hz
Difference of time: $t_2 - t_1$=17.971505 – 17.776596 = 0.194909 sec.</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Results of time, when begun changing frequency from 47.2 Hz</td><td>Results of time, when changed frequency to 137.2 Hz</td></tr>
<tr><td colspan="2">Difference of frequency: $f_2 - f_1 = 137.2 – 47.2 = 90$ Hz
Difference of time: $t_2 - t_1$=2.943576 – 2.748299 = 0.195277 sec.</td></tr>
</table>

Results of research in chip Arduino

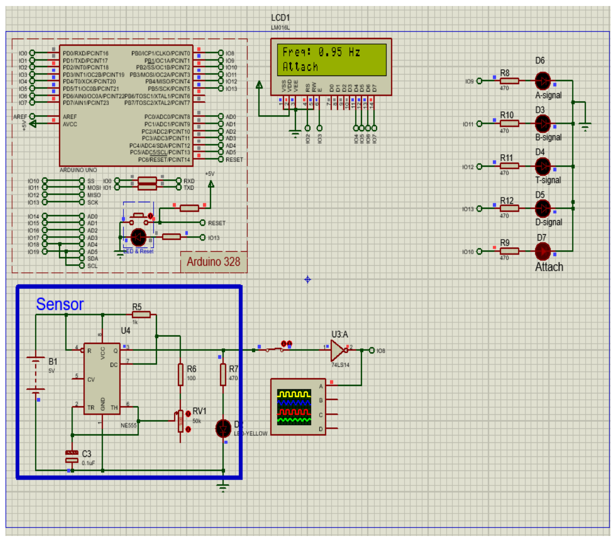
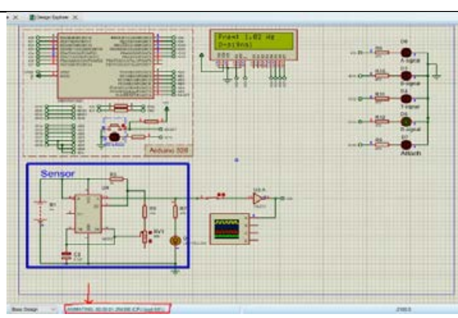
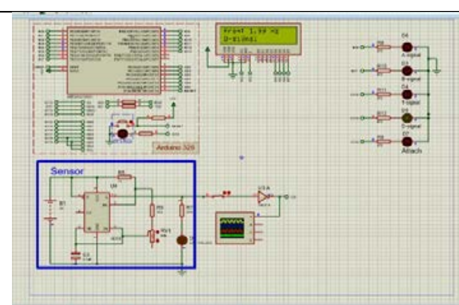
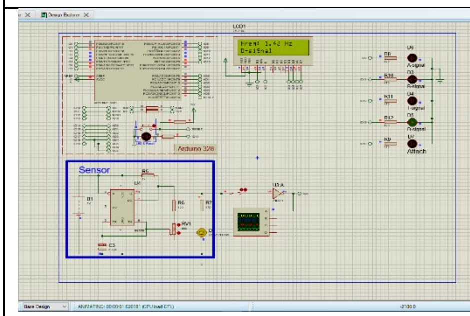
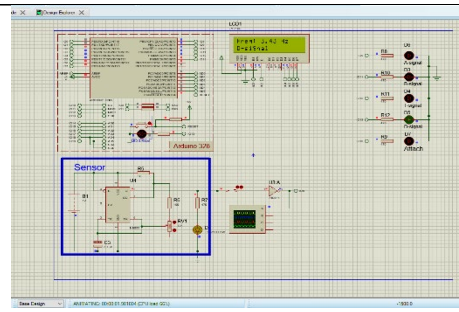
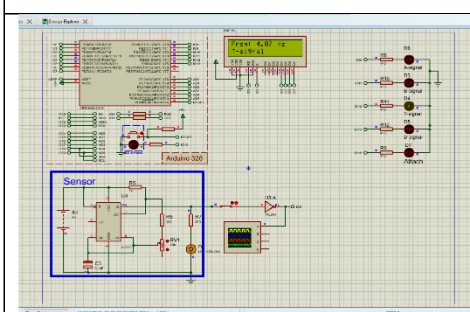
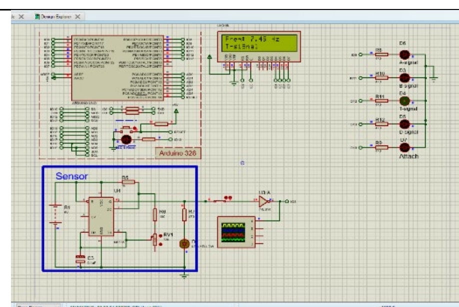
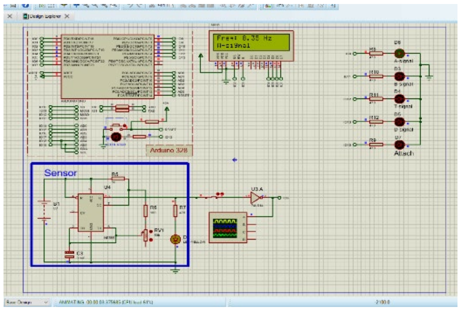
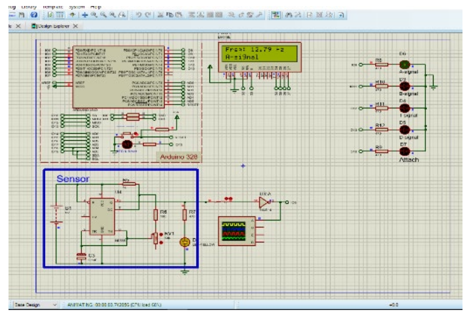
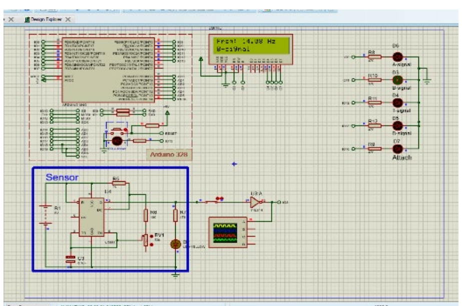
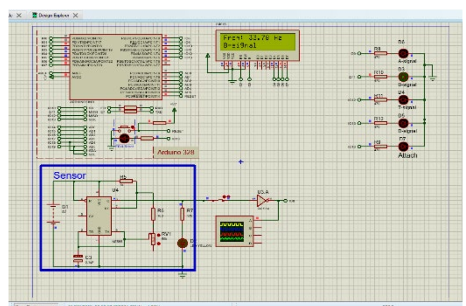


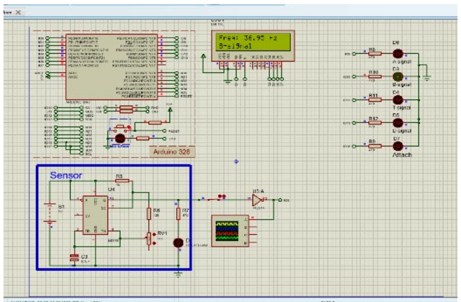
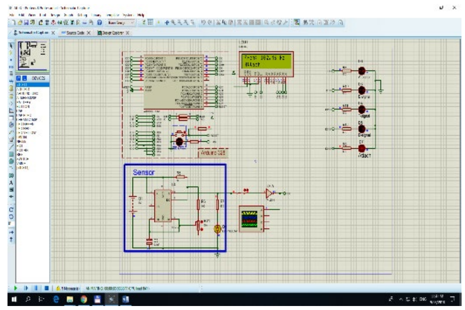
Figure 22 Main research model and results for Arduino 328 frequency equal to 0.95 Hz

Table 3 Model and results of research-imitations on Proteus 8 Arduino- Processor to measure the time-change between frequencies

Results of time changing processes, when frequency begun from 1.02 Hz	**Results of time changing processes, when frequency begun to1.99 Hz**
Difference of frequency: $f_2 - f_1 = 1.99 – 1.02 = 0.97$ Hz **Difference of time:** $t_2 - t_1 = 1.625765 - 1.254390 = 0.371375$ sec.	
	
Results of time changing processes, when frequency begun from 1.43 Hz	**Results of time changing processes, when frequency begun to 3.43 Hz**
Difference of frequency: $f_2 - f_1 = 3.43 – 1.43 = 2$ Hz **Difference of time:** $t_2 - t_1 = 1.981804 - 1.620181 = 0.361623$ sec.	
	
Results of time changing processes, when frequency begun from 4.07 Hz	**Results of time changing processes, when frequency begun to 7.49 Hz**
Difference of frequency: $f_2 - f_1 = 7.49 – 4.07 = 3.42$ Hz **Difference of time:** $t_2 - t_1 = 4.320099 – 3.954537 = 0.365562$ sec.	

<table>
<tr><td></td><td></td></tr>
<tr><td>Result of time changing process, when frequency begun from 8.35 Hz</td><td>Result of time changing process, when frequency begun from 12.79 Hz</td></tr>
<tr><td colspan="2">Difference of frequency: $f_2 - f_1 = 12.79 – 8.35 = 4.44$ Hz
Difference of time: $t_2 - t_1$=3.742056 – 3.375685 = 0.366371 sec.</td></tr>
<tr><td></td><td></td></tr>
<tr><td>Result of time changing process, when frequency begun from 14.08 Hz</td><td>Result of time changing process, when frequency begun from 33.78 Hz</td></tr>
<tr><td colspan="2">Difference of frequency: $f_2 - f_1 = 33.78 – 14.08 = 19.7$ Hz
Difference of time: $t_2 - t_1$=1.626004 - 1.245520 = 0.380484 sec.</td></tr>
</table>

	
Result of time changing process, when frequency begun from 36.95 Hz	**Result of time changing process, when frequency begun from 102.46 Hz**

Difference of frequency: $f_2 - f_1 = 102.46 – 36.98 = 65.48$ Hz

Difference of time: $t_2 - t_1 = 3.563877 – 3.206328 = 0.357549$ sec.

Table 4 Time and Frequency difference values for Arduino

	Differences of frequency (Hz)	Differences of times (sec)
1	0.97	0.371375
2	2	0.361623
3	3.43	0.365562
4	4.44	0.366371
5	19.7	0.380484
6	65.48	0.357549

.

Table 5 Time and Frequency difference values for PIC16F877A

	Differences of frequency (Hz)	Differences of times (sec)
1	1.83	0.199746
2	1.75	0.20043
3	4.51	0.200821
4	0.76	0.198488
5	30.28	0.194909
6	90	0.195277

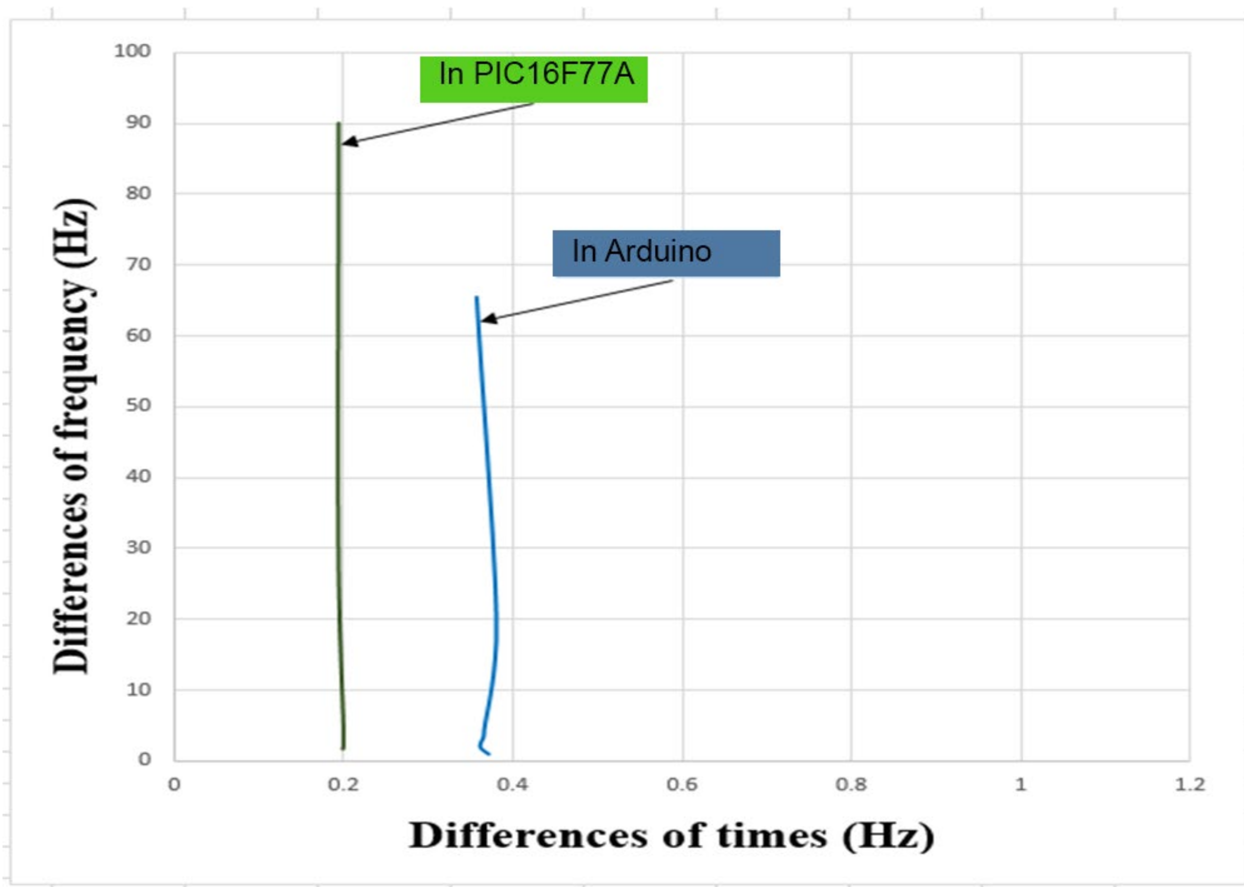


Figure 23 Frequency-Time related values (PIC16F877A-Arduino)

The result showed that the increase or decrease in the difference between frequencies does not affect the microcontrollers' detection time.

5.4 FFNN System model and problem formulation

The research proposes an FFNN based machine-learning approach to overcome the problem of non-linearity of a seizure attack. As the observe in Figure 24, the brain signal is passing through the proposed tolerance point (pre-seizure attack). Using a neural network trained model that combines the different distributions in one desirable distribution with consideration for the non-linearity of the seizure attack is provided with a simple specification of the problem in the coming sections.

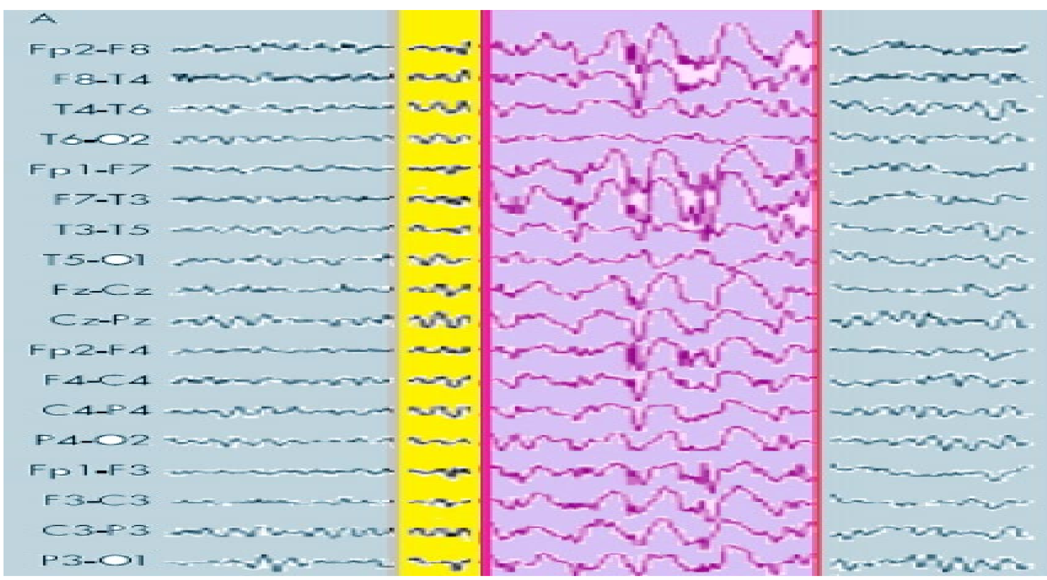


Figure 24 Example of an EEG A signal detailing normal behaviour (light Blue Colour Normal Brain waves, Yellow colour is the tolerance point /pre- attack, Pink Colour is the brain activity during a seizure attack) [66]

FFNN is applied to the diagnosis of a nonlinear signal using a WSN-EEG algorithm approach and a tolerance point for abnormal behaviour signs of possible seizures is identified in section 4.4.4. A faulty dictionary was first created containing responses observed at all inputs and outputs of the brain wave behaviours for epilepsy patients. The FFNN machine-learning approach was considered as a WSN-EEG approximation algorithm to capture mapping enclosed within the fault dictionary. In addition, this method was used as an algorithm tool for searching the fault dictionary in the diagnostic phase.

In the FFNN model, the brain wave's time domain and frequency domain measurements are taken as data for the WSN-EEG device data-sheets-values. The abnormal signal behaviour and duration were set as an output set of data per fault. Changes in electrical activity in the brain and seizure symptoms can be correlated to provide information about future seizures, their duration, and their severity. However, this correlation between EEG signals and symptoms composes a complex non-linear problem, which can be solve using neural networks, provided with a simple specification of the problem. Moreover, FFNN may provide optimization for the prediction rate of a neural-network-based system by removing inter-layer connections between the neural networks.

5.3.1 The Model

Electrical activity in the brain can be measured non-invasively via an Electroencephalogram (EEG for short), using electrodes attached to the scalp that measure voltage fluctuations within neurons in the brain, producing a time-dependent function:

$$S: \mathbb{R} \to \mathbb{R} \tag{1}$$

This can be sampled in time by the EEG into a finite collection of values $\tilde{S}$ (a set), of the form:

$$\tilde{S} = \{S(t) \mid t \in T\} \tag{2}$$

when sampled in a collection of discrete time instants,

$$T = \{t_i \geq 0 \mid i = 0, \dots, N\} \tag{3}$$

Assuming that normal brain activity leads to periodic functions (periodic signals), a seizure in an EEG signal is observable via two separate phenomena: a rapid change in the frequency of oscillation (an increase in frequency) alongside a rupture in the signal's periodicity, which can be monitored in three states of EEG waves as showcased in Figure 24.

These are a normal state (light blue background), a pre-seizure state (pre-state for short, yellow background), and a seizure state (light pink background). Thus, provided with a discrete time frame T with samples of a given signal S, then partition the collection T in three (possibly empty) subsets of T_{norm}, T_{pre}, and T_{seiz} such that

$$T = T_{norm} \cup T_{pre} \cup T_{seiz} \tag{4}$$

Thus, the signal S can be divided likewise into three subsets:

$$S_{norm} = \{S(t) \mid t \in T_{norm}\}$$
$$S_{pre} = \{S(t) \mid t \in T_{pre}\}$$
$$S_{seiz} = \{S(t) \mid t \in T_{seiz}\} \tag{5}$$

During the pre-state and the seizure, seizure symptoms (e.g. hallucinations, muscle contractions, etc.) begin to appear on the patient, whose severity, none (no), mild (mi), moderate (mo), or severe (sev) define additional criteria for the classification of EEG function samples. According to this partition, a discrete signal S can be written as:

$$\tilde{S} = \left\{ S(t_{state}^{(ty)}) | t_{state} \in T_{state}, state \in \{norm, pre, seiz\} \wedge ty \in \{no, mi, mo, sev\} \right\} \quad \textbf{(6)}$$

5.3.2 Seizure Prediction using Feed Forward Neural Networks

To create an FFNN-based strategy for seizure prediction, the variables and concepts defined on Section 5.2.3.1 were taken to define a *deviation* measure in EEG signals to distinguish between normal and *abnormal* brain activity, and propose a strategy to feed an FFNN an input (subsets of an EEG signal) to produce an output (a predicted signal).

5.3.3 Stage-Learning Hypothesis

If it is planned to use the FFNN paradigm to forecast seizures, using the severity of symptom signs under the notation provided in Section 5.2.3.1, it is necessary to identify the time-frames in which *abnormal* brain activity *in an EEG occur* $T_{ab} \subseteq T$ as

$$T_{ab} = \left\{ t^{(ty)} | ty \in \{mi, mo, sev\} \right\} \quad \textbf{(7)}$$

Under this definition, the *normal* brain activity time-span defined as the complement of T_{ab}

$$T_{norm} = T \setminus T_{ab} \quad \textbf{(8)}$$

Given a signal, define the *duration* of seizure symptoms using the set diameter of $T^{(ty)}$ as

$$\Delta T^{(ty)} = max\left\{ |t_1 - t_2| : t_1, t_2 \in T^{(ty)} \right\}, ty \in \{mi, mo, sev\} \quad \textbf{(9)}$$

In addition, given a non-empty time-frame $\tilde{T} \subset T$ to define the *variation* of S in $\tilde{T}$ as

$$\Delta S(\tilde{T}) = \ max\{|S(t)|: t \in \tilde{T}\} \qquad \textbf{(10)}$$

Thus, a *spike* in brain activity can be easily detected as

$$\frac{\Delta S}{\Delta \tilde{T}} = \frac{\Delta S(\widetilde{T})}{\Delta \tilde{T}} \geq S_{spike} \qquad \textbf{(11)}$$

for some tolerance value $S_{spike} > 0$.

Provided with a *baseline* signal $\hat{S}$ of brain activity (deduced from expected brain activity), the *deviation* signal from the baseline $\hat{S}$ can be defined as:

$$DS(t) = \{S(t) - \hat{S}(t): t \in T\} \qquad \textbf{(12)}$$

and an absolute measurement of the deviation taking its norm:

$$\|D\| = \ max\{|S(t) - \hat{S}(t)|: t \in T\} \qquad \textbf{(13)}$$

Isolating the timeframes in which seizures occur, can be done provided with tolerance values $S^{(mi)}, S^{(mo)}, S^{(sev)} > 0$ that determine abnormal brain activity:

$$T_{ab}^{(ty)} = \{t \in T: |D(t)| > S^{(ty)}\}, ty \in \{mi, mo, sev\} \qquad \textbf{(14)}$$

And the amplitude values of S of abnormal brain activity as:

$$S_{ab}^{(ty)} = \{S(t): t \in T_{ab}^{(ty)}\}, ty \in \{mi, mo, sev\} \qquad \textbf{(15)}$$

This will account for the duration of a seizure. However, to produce seizure-like brainwaves, this will construct a discrete representation of these as the output of the neural network, this will be done in the following subsection, taking advantage of basic concepts in signal processing.

5.3.4 Optimization Stage

Provided with a baseline signal $\hat{S}$ for normal brain activity, the FFNN paradigm is applied to the problem of determining the type of future seizures a patient will suffer by producing a signal S_{next} (the output) from three given inputs:

i. $X_1 = T_{ab}^{(mi)} \cup T_{ab}^{(mo)} \cup T_{ab}^{(sev)}$

ii. $X_2 = S_{ab}^{(mi)} \cup S_{ab}^{(mo)} \cup S_{ab}^{(sev)}$

iii. $X_3 = \Delta D\left(T_{ab}^{(mi)}\right) \cup \Delta D\left(T_{ab}^{(mo)}\right) \cup \Delta D\left(T_{ab}^{(sev)}\right)$

The resulting signal will be of the form $S_{next}(t) = F(X_1, X_2, X_3)$. Classically, to construct F as a linear combination of the input variables at each time step. However, this step a small detour to produce a signal due to the fact that the inputs of the neural network are of a different nature (time, amplitude, and variation).

Brainwave signals are produced by a combination of oscillations, which can be better analysed in the frequency domain of $S(t)$ with consider to the *Fourier expansion* in the following form:

$$S(t) = \sum_{n\geq 0} S_n \cos(\omega_n t + \varphi_n) \qquad \textbf{(16)}$$

For $S_n, \omega_n, \varphi_n \in \mathbb{R}$ are called the *harmonic* (or *Fourier*) *coefficient*, the *wave number*, and the *phase*, respectively. Equation (18) can be simplified to avoid the phase value by noticing that

$$\cos(\omega_n t + \varphi_n) = \cos(\omega_n t)\cos(\varphi_n) - \sin(\omega_n t)\sin(\varphi_n) \qquad \textbf{(17)}$$

So that the signal can be written as a sum of basic trigonometric functions of the form

$$S(t) = \sum_{n\geq 0} A_n \cos(\omega_n t) + B_n \sin(\omega_n t)$$

Over a given time interval, to calculate the harmonic coefficient A_n over a signal $S(t)$ over a time interval $[0, T]$ by fixing the wave number using

$$\omega_n = \frac{2\pi n}{T} \tag{18}$$

So that the coefficients can be calculated using the standard Fourier formulas (as presented for example in [70]) adapted to the time interval

$$A_n = \frac{2}{\pi T}\int_0^T S(t)\cos\left(\frac{2\pi n}{T}t\right)dt$$

$$B_n = \frac{2}{\pi T}\int_0^T S(t)\sin\left(\frac{2\pi n}{T}t\right)dt$$

At each stage of the neural network, functions S_{ty}^{k} are specific linear combinations of preassigned fundamental frequencies that are divided into four *wave-types* (Delta, Theta, Alpha, and Beta) whose frequency ranges in Hertz (Hz) are presented in Table 6.

The output of the neural network then will be the collection of Fourier coefficients that define $S_{next}(t)$ which is relatable to a seizure, as in symptoms and their severity.

Table 6 Frequency values dividing brainwave types.

wave-type	Range (Hz)	ε (Hz)	f_{min} (Hz)	f_{max} (Hz)
Delta	[1,3.5]	0,5	1,5	3
Theta	[4,7.5]	0,5	4,5	7
Alfa	[8,13]	0,5	7,5	12,5
Beta	[14,50]	0,5	14,5	49,5

During normal brain activity, the behavior of brain waves should be repeated in intervals. Such an interval in which the wave repeats itself is defined by the wavelength, λ. Thus, if v denotes the speed in Hz/sec at which this repeating pattern will occur, therefore the period T occurs simply given by

$$T = \frac{\lambda}{v} \qquad \textbf{(19)}$$

Therefore, that it can find the harmonic coefficients in terms of wavelength and velocity as

$$A_n = \frac{2v}{\pi\lambda}\int_0^{\lambda} S(x)\cos\left(\frac{2\pi vn}{\lambda}x\right)dx$$

$$B_n = \frac{2v}{\pi\lambda}\int_0^{\lambda} S(x)\sin\left(\frac{2\pi vn}{\lambda}x\right)dx$$

Exchanging the time domain for the *frequency* domain. The accepted wave speed for brainwaves will be taken as $v = 300 Mb/sec$, and the different wave-lengths can be obtained via the following relation

$$\lambda_u^{(w)} = \frac{f_u^{(w)}}{v} \qquad \textbf{(20)}$$

Where $v \in \{min, max\}$ and w is the wave-type (delta, theta, alfa, or beta) as presented in Table 6.

5.3.2.1.1 Optimization Stage

When using the Feed-Forward paradigm, the structure of the network preserves the linearity of the output by avoiding cycles within neurons (see Figure 25) by multiplying just the frequency coefficients and not the generated functions of sine and cosine.

On the one hand, the FFNN paradigm allows us to treat the problem of generating an output signal in terms of the classical basis of Fourier series[70], while on the other, the introduction of multiplication along the different layers of the neural network includes -implicitly- a travelling wave phenomena, that would require us to state brain wave signals in not one, but two variables (see [70] for a presentation on travelling wave phenomena).

To guarantee the structure of an FFNN provided with the input, a separation of the network in a series of hidden layers $O_j, j = 1, \dots, P$ done, so that the input of each layer depends on a linear combination of the inputs of the previous one.

In layer O_j, if S_j^k denotes the input function of neuron n_k , S_j^k is of the following form

$$S_j^k(t) = \sum_i \alpha_{ij}^k S_{j-1}^i(t) \tag{21}$$

Where both S_j^k and S_{j-1}^kshare the same wave numbers. In our case, the first layer of the neural network (the *input* layer) is defined by functions $F_i, i = 1,2,3$ of the form:

$$F_i(X_i) = \sum_{t \in T_{ab}^{(mi)}} w_i^{(mi)} X_i(t) \sum_{t \in T_{ab}^{(mo)}} w_i^{(mo)} X_i(t) + \sum_{t \in T_{ab}^{(sev)}} w_i^{(sev)} X_i(t)$$

This poses a conceptual problem, since the variables are in different units and of different nature. However, the responsibility of the first layer of neurons is to guess the relation between times and values and to produce an output to be a vector in the size of the Fourier series expansion desired.

Moreover, the frequency values presented in Table 6 determine the size of the input of each neuron for which they define the ranges of frequencies in the brain (1.5 to 49.5 Hz). In addition, if the network has $N+1$ layers (with layer 0 being the input layer), the output S_{next} will be defined by a function of the form

$$S_{next}(t) = \sum_{k} w_{N-1}^{(mi)} S_{(mi)}^{k}(t) + w_{N-1}^{(mo)} S_{(mo)}^{k}(t) + w_{N-1}^{(sev)} S_{(sev)}^{k}(t)$$

Where the summation is taken over the number of neurons in the $(N-1)$-th layer, and $S_{(ty)}(t)$.

Under the description of brain waves provided by Fourier series (Equations 16 - 21), the neural network is learning to discriminate on the *morphology* of normal EEG brain-waves (in terms of wavenumbers and Fourier Amplitude coefficients) to help discriminate normal from abnormal states depending on the combination of wave numbers.

Indeed, normal brain waves are *rhythmic*, and depend on a smaller set of fundamental harmonics, while *transient* states (as observed in the onset of a seizure, and the seizure itself) require extremely high frequencies and occur during brief periods of time.

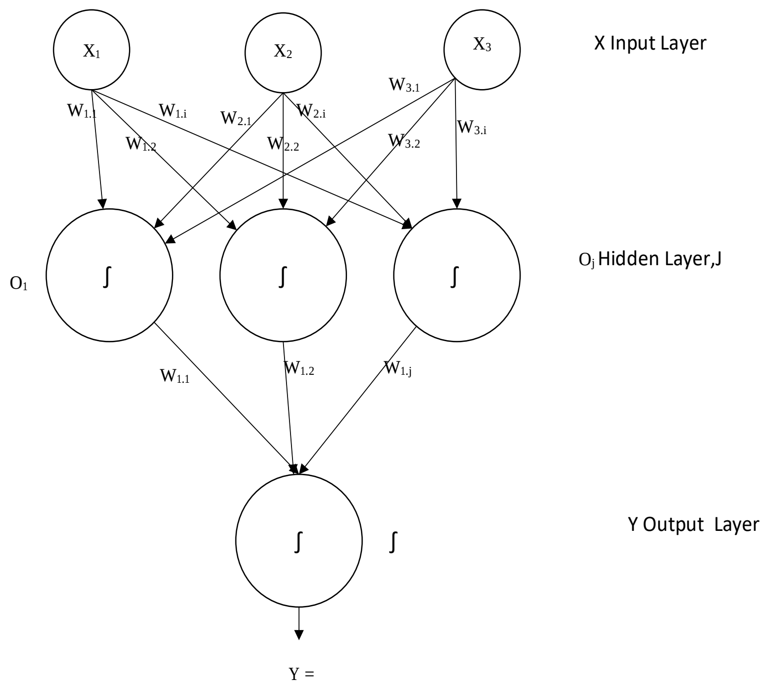


Figure 25 Proposed structure of the Feed-Forward Neural Network (FFNN).

In this sense, the values of $S_{ab}^{(ty)}$ provide us with the input for calculating the harmonic coefficients, while the time-frame values $T_{ab}^{(ty)}$ will help support the neural network in determining the onset and duration of a seizure, as stated in the medical literature[71].

Normal brainwaves (alpha waves) will appear *naturally* in the output signal of the neural network $S_{next}(t)$ associated with smaller Fourier coefficients, and the recognition of mild to severe seizures are internally correlated by the neural network with increased coefficients within the beta range.

5.3.5 Application Stage

The predicting signal S_{next} constructed is provided with an accurate baseline signal $\hat{S}$ and could provide patients with a more detailed prognosis on their condition, whether they are prone to seizures, and the type of seizures they will suffer. However, extrapolating baseline signals, as well as the tolerances proposed in Section 5.2.3, depends on the medical records of a patient that must be weighted by additional factors (e.g. emotion, sleep patterns).

The range of values used to separate normal from abnormal behavior depends on two factors: (1) distinguished *values* of $S(t)$, and (2) the oscillation *frequency* as presented in Table 6. Given a frequency range for a specific type $\left[a_{min}^{(ty)}, a_{max}^{(ty)}\right]$, the lower and upper boundary (onset) frequencies are calculated using a *tolerance* value $\varepsilon^{(ty)}$ as follows:

$$f_{min}^{(ty)} = a_{min}^{(ty)} + \varepsilon^{(ty)} \tag{22}$$

For the lower bound, while the upper bound is defined as

$$f_{max}^{(ty)} = a_{max}^{(ty)} - \varepsilon^{(ty)} \quad \textbf{(23)}$$

Thus, seizure symptoms are expected in the 4,5 Hz - 49,5 Hz range and the correlations of seizure symptom severity are a construct deduced by the neural network.

The signals obtained here are a *construct*, devised by the neural network that affected by the latency of the EEG-WSN wearable. Be mindful that the EEG signal arrives to the neural network *quantized* in UDP packets. In this sense, it is denoted by $S_{true}(t)$ as the real EEG signal belonging to a seizure-prone patient, then our $S_{next}(t)$ can be written as

$$S_{next}(t) = S_{true}(t) * E(t) \quad \textbf{(24)}$$

Where $E(t)$ is an error function that convolves the true signal (and that the neural network is implicitly minimizing), must depend on the following parameters:

- UDP Packet size: S_p
- Number of transmitted packets per second: N_p
- Packet delay: δ (μsec)

- Security over-check impact S_I (μsec)
- The length of the packet queue $Q_{size}(t)$ at a given time instant

That defines a convolution of the *real* (theoretical) signal $S_{true}(t)$. Particularly, these parameters warp the wave-lengths of the EEG-WAN signals by the following factor:

$$\tilde{\lambda}_u^{(w)} = N_p S_p + Q_{size}(t)\lambda_u^{(t)} + \delta \qquad \textbf{(25)}$$

Where $\tilde{\lambda}_u^{(w)}$ is the value used in the Fourier transform, and $\lambda_u^{(w)}$ is the real value of the theoretical signal (recall Equation 20).

The obtained results of the proposed application can be implemented in different model approaches for WSN-EEG for epilepsy diagnoses or prediction tools in the EEG system.

Chapter 6 Conclusions and Future work

In conclusion, this thesis contributes to an innovative perspective on challenges linked to improving the quality of an epilepsy patient's life by combining the development of ICT and medical treatments. This research has presented a wearable WSN-EEG predictor and monitor for epilepsy patients. The WSN-EEG used a data flow algorithm and FFNN to identify the brain waves in three periods; the normal brain waves, the tolerance period (pre-attack) brain waves, and the abnormal seizure attack period. These identifications in the system can enable a precautionary period to allow patients to take protective measures for continuing abnormal brain waves before the seizure attack. This thesis presented a prediction algorithm using data flow manipulation concept for data setting and controller to differentiate between normal and abnormal brain waves. The FFNN machine-learning approach deployed as a part of the prediction algorithm to analyse, study signal relationships, signal settings and irrupted single time differences as a hidden node to predict and differentiate seizure attacks with correlation to seizure signs and symptoms.

In addition, the proposed model can be integrated in other wireless sensor system solutions based on the similar FFNN concept implementation to predict epilepsy attack. The WSN-EEG can help patients to take emergency steps to save lives and avoid the seizure risks in cases such as inhaling vomit and thrombotic lesions, in the elderly and childhood stage. This will give hope and confidence in life expectancy for epileptic patients.

This thesis shows the difference in time performances for brain wave measurements using PIC16F877A and Arduino chip systems design. This shows a significant importance to consider feature aspects such as system specification, validation, and synthesis for any WSN-EEG environments functions among hardware and software performance applications.

Finally, the thesis shows the importance of time performance and data privacy in medical applications, it can affect and degrade the quality of the detection system and seizure prediction. This degradation happened due to the nonlinearity of the added security headers for the transmitted data. On the other hand, this thesis showed that the data processing increases with increasing amount of data implementing security and privacy protocols, therefore in such applications, the privacy will affect the prediction process, the analysis results in the system and it may put patient's life at risk.

Future work suggested:

- Further improvement on the proposed algorithm and implement different neural network architectures

- Perform different measurements with a further sample of different seizure type attacks and different patient groups and ages
- Implement the WSN-EEG system in a clinical setting
- Study power consumptions for the proposed sensor networks
- Study different wireless sensor transition techniques, implement different security protocols and privacy issues
- Focus on the patient's daily life and medical history to improve the patient's needs and life-saving

Tables

Figures

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List of Publications

1. Title: Biomedical Epilepsy Multiprocessor Network on Chip EEG Utilizing IEEE802.11n Systems Link ieeexplore.ieee.org/document/8108814/ Published in IEEE 14th International Conference on Mobile Ad Hoc and Sensor Systems (MASS) Orlando, Florida, USA _October 22-25, 2017

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