Deanship of Graduate Studies
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Diagnosing Epilepsy Disease Using Adaptive Neuro-Fuzzy Inference System

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Thesis Approval

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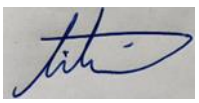
3.External Examiner: Dr. Lilia Mashal Signature 

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Dedication

To my loving and supportive family: my spectacular mother and father and my wonderful brothers and sisters.

To my best friend and the one who always makes my life brighter: my dear husband Ibraheem.

To all my beloved ones… I dedicate my thesis.

Thank you and I love you all!

Wala’ M. Bseiso

Declaration:

I certify that this thesis submitted for the degree of master is the result of my own research, except where otherwise acknowledged, and that this thesis (or any part of the same) has not been submitted for a higher degree to any other university or institution

Signed: 

Wala' Mohammad Hashem Bseiso

Date: 6 / 8 / 2022

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Wala' M. Bseiso

Abstract

Epilepsy disease is one of the most common and serious brain disorders that has many possible causes and presentations. It affects around 50 million people worldwide, -neonates and elderly.

In this study, an Adaptive Neuro-Fuzzy Inference System (ANFIS) that has the ability to diagnose epilepsy was established. Thirty epilepsy patients and thirty healthy people participated in the study. Their EEG signals were recorded with a computer-based data acquisition system (Nicolet NicVue). The power spectra were achieved from their EEGs using Fast Fourier transformation, and the five frequency sub-bands (delta, theta, alpha, beta and gamma) were extracted. 67% of the data was used as a training dataset for ANFIS and the rest 33% as a test dataset.

Eventually, ROC curves were established. For electrode position P3 the resulted values of sensitivity, specificity and accuracy at the cutoff point ~ 0.4 were 100% each.

The results of this research will help neurologists and researchers deal more easily with EEG tests, and assist doctors in making the right diagnosis.

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Acronyms

ANFIS	Adaptive Neuro-Fuzzy Inference System
EEG	Electroencephalogram
ROC	curve Receiver Operating Characteristic curve
FFT	Fast Fourier Transform
PSD	Power Spectral Density
ANN	Artificial Neural Network
FL	Fuzzy Logic
SPSS	Statistical Package for the Social Sciences
AM	Autoregressive Model
WT	Wavelet Transform
AI	Artificial Intelligence
MEG	Magnetoencephalography
F	Frontal
C	Central
P	Parietal
O	Occipital
RMSE	Root Mean Square Error
MF	Membership Function
Trimf	Triangular Membership Function
Pimf	Pi-shaped Membership Function
Gbellmf	Bell-shaped Membership Function
Gaussmf	Gaussian Membership Function
Gauss2mf	two-sided Gaussian Membership Function
Trapmf	Trapezoidal Membership Function
Psigmf	Product of two Sigmoid Membership Function
Dsigmf	Difference between two Sigmoid Membership Function
TP	True Positive
TN	True Negative

FP	False Positive
FN	False Negative
TPR	True Positive Rate
FPR	False Positive Rate

Chapter One: Introduction

1.1 Overview

Epilepsy is a neurological disease that affects around 50 million people worldwide, it is one of the most common neurological diseases globally (WHO, 2019). It is characterized by repeated seizures due to a serious brain disorder (Dekker, 2002). Epilepsy disease is usually diagnosed by an electroencephalogram (EEG) test; a recording of brain electrical activity that contains important information associated to the different physiological states of the brain.

In dealing with epilepsy disease, the causes and the consequences are not always obvious, and the presentations of the disease vary from one case to another (Duncan et al., 2006). These complications made it difficult for physicians to be completely certain of their diagnosis. EEG tests and brain images are currently the main basis for the diagnosing process. Specialists check certain abnormalities in EEG spectra that may be indicators of epilepsy (Duncan et al., 2006).

EEG signals contain valuable information that can determine the positions and relative strengths of electrical activity in the various brain regions (Jung, 2012). However, there are many sources of artifacts in the signal. The major sources of these artifacts are blinking of the eyes during the procedure, muscular movements, and electrical noise (Kousarrizi et al., 2009).

In signal processing, there are different methods used to reject and eliminate artifacts. One of the common methods is Fast Fourier Transform (FFT) which uses mathematical tools to analyze EEG data. FFT represents the EEG signal by power spectral density (PSD) estimation which contains the main characteristics of the signal. Five frequency sub-band (delta, theta, alpha, beta and gamma) are extracted from the PSD estimation. These sub-bands contain the major characteristic waveforms of EEG spectrum (Al-Fahoum & Al-Fraihat, 2014).

In recent years, computer science and artificial intelligence are widely employed in analyzing complex medical data (Ramesh et al., 2004). Researchers have been trying to demonstrate certain levels of machine intelligence inspired by the sophisticated functionality

of the human brain (Khan, 2018). These attempts to achieve this level of artificial intelligence were successfully executed. Artificial Neural Networks (ANN) simulates human brains where hundreds of billions of neurons process information in parallel (Khan, 2018). ANNs gather their knowledge by detecting the patterns and relationships in data to provide machine learning through experience (Agatonovic-Kustrin & Beresford, 2000).

Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the advantages of both Artificial Neural Networks (ANNs) and Fuzzy Logic (FL) in the same framework (Chopra et al., 2021). An ANFIS model is developed within this study to detect and diagnose epilepsy disease by the process of training and testing.

1.2 Objectives of the thesis

The main objective of this research is to introduce a new approach to diagnosing epilepsy disease using ANFIS.

On the other hand, a sub-objective of this study is to find the most related sub-bands to epilepsy disease.

1.3 Scope of the work

To achieve the objectives of this study, the following issues will be discussed:

1- Obtaining EEG signals for both normal and epileptic people.
2- The use of eeglab on MATLAB to extract the power spectrum density of the five frequency sub-bands of EEG.
3- Finding the most related sub-bands to the disease using SPSS program.
4- Applying ANFIS tool to predict and diagnose epilepsy disease.

1.4 Significance of the work

Epilepsy is a chronic neurological disease of the brain that causes frequent seizures and affects around 50 million people worldwide. It is a life-lasting disorder, although the seizures may start at any time during patient's life and occur sporadically or frequently (Dekker, 2002).

The most common test in diagnosing epilepsy is EEG; a monitoring method used to record electrical activity of the brain. After a person undergoes an EEG test, the neurologist observes the EEG for any abnormal peaks. It is common for epilepsy patients to have different pattern of brain waves than normal people.

This study provides a novel approach to diagnosing epilepsy by utilizing artificial intelligence techniques. An ANFIS model was designed to predict whether the person suffers from epilepsy or not based on his EEG.

The results of this research will help neurologists and researchers deal more easily with EEG tests, and assist doctors in making the right diagnosis. In other words, the system that will come out of the study is going to be a supportive and helpful tool for the doctors to ensure their decisions. A quite promising future studies could be based on this work.

1.5 Organization of thesis

This thesis in divided into five chapters as follows: Chapter One (introduction), Chapter Two (Literature Review), Chapter Three (Methodology), Chapter four (Results and Discussion) and Chapter five (Conclusion and Future work).

The first chapter includes an overview of the research idea, the objectives of the research, the scope of the work, the significance of the research and the organization of the thesis.

The second chapter introduces a brief background on epilepsy disease, Electroencephalogram (EEG), Power Spectral Density (PSD) estimation, Fast Fourier transform (FFT), EEG frequency sub-bands, Artificial Intelligence (AI) and Adaptive Neuro-Fuzzy Inference System (ANFIS). Then it references some of the previous studies made in this field.

Chapter three then explains the subjects of the study, the data acquisition and the methodology of the research.

Chapter four presents the results and discussion in three parts: Part 1 includes the data analysis, Part 2 represents the training and testing of the ANFIS model and Part 3 represents the ROC curves and the calculation of sensitivity, specificity and accuracy.

Finally, chapter five concludes the whole work and suggests future work to develop these types of study areas.

Chapter two: Literature Review

2.1 Introduction

This chapter introduces the definition of epilepsy disease, and it explains electroencephalography (EEG); the best and most common brain imaging technique used to diagnose the disease. EEG consists of five frequency sub-band that can be extracted from the main signal by applying Fast Fourier Transformation (FFT). The last section of this chapters contains an overview on some the past researches made in this area of study.

2.2 Epilepsy Disease

Epilepsy is a common condition characterized by repeated seizures due to a disorder in brain cells. It can affect the whole age range. The disorder may develop due to a particular event or injury, or it may occur without any identifiable cause (Dekker, 2002).

A seizure is a sudden abnormal function of the body, caused by an excessive discharge in the brain nerve-cells (Dekker, 2002). Seizures can be focal in which they occur due to an abnormal activity in a single area of the brain, or generalized which involve all areas of the brain.

Epilepsy disease has a high prevalence rate, making it one of the most common neurological diseases globally. Around 50 million people worldwide have epilepsy. In high-income countries, nearly 49 per each 100000 people are diagnosed with epilepsy each year. This number increases in low- and middle-income countries to around 139 per 100000 (WHO, 2019). In Arab countries, a 2021 review found that the median incidence of epilepsy is 89.5 per 100000 (Idris et al., 2021).

In terms of diagnosis, brain imaging is making great progress in identifying the structural and functional causes and consequences of epilepsy (Duncan et al., 2006). Electroencephalogram (EEG) is the most common test to diagnose this disease. EEG can determine the relative strengths and positions of electrical activity in different brain regions (Teplan, 2002).

2.3 Electroencephalography

Electroencephalography (EEG) is the measurement of the electric potentials on the scalp surface generated by neural activity originating from the brain (Nunez et al., 2021). An EEG test is capable of reflecting both normal and abnormal electrical activity of the brain. It is a completely non-invasive procedure that can be applied repeatedly on patients and has no risks (Teplan, 2002). This made EEG tests one the most powerful tools in the field of neurology and clinical neurophysiology.

EEG is the only neuroimaging modality that does not require the participant's head or body to be fixed, in fact, it can enable the monitoring of the participant's brain while performing his normal tasks or even a specific task under study (Jung, 2012).

In an EEG test, the participant is usually asked to sit or lie down as shown in figure 2.1. Then, a technician measures the head and marks where to place the electrodes. After that, he attaches the electrodes with an adhesive gel to the scalp of the participant.

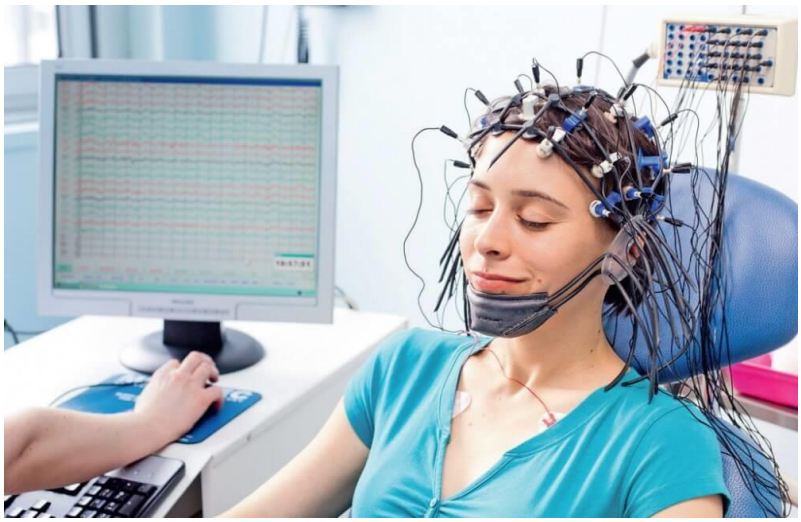


Fig. 2.1: EEG test (https://tebmedtourism.com/eeg/).

These electrodes pick up the electrical activities of the brain neurons and display them on a computer screen as a series of waves. Figure 2.2 demonstrates this procedure. The coupling between skin and electrode can be described as a layered conductive and capacitive structure, with series combinations of parallel RC elements.

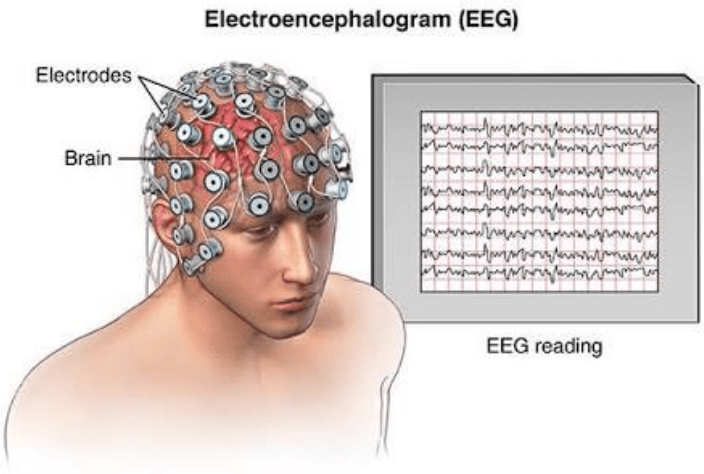


Fig. 2.2: EEG reading (https://www.michiganneurologyassociates.com/contents/testing-services/eeg).

2.4 Power Spectral Density (PSD)

The power spectral density or power spectrum shows the distribution of the signal frequency components. It represents the proportion of the total signal power contributed by each of the signal's frequency component (Dempster, 2001).

In order to analyze and study EEG signals, it is important to compute their power spectra. There are a several methods that are used to extract PSD from an EEG signal; including: Fast Fourier Transform (FFT), Autoregressive Model (AM) and Wavelet Transform (WT) (Doufesh et al., 2016).

This study uses the traditional FFT approach to compute and analyze EEG data.

2.4.1 Fast Fourier Transform (FFT)

"We start in the continuous world; then we get discrete." (Heckbert, 1995)

The "Fast Fourier Transform" (FFT) is an important computational tool in the science of signal analysis. It converts a signal into its individual spectral components and thereby provides frequency information about it. As shown in figure 2.3, Fourier analysis converts a signal from its original domain to a representation in the frequency domain.

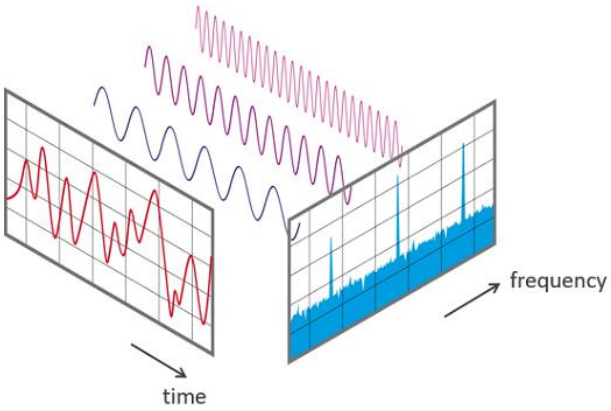


Fig. 2.3: Fast Fourier Transform: from complicated time domain signal to simpler frequency domain signal (https://www.nti-audio.com/en/support/know-how/fast-fourier-transform-fft).

It has already been proved that FFT methods are now greatly useful in a very wide range of digital problems such as spectral analysis, signal processing, Fourier spectroscopy, image processing, and the solution of differential equations (Cooley et al., 1969).

The Fourier transform (FT) of the function *f(x)* is the function *F(ω)*, where:

$$F(\omega) = \int_{-\infty}^{\infty} f(x) e^{-i\omega x} dx$$

Where $i = \sqrt{-1}$, $e^{i\theta} = cos\theta + isin\theta$, and *ω is the angular frequency*.

2.4.2 Frequency domain signal of EEG

Using Fast Fourier Transformation the complex time series of the EEG signal can be broken down into a series of superimposed sinusoidal frequency domain signal as shown in figure 2.4 (Jung, 2012).

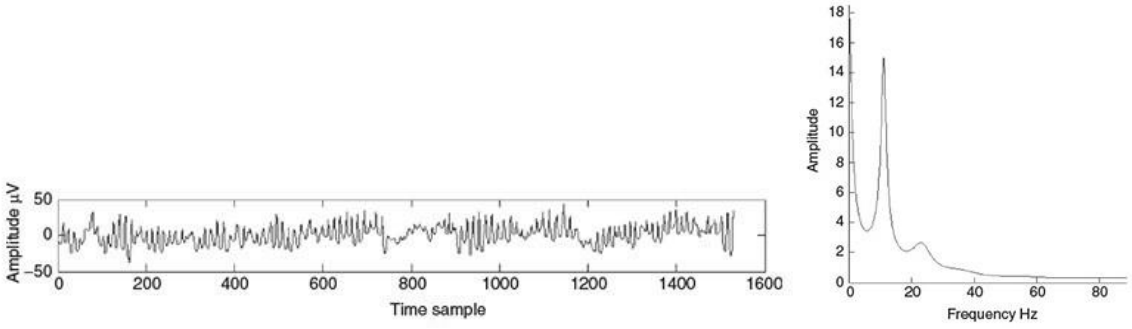


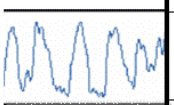
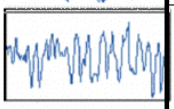
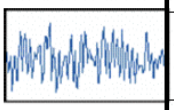
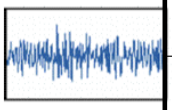
Fig. 2.4: EEG in time domain signal (right) and in frequency domain signal (left) https://thoracickey.com/fundamentals-of-eeg-signal-processing/

2.5 EEG frequency sub-bands

After performing FFT on the raw EEG signal, a power-frequency spectrum is derived. Although the spectrum is continuous, the brain state of the subject may make certain frequencies more dominant (Teplan, 2002).

Brain frequency waves is categorized in five sub-bands: Delta (0-3 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz) and Gamma (>30 Hz). Table 2.1 below explains the characteristics of each sub-band (Jung, 2012):

Table 2.1: Characteristics of EEG sub-bands (Jung, 2012).

	EEG Bands (Hz)	Subjective feeling	Associated tasks & behaviors	Physiological correlates
	Delta 0.1-3	deep, dreamless sleep, non-REM sleep, unconscious	lethargic, not moving, not attentive	not moving, low-level of arousal
	Theta 4-8	intuitive, creative, recall, fantasy, imagery, creative, dreamlike, drowsy	creative, intuitive; distracted, unfocused	healing, integration of mind/body
	Alpha 8-12	relaxed, not agitated, but not drowsy	meditation, no action	relaxed, healing
	Beta 12-30	alertness, agitation	mental activity, e.g. math	alert, active
	Gamma >30	Focused arousal	high-level information processing, "binding"	information-rich task processing

2.6 Artificial Intelligence (AI)

Artificial intelligence (AI) is a way of making a computer, a robot or a software think intelligently; in a similar manner human intelligence works. It is achieved by studying how the human brain works, thinks, learns, decides and solves problems (Pothe, 2022).

AI is an application that can re-create human perception. It normally requires obtaining input to endow AI with analysis or dilemma solving, as well as the ability to categorize and identify objects (Al-shamasneh & Obaidellah, 2017). AI utilizes machine learning techniques in facing problems. Learning techniques can be classified as supervised, unsupervised and reinforcement learning (Sathya & Abraham, 2013).

The potential of AI to extract meaningful relationships within a dataset made it a useful tool in medical applications. It is now used in diagnosis, treatment and predicting outcomes in many clinical cases (Ramesh et al., 2004).

2.6.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Inspired by the sophisticated functionality of human brains where hundreds of billions of interconnected neurons process information in parallel, researchers have successfully demonstrated certain levels of intelligence now called Artificial Neural Networks (ANN) (Khan, 2018). ANNs gather their knowledge by identifying the patterns and relationships in data and learn through experience (Agatonovic-Kustrin & Beresford, 2000).

In artificial intelligence (AI) systems, Fuzzy Logic (FL) is used to imitate human reasoning and cognition. Unlike strictly binary cases of truth, fuzzy logic uses 0 and 1 as extreme cases of truth but with several intermediate degrees of truth.

Adaptive Neuro-Fuzzy Inference System (ANFIS) blends the benefits of both ANNs and FL in a single framework (Chopra et al., 2021). ANFIS can be easily applied for a given input/output task, which makes it suitable for many application purposes including various biomedical applications (Doufesh et al., 2016), such as the detection and classification of epileptic seizures (Najumnissa & Rangaswamy, 2012), prediction of the presence of prostate cancer (Benecchi, 2006), prediction of Alpha band power of EEG during Muslim Salat (Doufesh et al., 2016), detection and diagnosing breast cancer (Al-shamasneh & Obaidellah, 2017) and many more.

ANFIS is the most popular of the neuro-fuzzy models for approximating highly nonlinear and complex systems, its structure is based on supervised machine learning and training, not programming (Agatonovic-Kustrin & Beresford, 2000). A train dataset that includes the inputs and their previously known outputs is firstly introduced to the ANFIS Model, the model then becomes capable of predicting the possible outcomes for any comparable inputs.

2.7 Previous Studies and Applications

In recent years, ANFIS models are widely used in medical applications. Using fuzzy systems enabled using the uncertainty of the inputs and increase the credibility of the outputs (Güler & Übeyli, 2005).

In 2012, Zadeh et al. proposed a new approach to diagnosing breast cancer with the aid of fuzzy logic. A thermal camera was used for imaging 200 patients including 15 patients diagnosed with breast cancer via mammography. The images were processed and the resulted data were entered in a fuzzy neural network for clustering breast cancer. Results showed a sensitivity of 93%.

A research in 2014 by Deshmukh and Khule proposed an ANFIS model for the detection of brain tumor. The research aimed to help in the treatment planning and follow up by providing anatomical information of the normal and abnormal tissues. ANFIS model was used for images classification and results comparison. The results proved ANFIS is a promising image classifier with an accuracy of 98.67%.

A study presented in 2005 by Güler and Übeyli used ANFIS to classify EEG signals. Decision making was performed in two stages: feature extraction using the wavelet transform and the ANFIS training with the backpropagation gradient descent method in combination with the least square method. The total classification accuracy for their ANFIS model was 98.68% (Güler & Übeyli, 2005).

In 2015, Deshprabhu and shnevi aimed to classify the EEG signals and diagnose the epileptic seizures directly by using wavelet transform and an artificial neural network model. The components of the EEG signals were extracted using wavelet transform by sub-band decoding. These components were applied as inputs to the neural network which then was trained to give two outputs that classify whether the signal is epileptic or normal.

In 2012 Najumnissa and Rangaswamy used ANFIS to classify epileptic seizures. The EEG signals of 20 normal and 30 seizure subjects were decomposed into time-frequency representations using wavelet transform. An ANFIS-based system was implemented for the classification of epileptic seizure. Then, BPN algorithm was used to study and compare the datasets. The classification of normal subjects and epileptic patients were established with an accuracy of 99% and 97%, respectively.

Douw et al.published a research article in 2010 representing that tumor-related epilepsy is related to theta band connectivity. 17 patients were assessed directly after neurosurgery, and 12 patients were assessed six months after neurosurgery. At these two time points (t1, t2), magnetoencephalography (MEG) was recorded for the participants. Increased theta band connectivity at t1 and t2 was associated to a higher number of epileptic seizures, suggesting that theta band connectivity change is a sign of tumor-related epilepsy.

On the other hand, a research published in 2012 by Larsson et al. Reported in 2012 that Alpha wave frequency differs between epileptic and non-epileptic patients. A total of 57 patients were included in the study, their EEG signals were recorded, and they were grouped as patients with epilepsy (Ep) and patients without epilepsy (nEp). Five different methods were used for alpha frequency estimation including guided and Fast Fourier transform. The results showed that Alpha waves were significantly different between Ep and nEp.

In 2013, Tikka and his group of researchers compared the absolute spectral power for the frequency bands between patients exclusively diagnosed with juvenile myoclonic epilepsy (JME) and a healthy control group. The results showed significant higher α and θ power in frontal position, θ power in left temporal, α and δ in right occipital, and δ, θ, α and β in central position. Due to the study, the researchers were able to correlate the significant difference in the quantitative EEG measures with different clinical characteristics.

Chapter Three: Methodology

3.1 Introduction

This chapter describes the subjects included in the study, the data acquisition, and the methodology chosen to achieve the final model, passing through eeglab and SPSS to find the mean power values of the five frequency sub-bands for the entire sample of subjects (epileptic and normal people), and finally the training and testing of the final ANFIS model.

3.2 Subjects of the study

A sample of sixty subjects from various areas from Palestine participated in this study.

- Thirty of the participants were epilepsy patients at the mental hospital in Bethlehem, within the age-range between 10 and 60 years old.

- The other thirty participants were healthy people free from epilepsy or any neurological disorder within the age-range between 18-25 years old.

3.3 Data acquisition

EEG signals were recorded with a computer-based (Nicolet NicVue) data acquisition system. To avoid any artifacts due to physical movements, only one static position (supine) was considered.

EEG data were recorded by placing electrodes on the participants heads according to the international 10-20 system of electrode placement. In this system, the head is divided into proportional distances from certain skull landmarks (nasion, preauricular points, inion) to provide proper coverage of all regions of the brain. 10-20 refers to the proportional distances in percent between ears and nose, where the electrodes are placed (Figure 3.1). Electrode placements are labelled according adjacent brain areas: F (frontal), C (central), T (temporal), P (posterior), and O (occipital). The letters are accompanied by odd numbers at the left side of the head and with even numbers on the right side (Teplan, 2002).

Our EEG data were recorded from eight electrode positions on the scalp: homologous frontal (F3, F4), central (C3, C4), parietal (P3, P4), and occipital (O1, O2) as shown in figure 3.1 below.

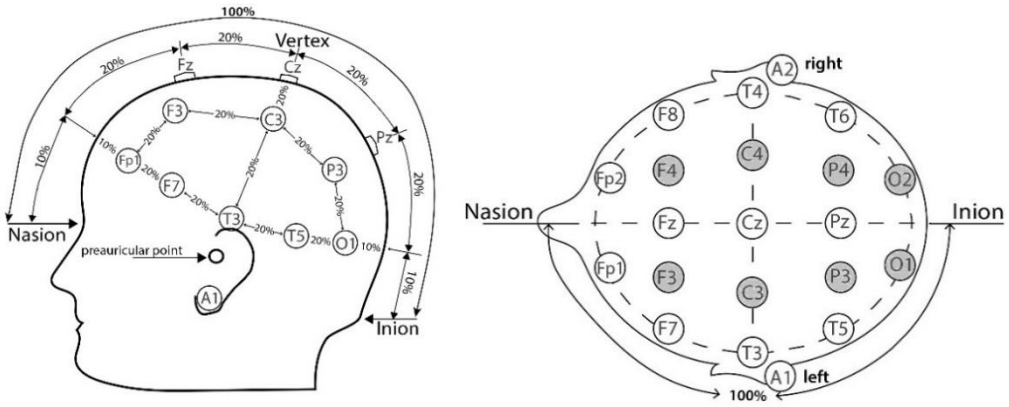
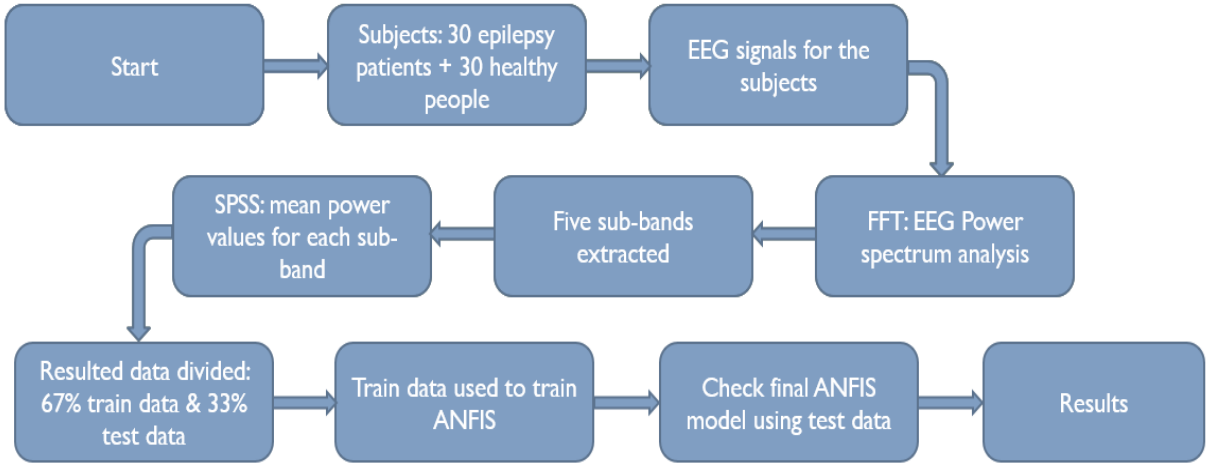


Fig. 3.1: electrode positions on the scalp according to 10-20 system. On the right, the eight electrode positions considered in our study are labeled. https://www.ternimed.de/EEG-Electrode-arrangement-according-to-the-international-10/20-system

3.4 Experimental protocol

The study started by collecting EEG data for 30 epilepsy patients and 30 normal people. Power-frequency spectra were extracted using FFT on MATLAB with sampling-rate of 1000 sample/sec in order to get the five frequency sub-bands (delta, alpha, theta, beta and gamma). Next, SPSS was used to find the mean power values for each of the sub-bands. Four sub-bands (theta, alpha, delta and beta) were considered in the ANFIS modification due to their obvious relation to the disease. The results were finally divided into two parts: 67% of the data were used as train dataset for ANFIS, while 33% of the data were used as test data. Table 3.1 concludes the methodology used in the study.

Table 3.1: Algorithm of the study.



Chapter Four: Results and Discussion

4.1 Introduction

Chapter four presents the results and discussion of this study in three parts:

Part 1: EEG signal analysis results and discussion for the epilepsy group and the normal group.

Part 2: ANFIS modification. Then training and testing of the final model using 67% and 33% of the data respectively.

Part 3: ROC curves and the calculation of sensitivity, specificity and accuracy for P3 position as an example.

4.2 Results and discussion

Part 1: EEG signal analysis

The collected data was first analyzed by Fast Fourier Transformation tool on eeglab-MATLAB. This analysis provided the power of each of the five frequency sub-bands (delta, theta, alpha, beta, gamma) for all the subjects.

Using SPSS, the mean values of the powers were extracted and graphed.

This process was repeated for eight electrode positions on the scalp: frontal (F3, F4), central (C3, C4), parietal (P3, P4), and occipital (O1, O2).

Note: the MATLAB code used to provide the power of each of the five frequency sub-bands for the subjects appear in appendix a.

Epilepsy Group data analysis:

Figures (4.1 to 4.8) below illustrate the results of the previous analysis in epilepsy patients. The results showed an obvious relation between sub-band theta and the epileptic abnormality. In all of the eight electrode positions sub-band theta dominated.

In electrode positions F3, F4, C3 and P3 the value of delta power was next to the value of theta power. Whereas in C4, P4, O1 and O2 theta power was followed by alpha power.

Beta power followed alpha and delta powers in all of the electrode positions except C3 where it had a mean value between delta and alpha.

Finally, gamma had the lowest mean power value in all of the electrode positions.

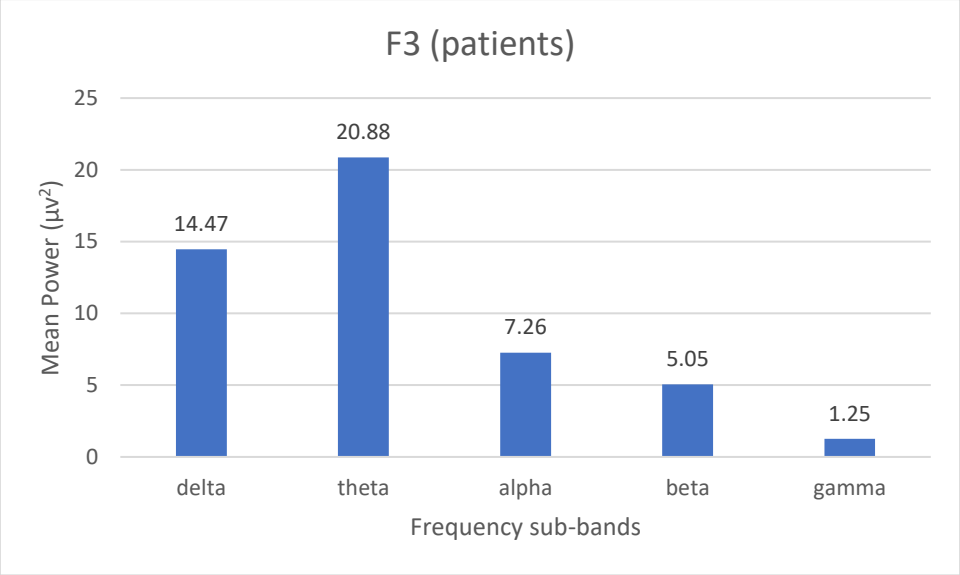


Fig 4.1: Mean power values of the five frequency sub-bands at the electrode position F3 for the epilepsy group

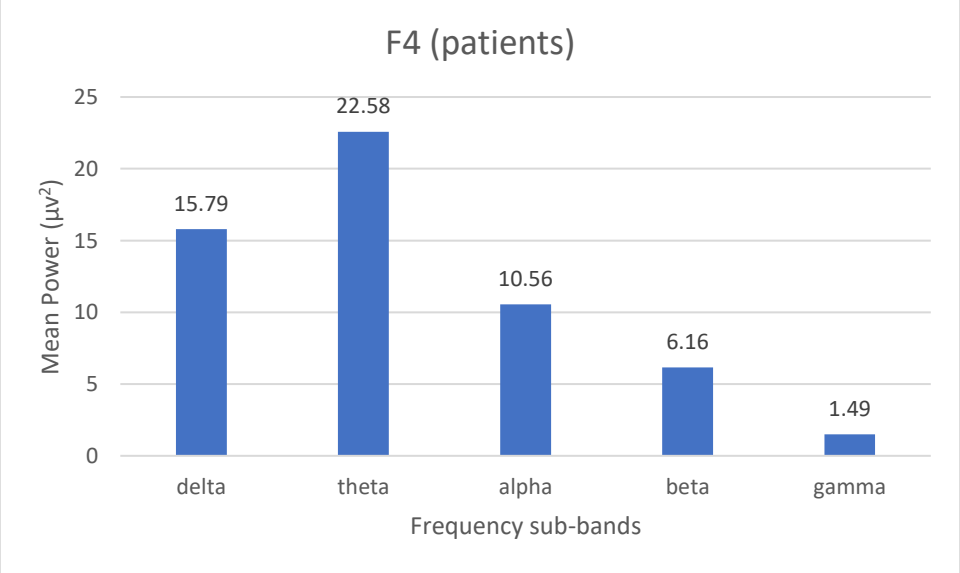


Fig 4.2: Mean power values of the five frequency sub-bands at the electrode position F4 for the epilepsy group

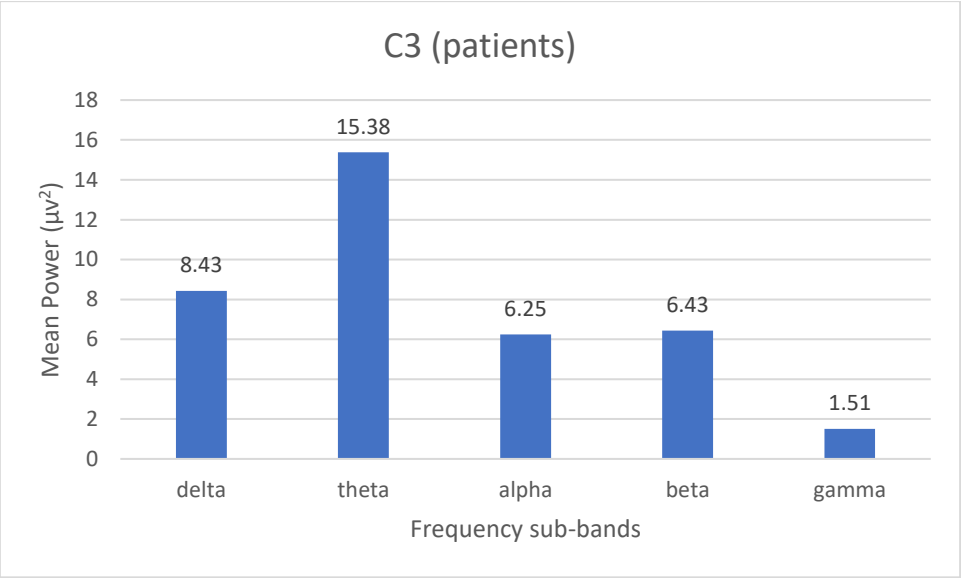


Fig 4.3: Mean power values of the five frequency sub-bands at the electrode position C3 for the epilepsy group

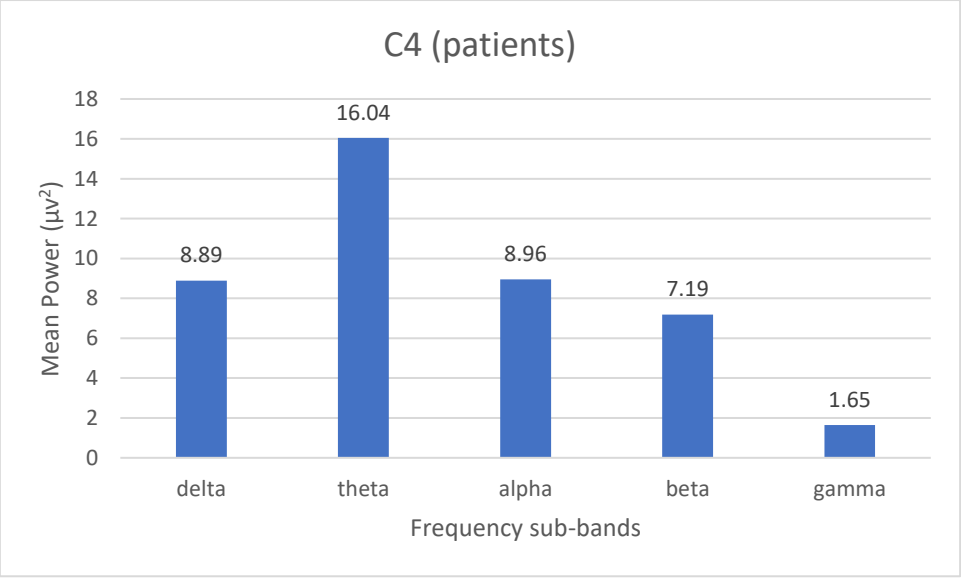


Fig 4.4: Mean power values of the five frequency sub-bands at the electrode position C4 for the epilepsy group

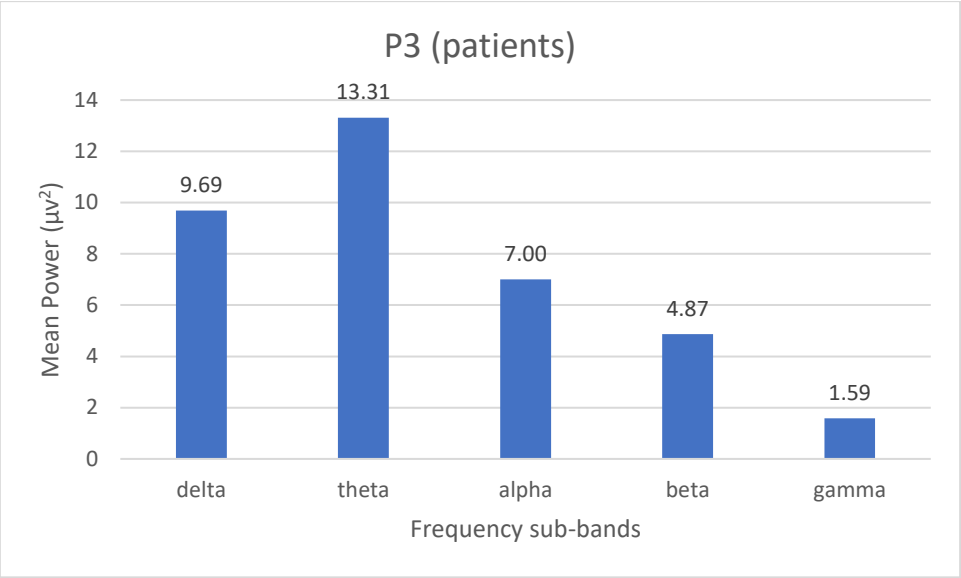


Fig 4.5: Mean power values of the five frequency sub-bands at the electrode position P3 for the epilepsy group

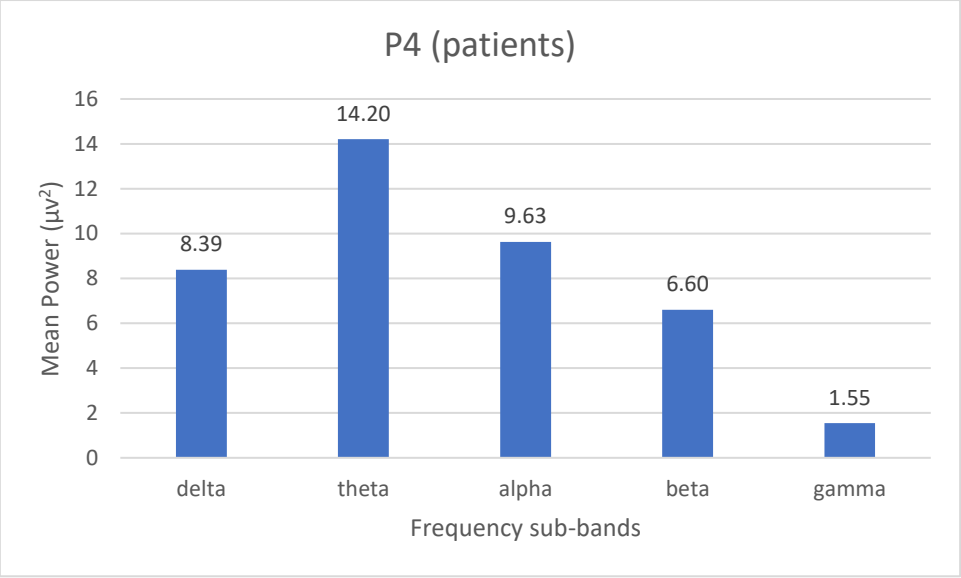


Fig 4.6: Mean power values of the five frequency sub-bands at the electrode position P4 for the epilepsy group

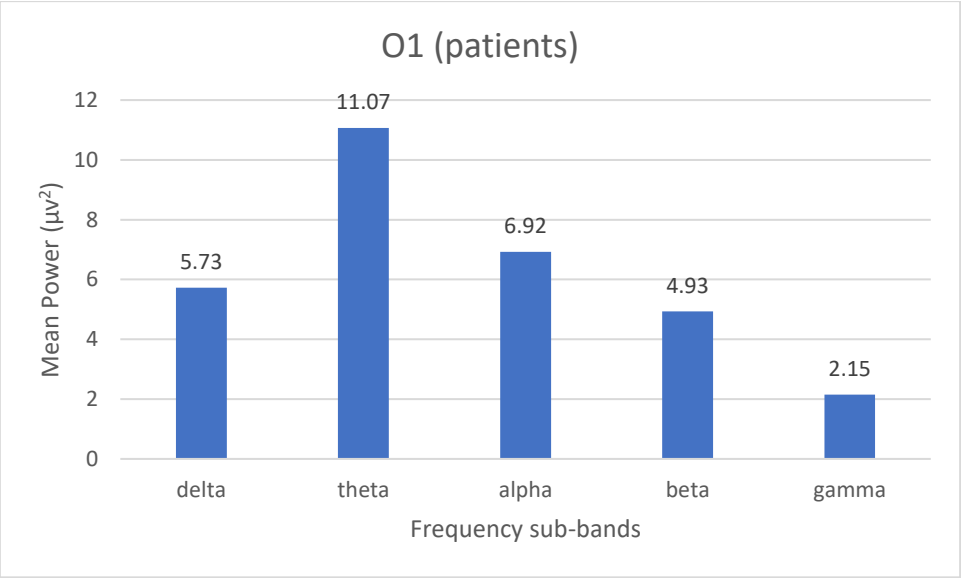


Fig 4.7: Mean power values of the five frequency sub-bands at the electrode position O1 for the epilepsy group

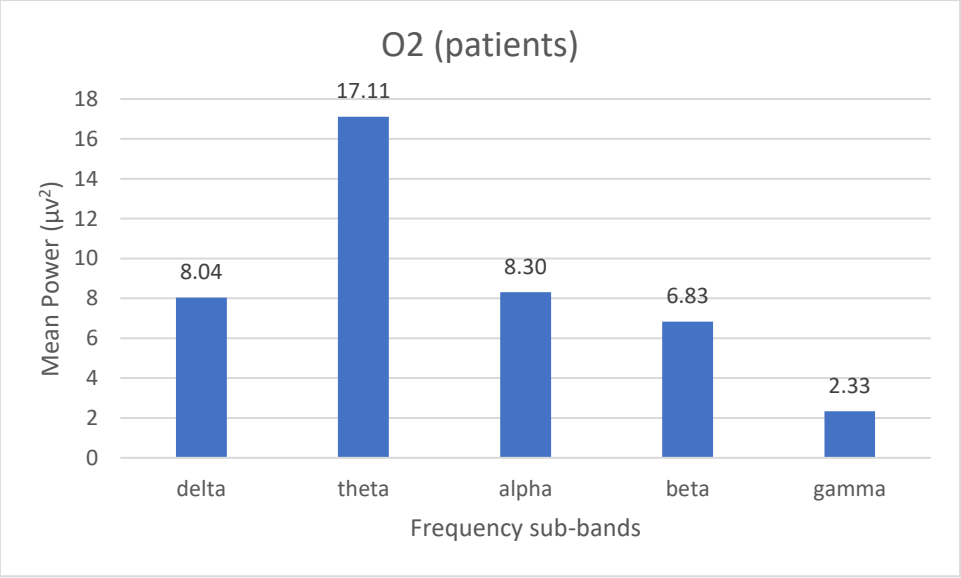


Fig 4.8: Mean power values of the five frequency sub-bands at the electrode position O1 for the epilepsy group

Normal Group data analysis:

Figures (4.9 to 4.16) below illustrate the mean power values of the five frequency sub-bands for the normal group (people without epilepsy or any other disease).

The results showed that delta power was the maximum power in all of the eight electrode positions. In F3, C3, C4, P3, P4, O1, O2 delta power was followed by alpha power then theta power and finally beta and gamma powers. In electrode position F4, delta power was followed by theta power then alpha power and finally beta and gamma powers with the lowest mean values.

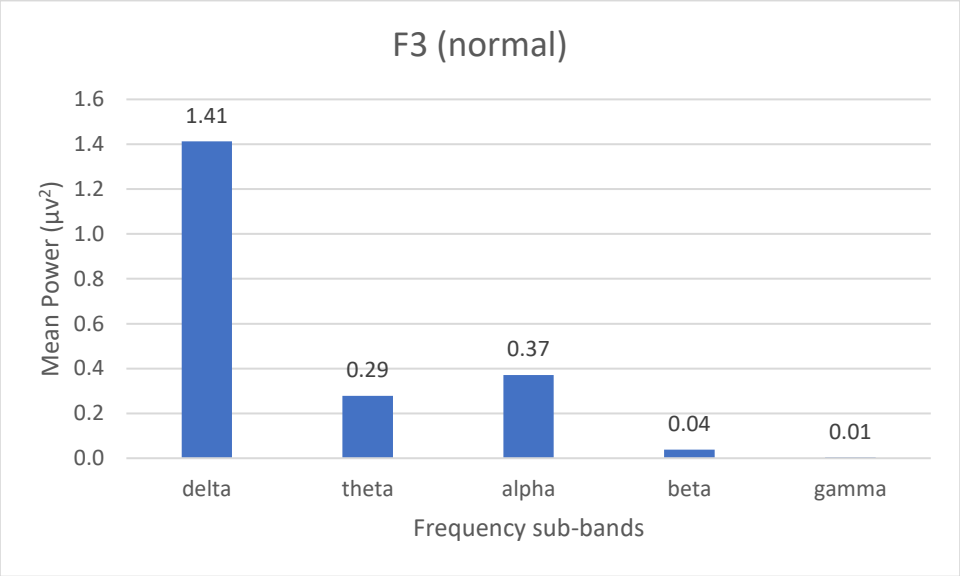


Fig 4.9: Mean power values of the five frequency sub-bands at the electrode position F3 for the normal group

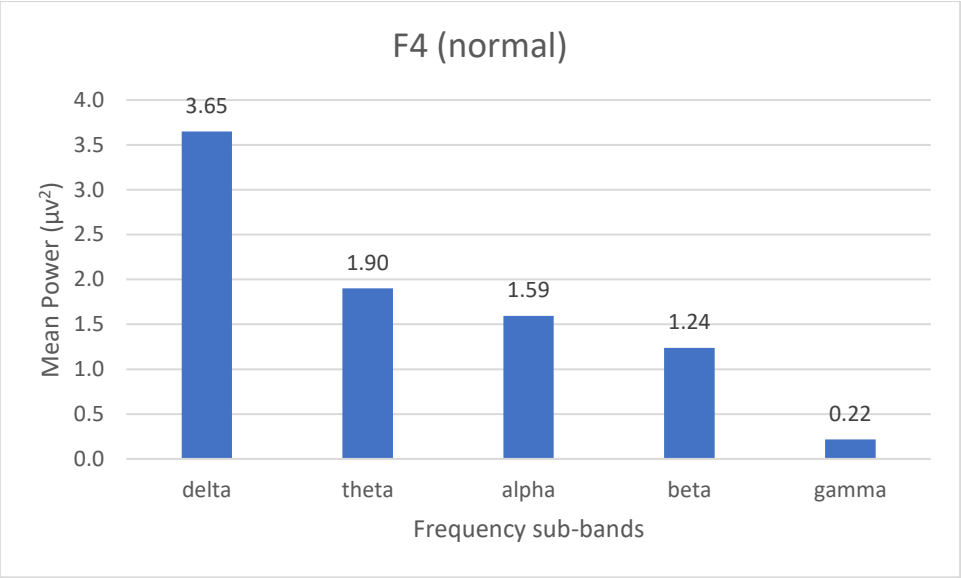


Fig 4.10: Mean power values of the five frequency sub-bands at the electrode position F4 for the normal group

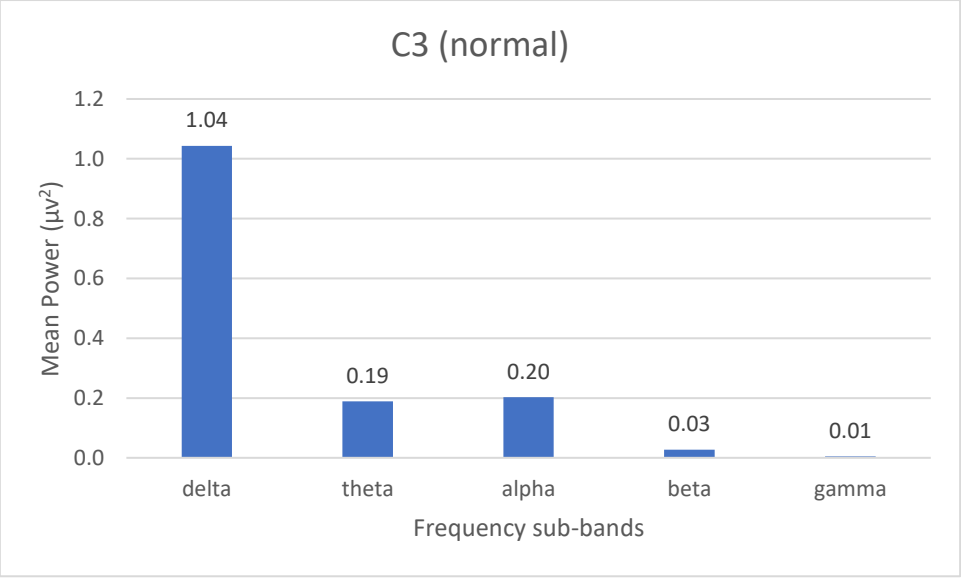


Fig 4.11: Mean power values of the five frequency sub-bands at the electrode position C3 for the normal group

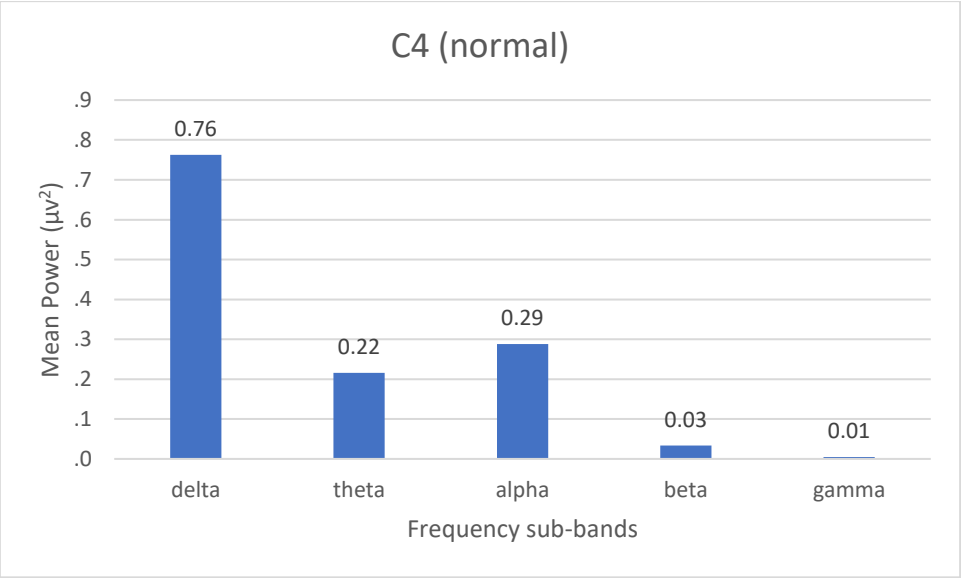


Fig 4.12: Mean power values of the five frequency sub-bands at the electrode position C4 for the normal group

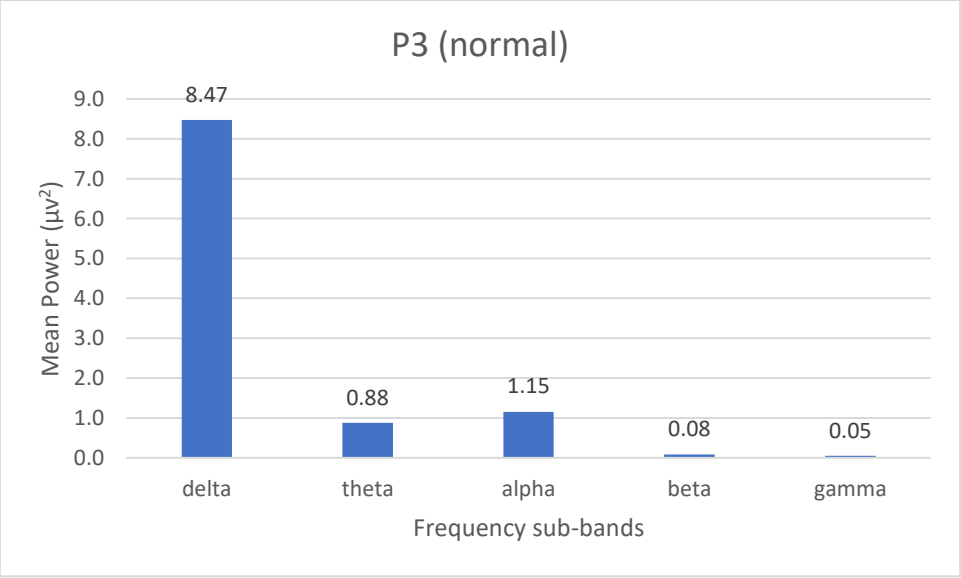


Fig 4.13: Mean power values of the five frequency sub-bands at the electrode position P3 for the normal group

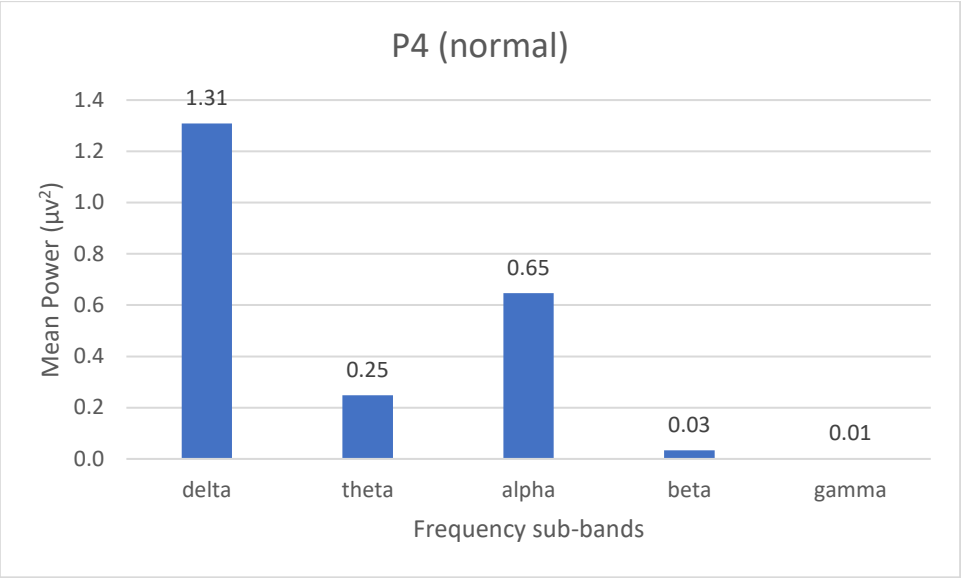


Fig 4.14: Mean power values of the five frequency sub-bands at the electrode position P4 for the normal group

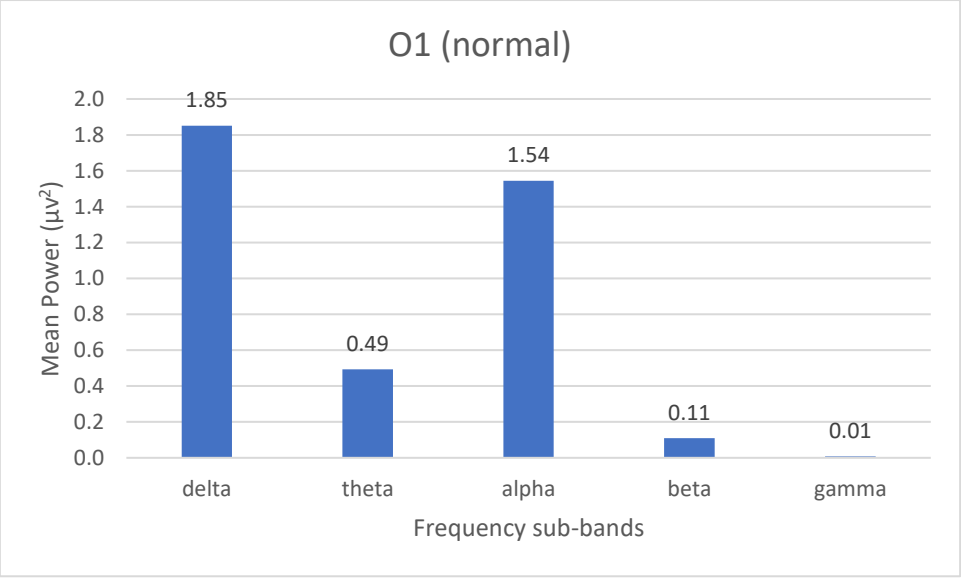


Fig 4.15: Mean power values of the five frequency sub-bands at the electrode position O1 for the normal group

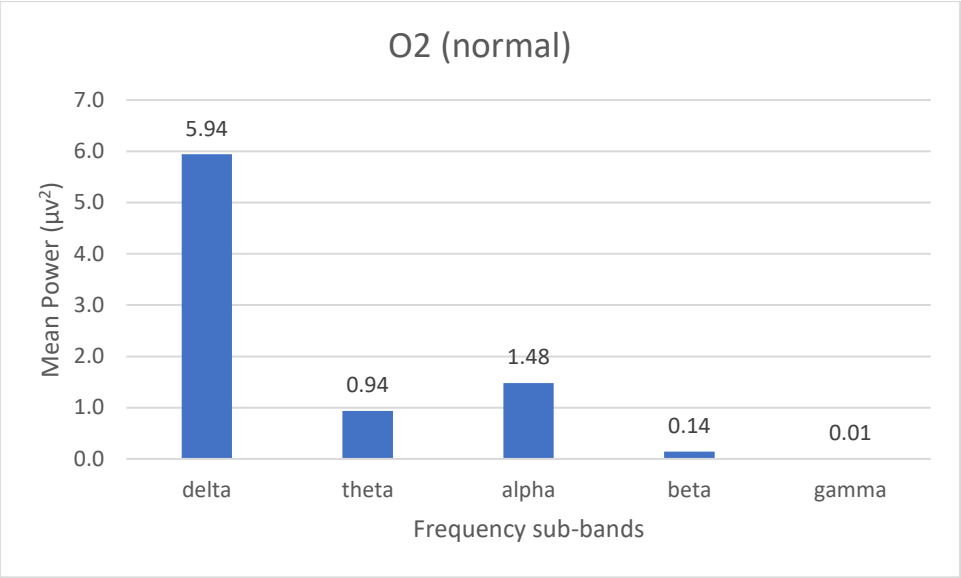


Fig 4.16: Mean power values of the five frequency sub-bands at the electrode position O2 for the normal group

Note: Tables of the mean power values and their associated standard deviations appear in appendix b.

Discussion:

One of the goals of this study was to find the most related frequency sub-bands to epilepsy disease. To achieve that goal, a Fast Fourier Transformation was applied using eeglab to subtract the power spectra for 30 epilepsy patients and 30 non-epileptic people. The power values of each sub-band in eight electrode positions (F3, F4, C3, C4, P3, P4, O1, O2) became available for the whole sample. SPSS program was then used to find the mean power values for each sub-band in all of the eight electrode positions.

The results showed different patterns between epileptic and normal groups. It is occasionally expected that epilepsy patients have higher frequencies and mean power values than the control group (Miyauchi et al., 1991).

Epilepsy group showed significantly high theta power, followed usually by alpha and delta with close mean power values, then beta power and finally gamma with the lowest mean power value.

These results agree with the results of Gelety and his group (Gelety et al., 1985) in which they suggested that the difference between the interictal EEG signals of their patients group and standard EEG signals of the control group in their study was due to the generation of abnormal amounts of activity in theta and delta frequency band. Furthermore, Douw and his group (Douw et al., 2010) suggested that theta band connectivity changes may be a sign of tumor-related epilepsy. On the other hand, Tikka and his group (Tikka et al., 2013) concluded the differences in frequencies between their Juvenile myoclonic epilepsy group and control group as follows: Power alpha and theta were higher in global, frontal and central positions. Theta power was higher in left temporal position. Alpha power and delta power were higher in right occipital position, and beta power was higher in central position. Furthermore, Pegg and her group (Pegg et al., 2021) described an increased alpha spectral power in idiopathic generalized epilepsy patients.

Corresponding to the previous results, theta, alpha, delta and beta power values were considered in part two of the study.

Part 2: Developing the ANFIS model

In part 2 of the study, certain parameters were selected to develop the optimal ANFIS model. These parameters are: the number and type of membership function for each input, the output membership function type (either linear or constant) and the training epoch number (training iteration number).

These parameters were selected according to the least square strategy. The main point of this approach is to modify the mentioned parameters so that the error (root mean square error RMSE) between the measured and predicted output is minimized (Doufesh et al., 2016).

Membership functions are used in the fuzzification and defuzzification steps of a fuzzy logic system, to turn the non-fuzzy input values into fuzzy linguistic terms and vice versa (Ross, 2000). A membership function can be formed in different shapes: triangular (trimf), pi-shaped (pimf), bell (gbellmf), gaussian (gaussmf), two-sided gaussian (gauss2mf), trapezoidal (trapmf), product of two sigmoid (psigmf) or difference between two sigmoid (dsigmf).

On the other hand, changing the number of the training iterations on the ANFIS model will affect the model's performances. As the training iteration number increased, the performance of the model became better. However, after a certain number of iterations, no improvement in the root mean square error (RMSE) accuracy of the prediction was observed. RMSE is usually used as a standard statistical metric to measure model performance. Table (4.1) below shows the effect in changing the training iteration number on the value of RMSE for the electrode position P3:

Table 4.1: The effect of changing the training iteration number on RMSE value for electrode position P3.

# of iterations	RMSE
10	0.3775
20	0.2668
30	0.1788
40	0.1256
50	0.1162
60	0.1162
70	0.1162

After modifying the parameters in our ANFIS model, the lowest RMSE value obtained for P3 was 0.1162, while the lowest RMSE value obtained for P4 was 0.2549. Table (4.2) below shows the final optimized parameters for both P3 and P4 ANFIS models:

Table 4.2: The final optimized parameters for P3 and P4 ANFIS models.

Electrode position	Input MFs' type	# of input MFs	Output MF's type	# of iterations	RMSE
P3	trapmf, pimf, pimf, trimf	2 2 2 2	Linear	50	0.1162
P4	trimf, gaussmf, trimf, trimf	2 2 2 2	Linear	50	0.2549

The same optimization process was used to enhance the other ANFIS models' parameters at F3, F4, C3, C4, O1 and O2.

Figure (4.17) shows the final results of the measured and predicted outputs at P3 using our modified ANFIS model. While figure (4.18) shows the improvement in RMSE value due to increasing the number of training iterations.

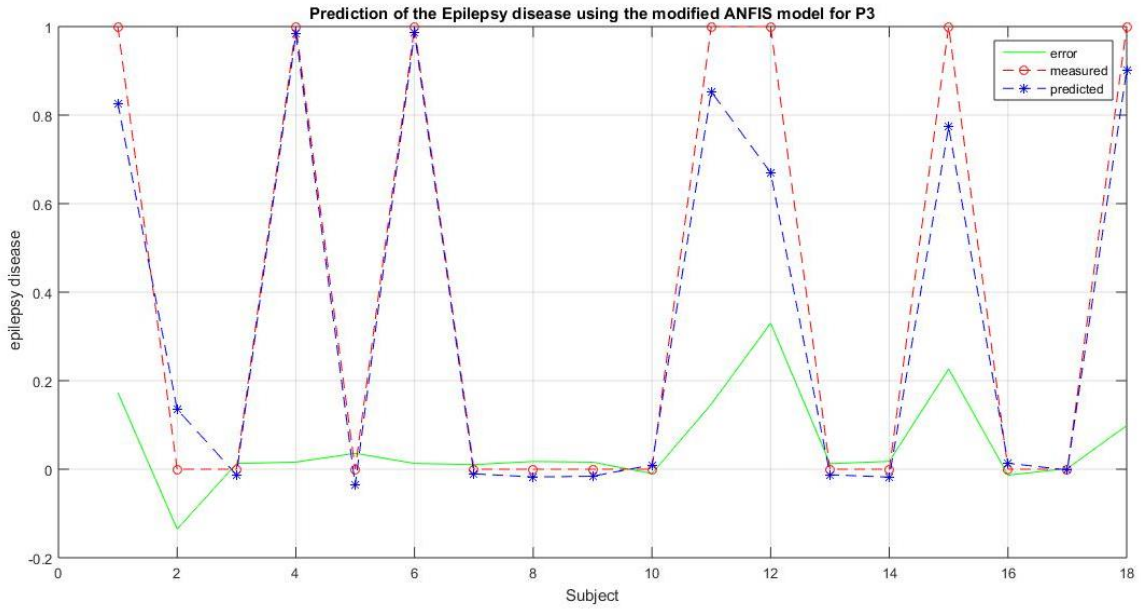


Fig 4.17: the final results of the measured and predicted outputs at P3 using our modified ANFIS model

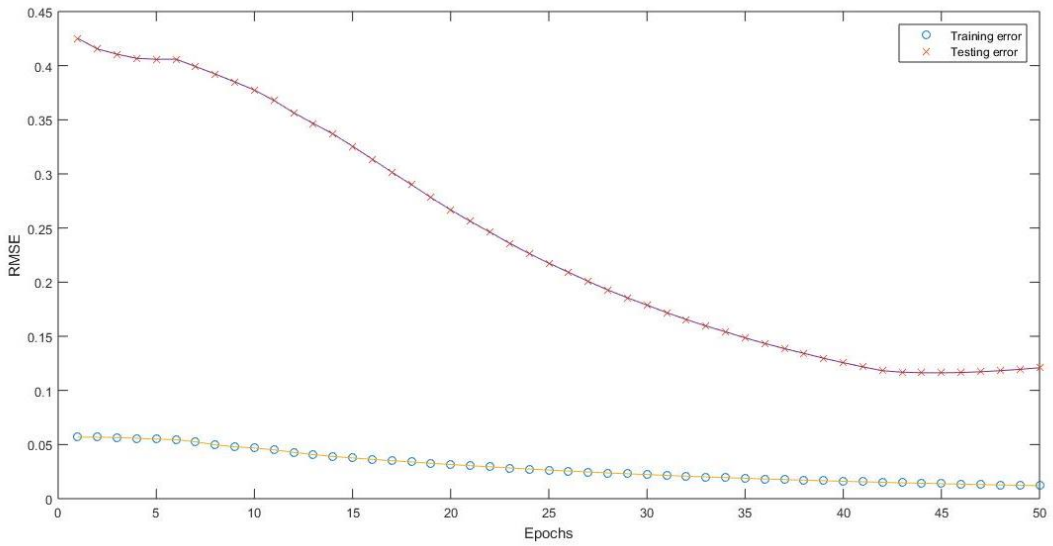


Fig. 4.18: the improvement in RMSE value due to increasing the number of training iterations

Note: the MATLAB code for the modified P3 ANFIS model appears in appendix c.

Part 3: ROC curve and the calculation of sensitivity, specificity and accuracy for position P3

There are some terms that are usually used along with the description of sensitivity, specificity and accuracy.

These terms are true positive (TP), true negative (TN), false negative (FN), and false positive (FP).

- TP: a test result is considered true positive if it indicates the presence of a disease in a person when the person actually proven to have the disease.

- TN: a test result is considered true negative if it indicates the absence of the disease when the disease is proven absent.

- FP: a test result is considered false positive if it indicates the presence of a disease in a person who actually doesn't have the disease.

- FN: a test result is considered false negative if it indicates the absence of a disease for a patient who has the disease for sure.

Table (4.3) below summarizes these terms:

Table 4.3: terms used to define sensitivity, specificity and accuracy.

Predicted outcomes of the diagnostic test	Actual result of the condition (e.g. disease)	
	Positive	Negative
Positive	TP	FP
Negative	FN	TN

Sensitivity, specificity and accuracy are described in terms of TP, TN, FN and FP (Zhu et al., 2010):

- Sensitivity = TP/(TP + FN)

  = (Number of true positive assessment)/(Number of all positive assessment)

- Specificity = TN/(TN + FP)

  = (Number of true negative assessment)/(Number of all negative assessment)

- Accuracy = (TN + TP)/(TN+TP+FN+FP)

  = (Number of correct assessments)/(Number of all assessments)

The numerical value of sensitivity represents the probability that a diagnostic test identifies patients who do in fact have the disease. The higher the numerical value of sensitivity, the less likely diagnostic test returns false-positive results. On the other hand, the numerical value of specificity represents the probability that a test is able to diagnose a particular disease with no false-positive results. Finally, the numerical value of accuracy represents the proportion of the true results (both true positive and true negative) in the selected population (Zhu et al., 2010).

For a diagnostic test:

- True Positive Rate (TPR)= TP/ (TP+FN), which is equivalent to sensitivity.

- False Positive Rate (FPR)= FP/ (FP+TN), which is equivalent to (1- specificity).

A ROC space is composed of all the possible combinations of TPR and FPR. FPR (which equals 1-specificity) is represented by x-axis, and TPR (which represents sensitivity) is represented by y-axis. Thus, ROC curve is a plot of a test's sensitivity vs. (1-specificity) for different cutoff points (Zhu et al., 2010).

Using SPSS, the ROC curve for our results at P3 was plotted (fig. 4.19), and a table (4.4) representing different cutoff points and their associated values of sensitivity and 1-specificity was extracted.

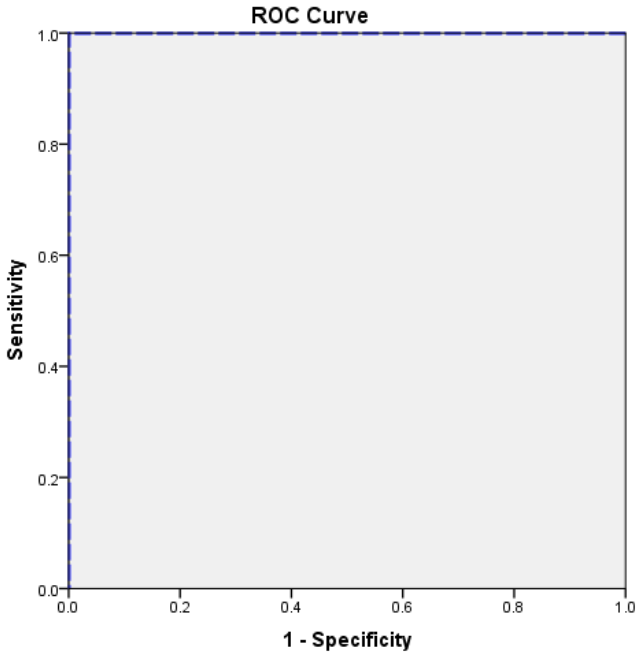


Fig 4.19: ROC curve for our modified ANFIS model at position P3

The area under the ROC curve equals 1 which indicates a perfect diagnostic test.

Table 4.4: chosen cutoff points and their associated values of sensitivity and 1-specificity.

Cutoff points	Sensitivity	1 - Specificity
-1.036000	1.000	1.000
-.026900	1.000	.909
-.017650	1.000	.818
-.016700	1.000	.727
-.014350	1.000	.636
-.012650	1.000	.545
-.011450	1.000	.455
-.006000	1.000	.364
.004050	1.000	.273
.011600	1.000	.182
.074400	1.000	.091
.402650	1.000	.000
.721750	.857	.000
.800050	.714	.000
.839800	.571	.000
.877200	.429	.000
.942650	.286	.000
.985400	.143	.000
1.986900	.000	.000

From table (4.4), the cutoff point 0.4 indicates 100% sensitivity, specificity and accuracy.

This means that if our diagnostic test predicts a value over 0.4 for a certain subject, we can undoubtfully conclude that the subject has epileptic disorder. However, if our diagnostic test predicts a value under 0.402650 for a certain subject, then we can undoubtfully conclude that the subject doesn't have epileptic disorder.

Chapter Five: Conclusion and Future work

5.1 Conclusion

This study aimed to provide an ANFIS model that can predict if a person suffers from epileptic disorder based on his EEG signal. The study started by collecting EEG data for 30 healthy subjects and 30 epileptic patients. In order to analyze the EEG signals, their power spectra were calculated by applying Fast Fourier Transformation using eeglab on MATLAB. Fourier analysis converts a signal from its original domain to a representation in the frequency domain. This step allowed us to extract the power values for the five frequency EEG sub-bands: Delta (0-3 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz) and Gamma (>30 Hz).

Then, using SPSS, mean power values were calculated for both epilepsy and normal groups. Theta, delta, alpha and beta were -respectively- the most relevant sub-bands to the disease. So, the data associated with these four sub-bands were used in training and testing the ANFIS model in part two.

Part two of the study concentrated on developing the optimal ANFIS model. This was obtained by selecting values for certain parameters in order to minimize the resulted error. These parameters are: the number and type of membership function for each input, the output membership function type (either linear or constant) and the training iteration number. The chosen values for these parameters are represented in table 4.2.

Finally, the performance of the enhanced ANFIS model was evaluated by the computation of the Receiver Operating Characteristic (ROC) curve. The ROC curve determines the values of sensitivity and specificity for our model at different cutoff points. The cutoff point that provided the highest sensitivity and specificity was ~ 0.4.

The resulted sensitivity, specificity and accuracy for our model was 100% each at 0.4 cutoff point.

This concludes that our model can successfully predict the epileptic disorder within a 100% certainty.

5.2 Future work

In the light of this research, it is recommended for the future researches to use ANFIS approach in attempting to diagnose other diseases, especially neurological disorders such as Autism and Parkinson disease.

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Appendices

Appendix a

```
% F3
[spectra,freqs] = spectopo(EEG.data(6,:,:), 0, EEG.srate);

 deltaIdxF3 = find(freqs>1 & freqs<4);
 thetaIdxF3 = find(freqs>4 & freqs<8);
 alphaIdxF3 = find(freqs>8 & freqs<13);
 betaIdxF3  = find(freqs>13 & freqs<30);
 gammaIdxF3 = find(freqs>30 & freqs<100);

 % Compute absolute power.
 deltaPowerF3 = mean(10.^(spectra(deltaIdxF3)/10));
 thetaPowerF3 = mean(10.^(spectra(thetaIdxF3)/10));
 alphaPowerF3 = mean(10.^(spectra(alphaIdxF3)/10));
 betaPowerF3  = mean(10.^(spectra(betaIdxF3)/10));
 gammaPowerF3 = mean(10.^(spectra(gammaIdxF3)/10));

% F4
[spectra,freqs] = spectopo(EEG.data(14,:,:), 0, EEG.srate);

 deltaIdxF4 = find(freqs>1 & freqs<4);
 thetaIdxF4 = find(freqs>4 & freqs<8);
 alphaIdxF4 = find(freqs>8 & freqs<13);
 betaIdxF4  = find(freqs>13 & freqs<30);
 gammaIdxF4 = find(freqs>30 & freqs<100);

 % Compute absolute power.
 deltaPowerF4 = mean(10.^(spectra(deltaIdxF4)/10));
 thetaPowerF4 = mean(10.^(spectra(thetaIdxF4)/10));
 alphaPowerF4 = mean(10.^(spectra(alphaIdxF4)/10));
 betaPowerF4  = mean(10.^(spectra(betaIdxF4)/10));
 gammaPowerF4 = mean(10.^(spectra(gammaIdxF4)/10));

% C3
[spectra,freqs] = spectopo(EEG.data(7,:,:), 0, EEG.srate);

 deltaIdxC3 = find(freqs>1 & freqs<4);
 thetaIdxC3 = find(freqs>4 & freqs<8);
 alphaIdxC3 = find(freqs>8 & freqs<13);
 betaIdxC3  = find(freqs>13 & freqs<30);
 gammaIdxC3 = find(freqs>30 & freqs<100);

 % Compute absolute power.
 deltaPowerC3 = mean(10.^(spectra(deltaIdxC3)/10));
 thetaPowerC3 = mean(10.^(spectra(thetaIdxC3)/10));
 alphaPowerC3 = mean(10.^(spectra(alphaIdxC3)/10));
```

```
betaPowerC3  = mean(10.^(spectra(betaIdxC3)/10));
gammaPowerC3 = mean(10.^(spectra(gammaIdxC3)/10));

% C4
[spectra,freqs] = spectopo(EEG.data(15,:,:), 0, EEG.srate);

deltaIdxC4 = find(freqs>1 & freqs<4);
thetaIdxC4 = find(freqs>4 & freqs<8);
alphaIdxC4 = find(freqs>8 & freqs<13);
betaIdxC4  = find(freqs>13 & freqs<30);
gammaIdxC4 = find(freqs>30 & freqs<100);

% Compute absolute power.
deltaPowerC4 = mean(10.^(spectra(deltaIdxC4)/10));
thetaPowerC4 = mean(10.^(spectra(thetaIdxC4)/10));
alphaPowerC4 = mean(10.^(spectra(alphaIdxC4)/10));
betaPowerC4  = mean(10.^(spectra(betaIdxC4)/10));
gammaPowerC4 = mean(10.^(spectra(gammaIdxC4)/10));

% P3
[spectra,freqs] = spectopo(EEG.data(8,:,:), 0, EEG.srate);

deltaIdxP3 = find(freqs>1 & freqs<4);
thetaIdxP3 = find(freqs>4 & freqs<8);
alphaIdxP3 = find(freqs>8 & freqs<13);
betaIdxP3  = find(freqs>13 & freqs<30);
gammaIdxP3 = find(freqs>30 & freqs<100);

% Compute absolute power.
deltaPowerP3 = mean(10.^(spectra(deltaIdxP3)/10));
thetaPowerP3 = mean(10.^(spectra(thetaIdxP3)/10));
alphaPowerP3 = mean(10.^(spectra(alphaIdxP3)/10));
betaPowerP3  = mean(10.^(spectra(betaIdxP3)/10));
gammaPowerP3 = mean(10.^(spectra(gammaIdxP3)/10));

% P4
[spectra,freqs] = spectopo(EEG.data(16,:,:), 0, EEG.srate);

deltaIdxP4 = find(freqs>1 & freqs<4);
thetaIdxP4 = find(freqs>4 & freqs<8);
alphaIdxP4 = find(freqs>8 & freqs<13);
betaIdxP4  = find(freqs>13 & freqs<30);
gammaIdxP4 = find(freqs>30 & freqs<100);

% Compute absolute power.
deltaPowerP4 = mean(10.^(spectra(deltaIdxP4)/10));
thetaPowerP4 = mean(10.^(spectra(thetaIdxP4)/10));
alphaPowerP4 = mean(10.^(spectra(alphaIdxP4)/10));
```

```
betaPowerP4  = mean(10.^(spectra(betaIdxP4)/10));
gammaPowerP4 = mean(10.^(spectra(gammaIdxP4)/10));

% O1
[spectra,freqs] = spectopo(EEG.data(5,:,:), 0, EEG.srate);

deltaIdxO1 = find(freqs>1 & freqs<4);
thetaIdxO1 = find(freqs>4 & freqs<8);
alphaIdxO1 = find(freqs>8 & freqs<13);
betaIdxO1  = find(freqs>13 & freqs<30);
gammaIdxO1 = find(freqs>30 & freqs<100);

% Compute absolute power.
deltaPowerO1 = mean(10.^(spectra(deltaIdxO1)/10));
thetaPowerO1 = mean(10.^(spectra(thetaIdxO1)/10));
alphaPowerO1 = mean(10.^(spectra(alphaIdxO1)/10));
betaPowerO1  = mean(10.^(spectra(betaIdxO1)/10));
gammaPowerO1 = mean(10.^(spectra(gammaIdxO1)/10));

% O2
[spectra,freqs] = spectopo(EEG.data(13,:,:), 0, EEG.srate);

deltaIdxO2 = find(freqs>1 & freqs<4);
thetaIdxO2 = find(freqs>4 & freqs<8);
alphaIdxO2 = find(freqs>8 & freqs<13);
betaIdxO2  = find(freqs>13 & freqs<30);
gammaIdxO2 = find(freqs>30 & freqs<100);

% Compute absolute power.
deltaPowerO2 = mean(10.^(spectra(deltaIdxO2)/10));
thetaPowerO2 = mean(10.^(spectra(thetaIdxO2)/10));
alphaPowerO2 = mean(10.^(spectra(alphaIdxO2)/10));
betaPowerO2  = mean(10.^(spectra(betaIdxO2)/10));
gammaPowerO2 = mean(10.^(spectra(gammaIdxO2)/10));
```

Appendix b

Statistics F3 patients					
	delta	theta	alpha	beta	gamma
Mean	14.470731	20.875508	7.256496	5.052638	1.254550
Std. Deviation	35.9034884	24.0849077	8.8124288	5.4200856	.7451394

Statistics F4 patients					
	delta	theta	alpha	beta	gamma
Mean	15.795552	22.584596	10.558989	6.157752	1.493815
Std. Deviation	41.6214729	25.5359277	14.0915818	7.9809396	1.2432506

Statistics C3 patients					
	delta	theta	alpha	beta	gamma
Mean	8.432369	15.377962	6.247385	6.430323	1.511673
Std. Deviation	15.7004274	13.9278681	5.5160971	7.9860495	1.0390048

Statistics C4 patients					
	delta	theta	alpha	beta	gamma
Mean	8.886896	16.043385	8.957611	7.186130	1.650422
Std. Deviation	9.5865529	16.9466003	12.4336257	11.1411141	1.3223446

Statistics P3 patients					
	delta	theta	alpha	beta	gamma
Mean	9.685824	13.307672	7.004624	4.873260	1.578044
Std. Deviation	15.6951299	15.1846827	6.2055092	2.9119494	1.0249858

Statistics P4 patients					
	delta	theta	alpha	beta	gamma
Mean	8.390233	14.202737	9.627893	6.604211	1.546422
Std. Deviation	8.4693363	16.4991468	15.1237192	11.3869670	1.1725306

Statistics O1 patients					
	delta	theta	alpha	beta	gamma
Mean	5.728500	11.066848	6.924422	4.931965	2.153591
Std. Deviation	6.3549712	11.7610277	6.8625720	3.3036530	1.6873227

Statistics O2 patients					
	delta	theta	alpha	beta	gamma
Mean	8.043646	17.110235	8.301562	6.832723	2.333481
Std. Deviation	8.5182911	17.1455464	8.7831275	9.2119312	2.0332149

Statistics F3 normal					
	delta	theta	alpha	beta	gamma
Mean	1.413070	.278700	.371463	.038747	.003630
Std. Deviation	1.7116949	.2527786	.2880800	.0292344	.0055446

Statistics F4 normal					
	delta	theta	alpha	beta	gamma
Mean	3.650295	1.900416	1.594384	1.238200	.215642
Std. Deviation	5.7992165	2.2694745	1.8350161	1.4242534	.2469764

Statistics C3 normal					
	delta	theta	alpha	beta	gamma
Mean	1.043323	.188687	.202537	.027110	.005197
Std. Deviation	3.3372670	.4494876	.1477324	.0330433	.0079726

Statistics C4 normal					
	delta	theta	alpha	beta	gamma
Mean	.762917	.216187	.288450	.033743	.004780
Std. Deviation	1.5884359	.4422587	.2407361	.0411930	.0080258

Statistics P3 normal					
	delta	theta	alpha	beta	gamma
Mean	8.472213	.875560	1.154787	.080507	.048300
Std. Deviation	33.6723422	2.4425688	.9974504	.1248111	.2300444

Statistics P4 normal					
	delta	theta	alpha	beta	gamma
Mean	1.309222	.248035	.646517	.033952	.002891
Std. Deviation	2.9748960	.3720645	.7461466	.0328121	.0044166

Statistics O1 normal					
	delta	theta	alpha	beta	gamma
Mean	1.850207	.492737	1.544793	.109230	.007900
Std. Deviation	3.7588904	.6587784	1.4920927	.0937779	.0106632

Statistics O2 normal					
	delta	theta	alpha	beta	gamma
Mean	5.944240	.935863	1.481210	.139773	.006860
Std. Deviation	17.5218036	2.1484159	1.4611460	.1620495	.0095103

Appendix c:

```
% Matlab Program for training and testing the ANFIS model used to predict whether a
person suffers from epilepsy or not based on his EEG.
% Wala' Bseiso, 2022.

%*************************************************************************
close all
clear all

load datatot.txt
numPts=55;
trndata=datatot(1:1.5:numPts,:);
chkdata=datatot(2:3:numPts,:);

%*************************************************************************
% Genfis1: generates an initial Sugeno-type FIS for the ANFIS training
% using a grid partition.
% Number of membership functions: 2
% Type of membership functions: trimf
%*************************************************************************

numMFs = [4 5 5 5];
mfType = char('gbellmf ','gaussmf ','gaussmf','gaussmf ');
% To generate an initial FIS
fismat=genfis1(trndata,numMFs,mfType, 'linear');

%*************************************************************************
% ANFIS: Adaptive Neuro-Fuzzy training of Sugeno-type FIS.
% Epoch number: 40
%*************************************************************************
numEpochs=110;

[fismat1,trnErr,ss,fismat2,chkErr]=anfis(trndata,fismat,numEpochs,NaN,chkdata);

trnOut=evalfis([trndata(:,1:4)],fismat1);
trnRMSE=norm(trnOut-trndata(:,5))/sqrt(length(trnOut))
chkOut=evalfis([chkdata(:,1:4) ] ,fismat2);
chkRMSE=norm(chkOut-chkdata(:,5))/sqrt(length(chkOut))

numepochs=1:numEpochs;

figure (1)
subplot(2,1,1);
plot(numepochs,trnErr,'o',numepochs, chkErr,'x');
ylabel('RMSE');
xlabel('Epochs');
legend('Training error','Testing error');
hold on
plot(numepochs,[trnErr chkErr]);
hold off
```

```
%*************************************************************************
% Evalfis: performs fuzzy inference calculations.
% anfis_y: the predicted top-oil temperature
% Using the input test data set to determine the alpha relative power (RPα)
%*************************************************************************
  anfis_y=evalfis([chkdata(:,1:4)],fismat2);

%*************************************************************************
% A plot of the measured and predicted alpha relative power (RPα) versus the
% Testing error
%*************************************************************************
E = chkdata(:,5) - anfis_y;
x=1:1:18;
figure (2)
% Plot the error between the measured and the predicted (RPα)
plot(x,E,'g');
hold
% Plot the measured (RPα)
plot(x, chkdata(:,5),'r');
hold on
% Plot the predicted (RPα)
plot(x, anfis_y,'b');
hold off
grid;
ylabel(' epilepsy disease');
xlabel('Subject');
legend('error','measured','predicted');
title('Prediction of the Epilepsy disease using the modified ANFIS model');
```

العنوان: تشخيص مرض الصرع باستخدام نظام الاستدلال العصبي التكيفي الضبابي

إعداد: ولاء محمد هاشم بسيسو.

إشراف: الدكتور حازم دوفش.

ملخص:

يعتبر مرض الصرع أحد أكثر اضطرابات الدماغ شيوعاً حيث ينشأ نتيجة عوامل متعددة، ويصيب حوالي خمسين مليون شخصاً في العالم من أطفال وبالغين.

لقد تم في هذا البحث تطوير نظام استدلال عصبي تكيفي ضبابي يستطيع تشخيص مرض الصرع من خلال إشارات الدماغ. حيث شارك في البحث فئتان: الفئة الأولى تشكلت من ثلاثين شخصاً مرضى بالصرع، والفئة الثانية تشكلت من ثلاثين شخصاً غير مصابين بأي مرض. تم الحصول على تخطيطات كهرباء الدماغ الخاصة بالمشاركين في البحث وحساب أطياف الطاقة من خلال تحويل فوريه السريع. بعد عملية التحويل هذه تم استخراج نطاقات التردد (دلتا وثيتا وألفا وبيتا وجاما).

67% من بيانات المشاركين تم استخدامها كمجموعة تدريبية لنظام الاستدلال العصبي التكيفي الضبابي الخاص بنا، و ال 33% الباقية تم استخدامها كمجموعة اختبارية.

أخيراً، تم حساب منحنى تشغيل خصائص المستقبِل للقطب الكهربائي الخاص بالمنطقة الخلفية للرأس، وقد كانت نتائج قيم الحساسية والنوعية والدقة مئة بالمئة عند عتبة ال 0.4.

نحن نرى أن نتائج هذا البحث ستوفر للأطباء والباحثين وسيلة أسهل للتعامل مع التخطيط الكهربائي للدماغ، كما ستساعدهم على اتخاذ القرارات التشخيصية للمرض بشكل أدق.