

Faculty of Electrical and Electronic Engineering Technology



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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Bachelor of Electronics Engineering Technology (Industrial Electronics) with Honours

DEVELOPMENT OF COMPUTER AIDED DESIGN FOR EEG SIGNALS EPILEPSY DIAGNOSIS USING ARTIFICAL NEURAL NETWORK

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A project report submitted in partial fulfillment of the requirements for the degree of Bachelor of Electronics Engineering Technology (Industrial Electronics) with



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DECLARATION

I declare that this project report entitled "DEVELOPMENT OF COMPUTER AIDED DESIGN FOR EEG SIGNALS EPILEPSY DIAGNOSIS USING ARTIFICAL NEURAL NETWORK" is the result of my own research except as cited in the references. The project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



APPROVAL

I hereby declare that I have checked this project report and in my opinion, this project report is adequate in terms of scope and quality for the award of the degree of Bachelor of Electronics Engineering Technology (Industrial Electronics) with Honours.

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DEDICATION

This thesis is dedicated to Ahmezul Bin Ahmad and Dawinah@Jaslina Bte Jugok, my beloved parents for their constant love, encouragement, and inspiration. To my supervisor Encik Khairul Azha Bin A. Aziz who never giving up to taught and guide me to complete my project. To my helpful classmate and hoursemate always keep supporting me.



ABSTRACT

Epilepsy is a brain condition that affects the whole brain nervous system and is characterised by high-frequency and high-voltage brain waves called seizures. This disorder is identified as one of the uncontrolled movements shown by epilepsy patients during an outbreak, resulting in loss of consciousness and convulsions. As a result, the purpose of this thesis is to construct an EEG Epilepsy Recognition System using Artificial Neural Networks (ANN). Their principal tool is the Cascade-Forward Neural Network technology, which their system designed to perform a process similar to that of a human brain. This brain-inspired technology was designed to mimic how human brains think. This thesis offers an epilepsy detection process implemented in MATLAB utilising Cascade-forward Neural Networks. Additionally, this study employed the Electroencephalogram (EEG) signal to diagnose and access human brain activity and disturbance by using a dataset collected from the University of Bonn (Bonn), which has been extensively used by other researchers doing epilepsy research. The MindLink EEG Sensor is used to collect external EEG data, which is subsequently utilised to test the neural network. As for the result, this Artificial Neural Network successfully carried out with 77.1% for training, 77.3% for validation, 74.7% for testing and lastly the overall accuracy is 76.2% by using 15 hidden neuron network.

ABSTRAK

Epilepsi adalah keadaan otak yang menjejaskan keseluruhan sistem saraf otak dan dicirikan oleh gelombang otak frekuensi tinggi dan voltan tinggi yang dipanggil sawan. Gangguan ini dikenal pasti sebagai salah satu pergerakan tidak terkawal yang ditunjukkan oleh pesakit epilepsi semasa wabak, mengakibatkan kehilangan kesedaran dan sawan. Hasilnya, tujuan tesis ini adalah untuk membina Sistem Pengecaman Epilepsi EEG menggunakan Rangkaian Neural Tiruan (ANN). Alat utama mereka ialah teknologi Rangkaian Neural Cascade-Forward, yang sistem mereka direka untuk melakukan proses yang serupa dengan otak manusia. Teknologi yang diilhamkan oleh otak ini direka untuk meniru cara otak manusia berfikir. Tesis ini menawarkan proses pengesanan epilepsi yang dilaksanakan dalam MATLAB menggunakan Rangkaian Neural Cascade-forward. Selain itu, kajian ini menggunakan isyarat Electroencephalogram (EEG) untuk mendiagnosis dan mengakses aktiviti dan gangguan otak manusia dengan menggunakan set data yang dikumpul dari Universiti Bonn (Bonn), yang telah digunakan secara meluas oleh penyelidik lain yang melakukan penyelidikan epilepsi. Penderia MindLink EEG digunakan untuk mengumpul data EEG luaran, yang kemudiannya digunakan untuk menguji rangkaian saraf. Hasil dari penyelidikan ini, rangkaian Neural Tiruan ini berjaya dijalankan dengan 77.1% untuk latihan, 77.3% untuk pengesahan, 74.7% untuk ujian dan akhir sekali ketepatan keseluruhan ialah 76.2% dengan menggunakan 15 rangkaian neuron tersembunyi.

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LIST OF SYMBOLS



RXNIVERSI Receiver NIKAL MALAYSIA MELAKA

TX	Transmitter
IA	Transmitter

- *a* Scaling Parameter
- *b* Location of the Parameter
- % Percentage

LIST OF ABBREVIATIONS

EEG	Electroencephalogram				
MIT	Massachusetts Institute of Technology				
CNN	Convolutional Neural Network				
СНВ	Children's Hospital Boston				
CWT	Continuous Wavelet Transform				
BoW	Bags-of-Words				
SVM	Support Vector Machine				
DWTMALAYS	Discrete Wavelet Transform				
FFT	Fast Fourier Transform				
AR	Autoregressive or Autoregression				
MLPNN	Multilayer Perceptron Neural Network				
ANFIS	Adaptive Neuro-Fuzzy Interference System				
KDD	Knowledge Discovery in Database				
RNN	Recurrent Neural Network				

- LSTM Long-Short-Term Memory
- **GRU** Gated-Recurrent Unit
- **STFT** Short-time Fourier Transform
- WT Wavelet Transform
- GPS Global Positioning System
- **ANN** Artificial Neural Network
- **UBonn** University of Bonn

CHAPTER 1

INTRODUCTION

1.1 Background

Seizures, odd behaviour, feelings, and even loss of consciousness are all symptoms of epilepsy, a neurological disorder. Patients who experience seizures are at a greater risk of several different kinds of trauma, including falls, head trauma, cuts, and burns. Patients may be unaware that seizures happen without warning, which increases their risk of harm. Epilepsy affects an estimated 4-5% of the world's population, according to current research[1]

Electroencephalography is a critical technique for diagnosing and analysing epilepsy (EEG). To diagnose brain illnesses such as epilepsy, autism, brain tumours, and depression, an electroencephalogram (EEG) is used. The EEG is a noninvasive, low-cost, well-established, and precise technique used to record brain activity. When electrodes are put on essential points on the patient's skull using proper mechanical and electrical support, the EEG detects the variations in brain electricity between the electrodes. To diagnose epileptic seizures, neurologists have typically relied on visual analysis of EEG recordings. However, this technique may be time-consuming and labour-intensive, especially when dealing with long-term recordings, and it is also subjective. A new method to automated diagnostics is therefore required as a result [2]. We utilized data from the University of Bonn in this study. A conventional electrode replacement procedure of 10-20 electrodes was used for the recording. The datasets are divided into five sets, each with 100 channels and labelled A through E. Data is digitalized at 173.61Hz sampling rate and 12bit A/D resolution using a 128-channel amplifier setup [1]

A Computer Program based on Artificial Neural Networks replicates human brain functions. This particular methodology incorporates human biology, which results in the ANN's, a mathematical model that can calculate, make decisions, and learn. [3] The Neural Network Toolbox in MATLAB will be used to examine EEG data using ANN in this project. This study is designed to illustrate how the information from an EEG may be used to distinguish epilepsy and normal patients.

1.1.1 Problem Statement

Seizures and behavioural abnormalities that recure often are indicators of epilepsy, a neurological condition that occurs when there is too much electrical activity in the brain. That shows that seizures will result from this abnormally high electrical activity in the brain. Seizures may cause unconsciousness and tremors. Seizures happen regularly, but the epilepsy sufferer does not know when or how they will occur. During a seizure, an EEG scan may reveal a particular pattern of brain activity changes. EEG measurements are used to examine the impact of epilepsy on the brain.

Due to the complex, pure, and direct nature of the oscillation, EEG recordings are seldom observed. Furthermore, because it is essential to use an algorithm to quantify EEG signals properly, the interpretation has not been extensively verified by analytics. As a preprocessing stage for an Artificial Neural Network (ANN) based on EGG disassembled data, the capabilities of the wavelet transform for data manipulation are examined in this recommended research. To ensure that the data meets specifications, the data is created using the MATLAB Neural Network toolbox, which utilises the Neural Network routine. Based on the data used, the ANN's capacity may be estimated.

Due to a large number of hospitalised people due to their epilepsy, the EEG recordings are exceedingly challenging to deal with since they comprise an enormous amount of time-to-day information. That will require an enormous quantity of data to be collected. As a consequence, the design and operation of this system must be optimised. Auto-Regression techniques minimise the amount of processing time required by setting out to collect as little data as possible.

Due to time consuming to load the EEG data, a MATLAB-based GUI (Graphical User Interface) platform have to be create to detect the existence of a brain disease and to provide a clear comparison between the afflicted and normal brain

1.2 Project Objective UNIVERSITI TEKNIKAL MALAYSIA MELAKA

The purpose of this project is as follow :

a) To develop a computer aided design for EEG signals epilepsy diagnosis using artifical neural network.

ي, تكند

- b) To analyze whether its able to recognize between healthy person and epilepsy person by evaluating EEG parameters.
- c) To evaluate genuine brainwave data, acquire it from an EEG sensor and train it using an Artificial Neural Network (ANN) using data from the University of Bonn's EEG dataset.

1.3 Scope of Project

The scope of this project are as follows:

- a) The Dataset for this Epilepsy Test is from Department of Epileptology at the University Hospital of Bonn.
- b) To categorise healthy and epileptic EEG data using the Matlab Neural Network toolkit.
- c) Use Neurosky Mindlink to monitoring signals generated by neural activity in brain.
- d) Use App designer (Matlab) to take out the wave from the Dataset.



CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The number of people who have epilepsy varies, but the worldwide total is estimated to be approximately 1 per cent. A very severe CNS disorder that increases a person's risk of having frequent seizures. A seizure is a sudden, involuntary alteration in behaviour, movement, feeling, or consciousness in the brain detected by a doctor. Changes in clinical behaviour are preceded and followed by waves in the electroencephalogram (EEG) which include single-frequency (monomorphic), multifrequency (polymorphic), and spike and sharp wave complexes.

2.2 EEG Brain Sensor

2.2.1 NeuroSky Mindset Sensor

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The NeuroSky Mindset Sensor is utilised in interpreting EEG data in several ways. The gadget will gather and transmit brain signals, which will then be translated into movements. The system will assess the size of the wave and modify the sensitivity such that the system will recognise it. NeuroSky monitors electrical activity in the human brain by attaching electrodes to the forehead and ears and applying unique thinking to this information. [5]. The design shown in Figure 2.1 fits snugly within the ear and has a probe at the end.



Figure 2.1: Neurosky Mindset Sensor

The NeuroSky Mindwave Mobile consists of eight pieces: an ear clip, an ear arm, a battery compartment, a power switch, an adjustable headband, a sensor tip, and a sensor arm. This electronic device has two sensors that measure and filter electroencephalogram (EEG) data. The sensor picks up the electrical signal on the forehead implanted in the brain's frontal lobe. Another sensor that is used to filter out electrical noise is an ear clip. NeuroSky Mindwave Mobile is very resistant to noise, and before transmitting the signal, it has been digitally coded. Additionally, it broadcasts unencrypted brain waves, also known as Emotive and Muse waves, without encryption. [6]

The NeuroSky method is used to characterise mental state by using the residual signal received after noise and muscle movements of raw brain wave data have been filtered. Two eSense signals are generated in this programme: attention and meditation signals. These signals indicate the attention and relaxation of the individual. This signal has a value of 0 to 100, with nil showing low concentration or relaxation and 100 signallings high concentration or relaxation. To function with Arduino, the EEG or NeuroSky Mindset sensors must be modified. The Arduino can only read input values of 0V to 5V, whereas the sensor outputs 0V to 5V. One example is the MindLink Sensor, which functions like the NeuroSkyMindset Sensor. The comparison of the kind of brain signal is provided in Table 2.1.

Waveband	Frequency (Hz)	Condition		
Delta	0.1 - 3	Deep Dreamless, Sleep or Unconsious		
Theta	4 - 7	Drowniness, deep relaxion, daydreaming		
Alpha	8 – 13	Relaxtion, medidation, quiet and conscious		
Low Beta	12-15	Relaxed but concentrated, constructive attention,		
		daydreaming and solving problem		
Mid-range	16-20	Thought, self awareness and surroundings		
Beta				
II' 1 D	ALAYS/4			
High Beta	21-30	Alert and restless		

Table 2.1: Comparison of Brain Signal Type

This sensor will turn brain impulses into directions that change human intellect into an electrical signal, and processors need to be installed to order mobile, medicinal, or even engineering applications. The EEG sensor communication may be linked to a phone or a computer using Bluetooth or a wireless unit. To connect an EEG sensor, the Arduino Uno and Bluetooth module were utilised.

2.3 Types of Signal Processing

2.3.1 Discrete Wavelet Transform (DWT)

Discrete Wavelet Transformation (DWT), epileptic electroencephalography (EEG) computer-assisted signal analysis has recently become a powerful temporal frequency technique for seized identification. In earlier research, the DWT parameters selected randomly or experimentally are among the main hurdles to DWT deployment. In addition,

the optimum DWT settings minimize seizure detection computational costs while enhancing accuracy. [7]

A spectral estimating methodology where every common operation may be expressed as an infinite Wavelet sequence. Furthermore, the wavelet analysis involves the extension and translation of a single mother wavelet, which is derived from the basic concept of signaling as a linear fusion of a given group of operations (wavelet transform, WT). [8]. Wavelet coefficients are referred to as coefficients of signal analysis as they include a set of coefficients. In addition, a linear combination of wavelet functions with wavelet coefficients is reconstructed as a signal. Wavelets separate themselves by their location of frequencies. It means that the majority of the energy of the wavelet is restricted to a short period. [9]

DWT has played an important role in algorithm development. A wavelet is an oscillating, swiftly vanishing phenomena that exists in both the frequency and temporal domains. The signal is broken down into scaled and translated representations of a single function known as the mother wavelet:

اونيور سيتي ٽيط t ليا مالاك
$$\Psi_{a,b}(t) = \sqrt{|a|}$$
 مالاك
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The scale and translation parameters are labelled with a and b, correspondingly. The discrete wavelet transformation, DWT, is achieved by extracting the a and b parameters. In its most common version, the DWT employs relational sampling, with a and b parameterized by these two powers: aaaa = 2jjjj and bbbb = kkkk2jjjj with j and k. By replacing wavelets in the equation above, relational wavelets may be obtained. [7]

$$\psi_{j,k}(t) = 2^{-j/2} \psi(2^{-j}t - k)$$
-----(2)

This DWT framework's whole algorithm may be separated into two major sections: Wavelet-Level Selection and Band-Feature Selection. One EEG segment is dissected to the greatest theoretical level so that a function for each mother wavelet may be extracted afterwards. For Band-Feature Selection, only the mother wavelet and the associated step of decomposition are maintained for any family of wavelets. This is done to provide the best level of categorization accuracy. Band-Feature Selection is used to develop the final prediction model by using the feature in select bands that leads to the best accuracy.[7] Figure 2.2 show that Framework Method based on wavelet.



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In essence, EEG signals are unpredictable. However, the display of such signals does not cause any difficulties. For example, due to the unpredictable behaviour of brain dynamics, immediate changes in EEG signals might be noticed in distinct frequency bands. Because it comprises a lot of information and subtleties in terms of frequency-time transformation and can represent bidimensional (2D) EEG data, the Continuous Wavelet Transform (CWT) is employed in specific studies.[10] Figure 2.3 show that process step of previous method.





With the Wavelet Transform, the window function, unlike the Short-Time Fourier Transform (STFT), executes a function called the primordial wavelet (WT). That affords long-term windows at low frequencies and brief intervals at high frequencies. The window widths in STFT are constant, and all frequency information is examined at the same resolution, whereas the CWT may split windows of various sizes to analyse high and lowfrequency data from time series optimally. For non-stationary data, such as EEG, CWT is a highly effective method. This approach uses a small scale for high frequencies and a massive size for low frequencies to obtain maximum resolution. [11] Figure 2.4 below shows standard epilepsy detection techniques, and the mathematical description of CWT is shown in the following equation in continuous time.



Figure 2.4: Coventional Methods to detect Epilepsy

 $W(s, \tau\tau\tau\tau)$ represents a wavelet coefficient, x(t) represents a time signal, and $\psi(t)$ stands for time signal. The fundamental wavelet function conjugate is denoted by (t), the scale by s, and the parameter location by. In prior research, the Morlet wavelet was employed for spectral analysis of non-stationary data for continuous wavelet transformation, which was shown to be more suited than the other wavelet groups. As it analyses the wavelet's time offset of particular expansions, the CWT offers a plethora of frequency values (components) for continuous time signal analysis. Scalogram refers to the measurement of this transition by the local time frequency energy density.

The Morlet Continuous Wave was used to apply the CWT transformation to the EEG data set. Because a scalogram picture was produced for each segment, the analysis comprised a total of 500 photos (100 for A, 100 for B, 100 for C, 100 for D, and 100 for E). Figure 2.5 show sample of Scalogram Image for each cluster.



Figure 2.5: Sample Scalogram changes for each sagment

2.4 Classifier

2.4.1 Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) is a system that performs comparable functions to those of the human brain. The neurons on the network are arranged in a standard ANN with a layer hierarchy and these levels. The neurons are linked by input and output layers to the outside world. Weights are the key long-term memory mechanism in ANN. The neural network notes that weights are regularly changing. The iteration efficiency of the network is boosted via weight adjustment. Consider a single perceptron (or neuron), for example, logistic regression.

ANN is a multi-layered collection of perceptrons/neurons. Because inputs are processed in one way or another, they are also known as a feed-forward neural network. The rules of learning, design and transfer all affect the behaviour of the neural network. There are three levels of ANN: input, hidden and output. The input layer gives input, the hidden layer processes the inputs, and produces the output layer. Essentially, every layer tries to learn some of its weights. Input, Hidden, and Output layers are shown in Figure 2.6.



Figure 2.6 : ANN Layers

According to [3], we use an autoregressive model to decrease the data before the classification process begins and three distinct AR model strategies for calculating the coefficients. The Matlab-based GUI may be used flexibly and visually for normal/epileptic EEG observation and test results. Users choose the training parameters and type of the neural interface network. Overall accuracy is used to evaluate the performance of the suggested model. Auto Regression methods simplify the data set, so that processing time is reduced.

In order to compare outcomes, we chose three distinct parametric methodologies, such as the Burg Algorithm, the Yule-Walker Method, and the Covariance Method.

The EEGs are then categorized using ANNs such Feed-Forward Backpropagation Network, Cascade– Future Backpropagation Network, and Elman Backpropagation Network. The integrated Matlab GUI lets users input AN Number, Target Number and Learning Rate parameters. The user-friendly Matlab GUI enables easy and flexible usage to acquire the best results for the categorization of epilepsy. Figure 2.6 shows the system block diagram.



Figure 2.7: Block diagram of the proposed system

ANN systems are composed of single-layer perceptrons and multi-layer perceptrons, according to [12]. The categorization of the data set provided was evaluated using linear and nonlinear systems for both perception types. The linear transfer function was used for both single-layer and multi-layer perceptron designs as the linear system activation function. The

nonlinear system's log-sigmoid transfer function was employed to analyze both neural network architectural designs. The default approach of Matlab, scale conjugate gradient, has been used for the learning process. Ten hidden layers have been used in multi-layer perceptron construction, and all linear and nonlinear systems are maintained constantly. Instead of using a GUI, a simulation using command line functions was carried out. Figure 2.8 shows the ANN process block diagram following [12]



Figure 2.8: Block Diagram of ANN Process

2.4.2 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is made up of an input and output layer and numerous hidden layers. The hidden layers are often made up of convolutional layers, pooling layers, and connected layers. Convolutional layers perform a convolution operation on the input and pass the results to the next layer. The coevolutionary model simulates the response of a single neuron to visual inputs. The next layer is a coevolutionary layer that merges into a single neuron. Mean pooling takes the preceding layer's average value and applies it to each cluster of neurons. Each neuron in a single layer is linked to each neuron in a different layer via fully linked layers. In principle, CNNs are comparable to traditional multi-layer neural perceptron networks.

Compared to classical classifiers, CNNs significantly excel high-dimensional data analyses. CNNs employ a parameter-sharing mechanism to maintain and increase the number of parameters in convolution layers. A pooling layer should control overfitting by lowering space size, number of parameters and computational representation in the network progressively. As the input layer, a multichannel time series was immediately integrated into the CNN based on time or frequency domain signals. Figure 2.8 shows the CNN visualisation and Figure 2.9 shows the CNN process block diagram.



Figure 2.9: Illustration of CNN



2.4.3 Recurrent Neural Network (RNN)

The recurring neural networks (RNNs) investigated in this study are well-known multilayer recurrent discrete-time perceptions. [13]. Temporary representation of these networks may be much better than merely feedback multilayer perceptrons or feedback networks with tapped-delay lines. In contrast to other networks, RNNs may express and encode heavily concealed statements, i.e. situations in which the output of a network relies on an arbitrary number of earlier inputs. However, despite its good design, in practical applications, RNNs were not extensively utilised mainly due to the absence of an efficient and universal training process. In recent years, RNNs with sophisticated recurring hidden

units, such as the Long-Short-Term Memory (LSTM) and Fixed-Recurrent Unit (GRU), were a popular option to simulate time sequence. The RNN, LSTM and GRU models are shown in Figure 2.11.



Figure 2.11: RNN, LSTM and GRU unit

Deep Recurrent Neural Network and an Early Seizure Detection System examine the use of RNN models for long term sequence learning. Specifically, deep GRU-hidden RNNs categorise one-channel EEG time series data into three conditions: healthy, inter-ictal and ictal. Data from a healthy individual for good health are captured, whereas Inter-Ictal EEG data from an epileptic patient and Ictal EEG data from an epileptic patient during an attack occur.

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According to [14], RNNs and GRUs may be quickly introduced before suggesting an RNN architecture to be used in the EEG categorization. First, they categorized an EEG segment in one of three states – healthy, inter-ictal, or ictal – as a classification challenge. EEG data were collected from five A, B, C, D and E subgroups. Subgroups including healthy = A,B, Inter-Ictal = C,D and Ictal = E, each of 100 EEG segments. 100 EEG segments are selected randomly for each subgroup and are used for training and research. When an attack occurs when the algorithm triggers a seizure event, it is important to recognize early convulsions. They test the efficacy of the early detection GRU RNN model by presenting the correctness of the model based on the number of EEG sub-sections used to establish which segments of the EEG group belongs. The finding shows that the GRU-RNN can forecast the commencement of an attack episode. Figure 2.12 shows the RNN procedure.



Figure 2.12: RNN process

2.4.4 Summary of ANN, CNN and RNN

Table 2.2 compares the summary prior research article in recognition technique for the three types of neural network, which are CNN, RNN, and ANN, based on the research studies that have been done. Each form of Neural Networks approach has its own set of benefits and drawbacks. The fundamental benefit of CNN, for example, is that it automatically discovers essential traits without the need for human intervention. The downside of CNN is that it might have difficulty generalising to new domains or learning undesirable associations. The benefit of RNN over ANN is that it can represent data sequences in such a way that each sample may be assumed to rely on the one before it. When it comes to drawbacks, RNN is very tough to train.



Author('s)	Title	Hardware	Software	Method	Dataset
		Used	Used		Source
R. Jaafar, N.	Classification of	-Default	-Matlab	-DWT	-University of
Mohamood,	healthy and epileptic	traning			Bonn
and M. S.	electroencephalogram	algorithm			
Mahdi	(EEG) by artificial				
	neural network				
M. Sharma,	A new approach to		-Matlab	-Data acuisation and	-University of
R. B.	characterize epileptic			Pre- Processing	Bonn
Pachori, and	seizures using			11000000000	
U. R.	analytic time-			Decompositon	
Acharya,	frequency flexible			through ATFFWT	
5	Wavelet transform	ai	عتى قد	-Selection	
	and fractal dimension			-Classification	
U	NIVERSIIITEKN	IKAL MA	LATSIA	and LA Cross Validation	
[A.	Statistical-Hypothesis		-GMM	-Nonlinear	-University of
Alqatawneh,	Aided Tests for		-SVM	feature-based	Bonn
R.	Epilepsy		-Matlab	Epilepsy	
Alhalaseh,	Classification			detection	
A. Hassanat,					
and M.					
Abbadi					

Table 2.2: Comparison On Previous Project
D. Chen, S.	A high-performance		-SVM	-DWT	-Children's
Wan, J.	seizure detection		-Matlab		Hospital
Xiang, and	algorithm based on		-DC		Boston,
F. S. Bao	Discrete Wavelet				Massachusetts
	Transform (DWT)				(MIT dataset)
	and EEG				-University of
					Bonn
S. S. Talathi	Deep Recurrent		-Matlab	-RNN and	-University of
	Neural Networks for			GRU hidden	Bonn
	seizure detection and			units.	
	early seizure			-RNN model	
EKu	detection systems			training	
1		U	IE	-Proposed	
	Ann			classification	
5	کل ملیسیا ملال	کنید	يتي تيھ	method	
G. U	The Detection of	IKAL MA	-Matlab	-Monitoring	
DogaliÇetin,	Normal and Epileptic			brain neural	
Ö. Çetin,	EEG Signals using			activities	
and M.	ANN Methods with			using	
Recep	MATLAB-based GUI			electrical	
Bozkurt				signal	
				-AR method	
				-ANN	

			-Feed-	
			Forward back	
			propagation	
Ö. Türk and	Epilepsy Detection		-CWT	-University of
M. S.	by Using Scalogram		-Resize	Bonn
	Based			
Ozerdem	Convolutional		images	
	Neural		-CNN	
	Network from EEG			
	Signals			
	ALAYSIA			

2.5 Summary

To measure neural activity in the brain, an electroencephalogram, or EEG, is employed. EEG is a method for measuring electrical brain activity. A brain sensor such as the NeuroSkyMindset Sensor or SmartLink is one of the proposed brainwave sensors for obtaining raw data of EEG epilepsy. The collected raw EEG data must then be analysed and evaluated at different scales using DWT, where the signal is split down into approximation and information coefficients. DWT also serves as a pre-processing step, dividing EEG signals into sub-band frequencies.

There are three kinds of classifiers that may be used to categorise data based on Neural Network. The previous researcher mostly employed CNN, RNN, and ANN as Neural Network Classifiers. The majority of the study study was based on the EGG Epilepsy database from the University of Bonn in Germany. CNN is a feedforward neural network that is often used for image recognition and object categorization. While RNN merely uses the notion of preserving the output layer and feeds it back to the input to forecast the output layer. At each layer, ANN is a collection of numerous perceptron/neurons. Because its inputs are solely processed in the forward direction, an ANN is also known as a Feed-Forward Neural Network.

The comparison of software implementation on those prior studies shown in the table above revealed that the majority of them are more acquainted with and comfortable with MATLAB software in various versions rather than Phyton software. MATLAB is a high-performance language for technical computing that can integrate, visualise, and even programme. Finally, one earlier research employed NeuroSky MindWave to retrieve raw data from the NeuroSky headset using an Android application and Bluetooth module.



CHAPTER 3

METHODOLOGY

3.1 Introduction

This part will be briefly informed of the progress of the project. The following will be an overview of the often used raw EEG dataset of the University of Bonn, a deconstructed raw signal using the DWT, explaining the early development of the research and the systembased effects of signal epilepsy via the Artificial Neural Network categorization. In the present phase, many sources are explored to guarantee that literature review, project improvement and research techniques are continued smoothly and completed. Furthermore, this chapter contains the description of the project, the block diagram, the project flow chart, the estimated results from the previous experiment done to identify the system between a healthy human or a person with epilepsy and the planned outcome of the project.

3.2 Methodology UNIVERSITI TEKNIKAL MALAYSIA MELAKA

This project is about recognizing and classifying EEG datasets from healthy people and people with epilepsy between interictal and ictal states, and then creating a GUI to illustrate the signal between the two. To identify the system, this project used electroencephalography (EEG), as tool often used for studying brain activity and diagnosing epilepsy. An EEG is often utilized in many research projects to predict or identify epilepsy.

This study use an artificial neural network to categorise it. Matlab software is used to carry out this project. It also includes a dataset that may be used to this project. The dataset utilised is from the University of Bonn and may be obtained from free sources such as the Internet. Many researchers have utilised this dataset, which has an accuracy of up to 99.1±0.9 percent. Table 3.1 displays data from the University of Bonn..

Set	Patients	Setup	Phase
А	Healthy	Surface EEG	Open Eyes
В	Healthy	Surface EEG	Eyes Closed
С	Epilepsy	Intracranial	Interical
ALAYSIA		EEG	
D	Epilepsy	Intracranial	Interical
TEKNIN	AKA	EEG	
E	Epilepsy	Intracranial	Ictal/Seizure
**Ainn		EEG	
لبسبا ملاك	کنیکل ما	رسىتى ئىھ	اوتيوم

Table 3.1: The University of Bonn's epilepsy dataset

From Set A through Set E, this epilepsy dataset was separated into five sets, each with 100 text files containing 4097 samples of one EEG time series in ASCII coding. This dataset includes both normal people and epilepsy sufferers. This dataset was collected during a period of 23.6 seconds for each subgroup, with a sample rate of 173.61 Hz. The acquisition system spectral bandwidth for this dataset is 0.5 Hz to 85 Hz.

Sets A (Z) and B (O) comprise EEG signals obtained from five healthy people while they were calm and awake, with their eyes open and closed. Sets C and D include EEG signals measured during seizure-free EEG signal recordings collected from seizure-free epilepsy patients (interictal), while Set E contains EEG signals collected during epileptic seizures experienced by epileptic patients (ictal). In addition, an EEG sensor was employed in this experiment to capture data in real-time.



Figure 3.1 : State in EEG Signals

As referring to Figure 3.1, the seizure relates to the ictal stage. The pre-seizure stage is the period immediately before the commencement of a seizure. The postictal state occurs after the seizure has ended. The interictal stage is when one seizure's postictal stage and the following seizure's preictal stage. The EEG signal is chaotic in the normal (interictal) condition. During an epileptic episode, the signals become less chaotic and take on a more regular structure. As a result, the chaoticity of the existing signal is an essential determinant of the upcoming seizure.



Based on Figure 3.2, EEG signals discovered using an EEG sensor will be preprocessed to reduce noise from the EEG data. Data will be tested as planned; however, first, the set data must be trained using a neural network. During testing, employ a different set of data to assess validity and reliance. The data given in the findings demonstrate whether the epileptic patient is inter-ictal or ictal.

3.3 Software Implementation

In this thesis, the software implementation goes via writing programming coding using MATLAB R2020a for the recognition system of epileptic seizure detection. The raw EEG information is loaded into the MATLAB programme as input data for the neural network's pattern recognition mechanism. This neural network recognition method makes use of a raw EEG dataset available from the University of Bonn's open-source data repository. The raw data matrix has a total size of (4097 x 500). Each of the five raw datasets (4097 x 100) matrix is then processed by translating the data into 8 sub-band frequencies.



The Discrete Wavelet Transform (DWT) converts data into the eight sub-band frequencies shown in the table above: high gamma, low gamma, high beta, low beta, high alpha, low alpha, delta, and theta. Each of the eight EEG waveforms then yields a (409700 x 1) matrix result. The (409700 x 1) matrix must then rearrange or reorganise its array to

become a (4097 x 100) matrix. The 8 sub-band data is then transformed into standard deviation using a MATLAB coding tool. Each of the eight EEG waves produces data with an 8 standard deviation. Then, for each standard deviation, a (1 x 100) matrix was produced. Following that, the total standard deviation for one set is a (8 x 100) matrix, and the complete complete standard deviation for five sets is a (8 x 500) matrix. The converted data's standard deviation is then supplied as an input for the following procedure.

Dataset EEG Signal	Subset EEG Signal	Target Vector
ALAYSIA		
A	Z	10000
2	×	
В	0	01000
1		
C	N	00100
10		
D	F	00010
E Molum	s Silai i	00001
1		- V J.

Table 3.3: Target Dataset

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From the Table 3.3, The target data is then divided into two categories: 0 and 1. This thesis divided the target data into five subsets: healthy people with open eyes (Set A), healthy people with closed eyes (Set B), epilepsy patients with interictal states (Set C and Set D), and epilepsy patients with ictal states (Set E). The target data's size is likewise represented as a matrix (5 x 500). More information on the target vectors may be found here.

Following that, the training stage in this research made use of the neural network toolbox from the MATLAB R2020a programme. Cascade-forward Neural Network is used for pattern recognition. It is a kind of neural network similar to feed-forward networks, but it incorporates a link to the succeeding layers from the input and each preceding layer. In a three-layer network with a hidden layer, the output layer is often intimately tied to the input layer. This Cascade-forward Neural Network employs ten hidden neurons inside its hidden layer. This is due to the fact that each of the hidden neurons is linked to the input and output layers, which are used to establish the neural network's accuracy rate.

The data usage ratio has already been designed to split into three categories during training: training, validation, and testing. As a result, the proportion of each data may be calculated as 70% for training, 15% for validation, and 15% for testing. The training toolbox displays the performance, confusion matrix, and Receiver Operating Characteristic findings (ROC). A performance must be plotted in order to get a train record error plot versus the number of training epochs. The confusion matrix reveals how well the classifier performed in the output of the individual class performance, and the Receiver Operating Characteristic (ROC) then indicates the diagnostic capability of the binary classification system as its discrimination threshold varies.

3.3.1 Arduino IDE and PLX DAQ Software

The use of this software is to read waves() function list in this programme is one of the most current brain data separated and written into this format, which is low alpha, high alpha, low beta, high beta, low gamma, high gamma, delta, and theta.





The programme Parallax Data Acquisition tool (PLX-DAQ) v2.11 is used in this thesis. This PLX-DAQ is more convenient when transferring data from Arduino to Excel in real-time. Columns and rows are used to paste the data. Since we labelled Arduino for eight EEG waves, the eight waves are then plotted as illustrated in Figure 3.4 below. To utilise this PLX-DAQ programme, the Arduino code must be uploaded, and the serial output must indicate that data is being read. This indicates that the sensor is connected successfully to the Arduino and that the data is being sent accurately. As a result, the data that the PLX-DAQ is capable of retrieving. After that, set its baud rate to 57600 in accordance with the Arduino's coding and its input port to the Arduino's COMM port.

E	5.6.						PLX-DAQ-v2					AHME	ZAN BIN AI	HMEZUL A				
Fil	e Home	Insert Page L	ayout Form	ulas Data	Review View	Add-ins Help	Q Tell me wh	at you want to do									ය Sha	are
	Cut	Arial	* 10	- A A =	= ≫ ~ §¢	Wrap Text	General	•	Sta	indard 2 Norn	nal		*		utoSum	× Azy	P	
Pa	te Ver Copy Ver	nter B I L	1 • 🖽 • 🖄	• <u>▲</u> • ≡		Merge & Center 👻	\$ ~ % • *	6 28 Conditio Formattin	nal Formatas Bar g ~ Table ~	d Goo	d	₹ Insert	Delete For	mat 🖉 C	llear ¥	Sort & F Filter ~ S	Find &	
	Clipboard	rs.	Font	ſs	Alignment	15	Number	r _s		Styles			Cells		Ec	diting		~
	•	$\times \checkmark f_x$																~
	A	В	С	D	E	F	G	н	1	J	K	L	М	N	0	Р	Q	F
1	TIME	TIMER	DELTA	THETA	LOW ALPHA	HIGH ALPHA	LOW BETA	HIGH BETA	LOW GAMMA	HIGH GAMMA							_	
2	12:07:08 AM	0.100006	7893	8187	5433	3807	3449	8077	9706	4630	Onon Pl	X DAO UI						
3	12:07:09 AM	1.100006	8687	17661	453	6055	3906	4551	5017	1672	openite	DAG OI						
4	12:07:10 AM	2.100006	7883	10517	8345	4942	2340	7522	5913	4412								
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6	12:07:12 AM	4.100006	23241	5921	46226	32648	6503	25262	13450	2467		PLX-DAQ f	or Excel "Ve	ersion 2° by N	let^Devil	×		
7	12:07:13 AM	5.081024	16449	21397	10958	4066	6316	1999	1183	778		100100	2	Control	í .			
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9	12:07:15 AM	7.091003	38255	36676	26087	19622	7987	7447	2911	1079		PLX-	DAO	Custon	n Checkbo	x1		
10	12:07:16 AM	8.081024	8957	45347	5780	6841	1536	2441	1419	621		Setting	16	Custon	Checkbo	XZ		
11	12:07:17 AM	9.081024	26348	43641	34067	19180	2816	4353	5496	3046		Oceening	4	Reset	п Спескоо	X 3		
12	12:07:18 AM	10.072020	23586	8245	1/11	512	2020	2687	/61	1134		Port	7	Reserve	I	^		
13	12:07:19 AM	11.079010	26068	21576	36523	17280	20588	6442	8811	4123		Baud:	57600	Reset Ti	mer			
14	12:07:20 AM	12.071010	61622	20181	6855	19661	3733	5344	3076	1238		Disco	anact	Class Cal	umpe			
15	12:07:21 AM	13.062010	46084	40589	4/31	6629	5405	3646	2906	1/60		Disco	meet	clear con				
16	12:07:22 AM	14.072020	30323	20540	6934	9416	5425	3255	2073	1068		Pause	pnippol	Display d	irect debug	=>		
1/	12:07:23 AM	15.062010	53505	46841	//59	5942	9280	3335	2925	1387								
18	12:07:24 AM	16.062010	22/44	10021	5796	4340	1951	2150	3043	1441		Sheet na	me to post	to: Simple	Data V	440		
19	12:07:25 AM	17.062010	4457	15036	1858	3053	6/18	1622	1430	1852		(reload a	fter renam	ing)				
20	12:07:26 AM	18.052000	64361	27856	1/98	5219	1989	1801	1929	885		-	Contro	ler Message	s			
21	12:07:27 AM	19.052000	23994	12050	2/14	1860	554	4697	/38	1519		-	Acception	data for Row	100			
22	12:07:28 AM	20.043030	14131	4365	5/94	1223	4037	3652	3067	2049		Desart	Accepting	and for roll	and the last	and a second		
23	12:07:29 AM	21.018010	21069	12350	10334	11486	8010	11036	3853	1521		Do not me	That mic	iht crash Exc	el !	ging :		
24	12:07:30 AM	22.013000	28183	10622	20122	15665	9898	2//3	2942	1870						-		
25	12:07:31 AM	23.003020	58970	31461	6958	9344	5907	3728	1837	1093								
26	12:07:32 AM	24.013000	34026	50384	3424	3256	5840	5978	2278	1693								
21	12:07:33 AM	24.993010	55059	29099	3630	3690	1427	3/15	1050	1554								
20	12:07:34 AM	25.999020	30001	24516	1000	7246	5573	5960	4073	3233								
29	12:07:35 AM	27.000000	14532	5448	9/18	6944	1646	2663	1859	1667								
30	12:07:36 AM	21.995030	10817	32038	19423	5307	1096	3312	2055	10/6								
31	12:07:37 AM	28.985020	5/99	30410	3129	5/91	8803	1500	3219	1244								
32	12:07:38 AM	29.985020	30357	50692	10259	0399	2940	14345	2/82	21/8								
33	12:07:39 AM	30.989010	10151	5011/	56/4	6996	2653	2889	4042	1/98								
34	12:07:40 AM	31.987030	1046	2040	20310	9037	4455	3515	2625	1012								
-	Sim	nple Data Fur	ther sheet	(+)				2750		12.10							-	F

Figure 3.4: PLX DAQ interface



Figure 3.5: NeuroSky MindLink Sensor

An EEG sensor is utilised to read brain cell activity in order to create the hardware for this thesis. The EEG sensor's capabilities may be accessed through a Bluetooth module (HC-05) or a wireless controller included inside the Arduino Uno. As a result, the data may be immediately associated with a computer, a smartphone, or any other device. VCC, GND, and TX are linked to the Bluetooth module's 5V, GND, and RX pins on the Arduino Uno (HC-05). The connections of the Bluetooth Module (HC-05) to the Arduino Uno is shown in Figure 3.5, followed by the connection of the EEG sensor to the Bluetooth.



3.5 Process Flowchart





Figure 3.5 : Block diagram Process

3.6 Outcomes

At the conclusion of the above technique, a dependable Epilepsy Reconnaissance System may deliver advantages for other researchers or any other scientists that need this kind of information on this subject. The most often utilized thesis was to import MATLAB raw EEG data, including Epilepsy sensor raw data and to decompose the signal to eight substring frequencies by utilizing DWT. Then this system can identify people and normal epileptics and compare data obtained from the MindLink sensor with data collected from the University of Bonn in real time. Last but not least, the awareness of this epilepsy illness and the right usage and treatment might be improved.



3.7 Gantt Chart

PROJECT PLAN	INING	3																																			
	Listdown the main activity for the project proposal. State the time frame needed for each activity.																																				
																		2	021																		
Project Activity	MA	AC			AP	R			М	AY	7		J	IUN	1		JU Y	L	J A		00	т			NO	v			DE	С				JAI	Ň		J
Y	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17 1	8	X X	1	2	3	4	5	6	7	8	9	10	11	2	13	14	15	16	17	18
Literature review																																					
Project Planning								ak																			ą										
Proposal Preparation								sre																			sre										
Study of EEG								rm F									er										rm F									er	
Study Matlab	Ę.							Tei								~	est	B									Te									est	ion
Study of Artificial Neural	Brie Brie	F						Mid								Stud	Sem	ninati	Sen								Mid								Stuc	Sem	ninati
Study of signal					-										-		Final	Fran																		Final	Exan
processing for EEG		_			_	_				_		_																									
classification																																					
Perform Analysis																																					
Study Discrete Wavelet Transform by using researcher previous study and try to			D.		X	21																															
implement into project		16	12			1	9	de.																													
Start progressing on Matlab by using Cascade Neural Network step by step	Y								8	N N A																	/										
Test the Classification																		Τ		1			N														
for the dataset	_	-	_	_	_		_			-	-	-	_			_		4	-	_			-	_			_										
Setting up hardware (Mindlink Sensor, Arduino, Bluetooth Module Connection)	100	7)					- 1													-		-	2														
Simulate and run hardware and software to compare both results	N									1	2	-				2	-																				
Report preparation	-	-	<u> </u>	10			1.1		4	Ļ									-		1	1		1	6		W	h	ľ		Т	Π	Π		Η	Т	
U	Nľ	V	E	R	S	T	1	T	Έ	k		11	K	A	L		٨٨	1	A	Y	SI	A		VI	E		A	K	()A								

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CHAPTER 4

RESULTS

4.1 Overview

The Artificial Neural Network Classification (ANN) outcomes will be discussed and evaluated in Chapter 4. Using the Epilepsy Recognition System, it is possible to determine whether the project's goal has been met. In this thesis, a comparison of the device's dependability before and after the dataset of EEG was converted into sub-bands using DWT was undertaken. We also looked at whether the hidden layer of the pattern recognition network had an increased or decreased number of neurons after applying DWT to break up the dataset into smaller bands. In order to compare the real-time EEG sensor data with an EEG epilepsy dataset received from the University of Bonn, we must first compare the realtime EEG sensor data.

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4.2 Analysis Before Transform Dataset into Sub-Band Using DWT

The analysis is then performed to determine the system's correctness before converting the dataset into sub-bands using the Discrete Wavelet Transform. According to the study conducted, low accuracy results in data not achieved with current development projects, where it is less than 70%.



Figure 4.1:Confusion matrix analysis before transform the dataset into sub-band.

Hence, the best performance for this analysis is 3.6 at epoch 70 with overall accuracy of 62.5%, 26.7% for validation and 26.7% for testing. Figure 4.1 above shows that the confusion matrix results indicates that the data before transform the dataset into sub-band.

4.3 Analysis Results for Raw EEG Dataset from University Of Bonn

In Germany, the University Hospital Bonn's Department of Epileptology's official website provides access to the raw dataset for this study. A, B, C, D, and E are the five data sets in the raw dataset. There are 100 ASCII-coded text files in each group containing 4097 samples of one EEG time series.

SET A	Z.zip	with Z000.txt - Z100.txt	(564 kB)
SET B	O.zip	with O000.txt - O100.txt	(611 kB)
SET C	N.zip	with N000.txt - N100.txt	(560 kB)
SET D	F.zip	with F000.txt - F100.txt	(569kB)
SET E	S.zip	with S000.txt - S100.txt	(747kB)

Figure 4.2: RAW data from Uni Of Bonn

Basically, the set A is denoted as subset Z (Healthy Person During Eye Opened), set B denoted as subset O (Healthy Person During Eye Closed), set C denoted as subset N (Epileptic Patients), set D denoted as subset F (Within Epileptic Zone before Seizure) and set E denoted as subset S (Region of Seizure Activity) as shown in Figure 4.2, Figure 4.3 and Figure 4.4.

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Size

Name	Date modified	Туре
SET F	12/13/2021 10:20 PM	File folder
SET N	12/13/2021 10:21 PM	File folder
SET O	12/13/2021 10:22 PM	File folder
SET S	12/13/2021 10:23 PM	File folder
SET Z	12/13/2021 10:20 PM	File folder

Figure 4.3: After extracting the RAW data

DATASET F.xlsx	12/13/2021 10:30 PM	Microsoft Excel W	2,012 KB
DATASET N.xlsx	12/13/2021 10:32 PM	Microsoft Excel W	2,002 KB
DATASET O.xlsx	12/13/2021 10:33 PM	Microsoft Excel W	2,024 KB
DATASET S.xlsx	12/13/2021 10:33 PM	Microsoft Excel W	2,198 KB
DATASET Z.xlsx	12/13/2021 10:34 PM	Microsoft Excel W	1,980 KB

Figure 4.4: From Text Files to Excel Files

The DWT approach may be implemented using the MATLAB R2020a script once all the data is organized. It is possible to apply and implement DWT coding in MATLAB R2020a to convert the EEG dataset from the University of Bonn into 8 sub-bands. Only one raw dataset is modified at a time to do this. As demonstrated in Figure 4.5, a single raw dataset yields 8 Sub-Band data waves, which are manually transferred in Excel. Repeat these processes for four more raw datasets.

Name	Date modified Type	Size
A8theta.xlsx	12/13/2021 10:45 PM Microsoft Excel W	7,033 KB
📭 D1highgamma.xlsx	12/13/2021 10:45 PMMicrosoft Excel W	6,707 KB
D2lowgamma.xlsx	12/13/2021 10:45 PM Microsoft Excel W	7,350 KB
D3highbeta.xlsx	12/13/2021 10:45 PM Microsoft Excel W	7,362 KB
D4lowbeta.xlsx	12/13/2021 10:45 PM Microsoft Excel W	7,356 KB
D5highalpha.xlsx	12/13/2021 10:45 PM Microsoft Excel W.	7,336 KB
🖬 D6lowalpha.xlsx	12/13/2021 10:45 PM [#] Microsoft Excel W	7,302 KB
D7delta.xlsxNIVERSITI TEKN	12/13/2021 10:45 PM S Microsoft Excel W.	7,255 KB

Figure 4.5: SET Z after been changed to DWT to 8 Sub-band waves

Every eight sub-band wave has a (409700×1) matrix, with 409700 rows and 1 column, each of which contains 409700 rows and 1 column. Next, a MATLAB script is used to transpose the (409700×1) matrix and reshape its array to (4097×100) . Repeat the same processes for the next dataset. Table 4.1 shows the whole process.

Type of Dataset	Sub-Bands	DWT Coefficient	Matrix	After Transpose
A	Delta	D7	409700 x 1	4097 x 100
	Theta	A8	409700 x 1	4097 x 100
	Low Alpha	D6	409700 x 1	4097 x 100
	High Alpha	D5	409700 x 1	4097 x 100
	Low Beta	D4	409700 x 1	4097 x 100
	High Beta	D3	409700 x 1	4097 x 100
	Low Gamma	D2	409700 x 1	4097 x 100
	High Gamma	D1	409700 x 1	4097 x 100
В	Delta	D7	409700 x 1	4097 x 100
	Theta	A8	409700 x 1	4097 x 100
	Low Alpha	D6	409700 x 1	4097 x 100
	High Alpha	D5	409700 x 1	4097 x 100
	Low Beta	D4	409700 x 1	4097 x 100
	High Beta	D3	409700 x 1	4097 x 100
	Low Gamma	D2	409700 x 1	4097 x 100
	High Gamma	D1	409700 x 1	4097 x 100
С	Delta	D7	409700 x 1	4097 x 100
	Theta	A8	409700 x 1	4097 x 100
ALAYSI	Low Alpha	D6	409700 x 1	4097 x 100
N. Contraction	High Alpha	D5	409700 x 1	4097 x 100
Y	Low Beta	D4	409700 x 1	4097 x 100
1	High Beta	D3	409700 x 1	4097 x 100
·	Low Gamma	D2	409700 x 1	4097 x 100
	High Gamma	D1	409700 x 1	4097 x 100
D	Delta	D7	409700 x 1	4097 x 100
	Theta	A8	409700 x 1	4097 x 100
1/MA	Low Alpha	D6	409700 x 1	4097 x 100
1.1.1	High Alpha	D5	409700 x 1	4097 x 100
1No hum	Low Beta	D4	409700 x 1	4097 x 100
	High Beta	D3	409700 x 1	4097 x 100
	Low Gamma	D2	409700 x 1	4097 x 100
UNIVERSIT	High Gamma	D1 A	409700 x 1	4097 x 100
E	Delta	D7	409700 x 1	4097 x 100
	Theta	A8	409700 x 1	4097 x 100
	Low Alpha	D6	409700 x 1	4097 x 100
	High Alpha	D5	409700 x 1	4097 x 100
	Low Beta	D4	409700 x 1	4097 x 100
	High Beta	D3	409700 x 1	4097 x 100
	Low Gamma	D2	409700 x 1	4097 x 100
	High Gamma	D1	409700 x 1	4097 x 100

Table 4.1:Overall steps results in table.

The next step is to use the MATLAB R2020a script to determine the standard deviation for each set that can be completed. Transposing each dataset yields (8 x 100) for each set, as indicated in the Table 4.2 below.

Type of Dataset	Std Dev	After Standard Deviation	Total Matrix After Standard Deviation
A	StdDelta	1 x 100	
	StdTheta	1 x 100	
	StdLowAlpha	1 x 100	
	StdHighAlpha	1 x 100	8 x 100
	StdLowBeta	1 x 100	
	StdHighBeta	1 x 100	
	StdLowGamma	1 x 100	
	StdHighGamma	1 x 100	
В	StdDelta	1 x 100	
	StdTheta	1 x 100	
	StdLowAlpha	1 x 100	
	StdHighAlpha	1 x 100	8 x 100
	StdLowBeta	1 x 100	
	StdHighBeta	1 x 100	
	StdLowGamma	1 x 100	
4	StdHighGamma	1 x 100	
c 🧊	StdDelta	1 x 100	
	StdTheta	1 x 100	
ů.	StdLowAlpha	1 x 100	
	StdHighAlpha	1 x 100	8 x 100
R	StdLowBeta	1 × 100	
	StdHighBeta	1 x 100	
	StdLowGamma	1 x 100	
. to	StdHighGamma	1 x 100	
D 🕘	StdDelta	1 x 100	اوىيەم سىت ، ي
	StdTheta	└── 1 x 100	G. Val
	StdLowAlpha	1 x 100	
UNI	StdHighAlpha	EKNI1x100 MAL	AYSIA ME 8 x 100
	StdLowBeta	1 x 100	
	StdHighBeta	1 x 100	
	StdLowGamma	1 x 100	
	StdHighGamma	1 x 100	
E	StdDelta	1 x 100	
	StdTheta	1 x 100	
	StdLowAlpha	1 x 100	
	StdHighAlpha	1 x 100	8 x 100
	StdLowBeta	1 x 100	
	StdHighBeta	1 x 100	
	StdLowGamma	1 x 100	
	StdHighGamma	1 x 100	

Table 4.2: Overall steps results shows in table

Each set of 8×100 standard deviation data is then manually aggregated and imported into Excel for further analysis. Data for all five datasets is thus organized in an 8 by 500 matrix. The 8 x 500 matrix is utilized as the input x, whereas the (5 x 500) matrix is used for the target dataset.

The standard deviation is utilized as the input data for this system to verify its correctness via a confusion matrix. However, the data was randomly partitioned since the dataset was trained using a Cascade-forward Neural Network recognition system or Cascade-forward net. Consequently, when it is run numerous times for training, the performance, confusion matrix, and Receiver Operating Characteristic (ROC) values will change from the baseline settings and sampling used in the first train. In this scenario, the number of neurons is increased from 10 to 20 to monitor and analyze the best outcomes possible from the systems.

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Figure 4.6: Confussion matrix of 15 hidden neuron

Based on the results, the best performance of this system is at 0.082 at epoch 177. The confusion matrix results with 15 hidden neuron used in Figure 4.5 shows that overall accuracy is 79.4% with all set during training, validation and test gives 79.4%, 88.0% and 70.3%.

4.4 Analysis by Changing the Number of Neurons in Cascade-forward Neural Network Hidden Layer in Matlab.

The study is then repeated by altering the number of neurons in the hidden layer of the Cascade-forward Neural Network. This study is used to determine whether or not the networks function well after training. Additionally, the default hidden neurons for the Cascade-forward Neural Network hidden layer are ten. Therefore. To compare the accuracy results in the confusion matrix, the number of neurons must be increased from ten to twenty. These procedures were completed prior to evaluating the new data. Figure 4.7 show the detail flow how to train the data and changing the number of neuron.



Figure 4.7: Process flow for Cascade-forward Neural Network Training Data.

Out of the twenty hidden layers in the Cascade-forward Neural Network recognition system that have been changed from neuron ten to twenty, only hidden neuron fifteen provides the system with the highest overall accuracy, achieving 76.2% classification accuracy compared to the other hidden neuron. The confusion matrix is shown in Figure 4.8 using fifteen hidden neurons.



Figure 4.8:Confusion Matrix of 15 hidden neuron

Nonetheless, when ten hidden neurons are utilized, the total accuracy of this system is 73.1%, which is the lowest result produced when the number of hidden neurons is increased from 10 to twenty. As seen in Figure 4.9, the confusion matrix is constructed using 10 hidden neurons.

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Figure 4.9: Confusion Matrix of 10 hidden neuron.

The summary in Table 4.3 below shows the percentages of training, validation,

testing, and total accuracy for various numbers of hidden neurons.

No. of Hidden	Training	Validation	Testing	Overall			
Neuron				Accuracy			
10	72.8%	73.3%	74.7%	73.1%			
11	72.6%	64.0%	71.6%	71.1%			
12	72.1%	76.5%	84.0%	77.0%			
13	78.2%	77.3%	74.7%	77.6%			
14	77.7%	77.3%	76.0%	77.4%			
15	77.1%	77.3%	74.7%	76.2%			
16	77.7%	80.0%	75.7%	77.8%			
17	77.7%	80.0%	73.3%	77.4%			
18 -	80.0%	74.7%	73.0%	78.2%			
19	78.6%	70.7%	75.7%	77.0%			
20	77.7%	73.3%	82.4%	77.8%			
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Table 4.3: The result of different hidden neuron with percentage of
training, validation, testing and overall accuracy

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4.5 Results Real Time Brainwave Data Using MindLink EEG Sensor

The goal of this thesis is to develop an epilepsy recognition system using artificial neural networks. The Arduino Uno, Bluetooth Module, and MindLink EEG sensor were used to collect data on eight distinct brainwave frequencies: low alpha, high alpha, low beta, high beta, low gamma, high gamma, delta, and theta. The results of the brainwave readings are also visible on the Serial Motor in the Arduino IDE programme, as seen in Figure 4.10 below. To gather real-time data on a subject, just one subject is required, which is a normal healthy individual. The brainwave data is collected and recorded using the Serial Monitor feature of the Arduino IDE software, and then transmitted using the Parallax Data Acquisition tool (PLX-DAQ) version 2.11. It took one hour and eleven minutes and thirty-three seconds to acquire and capture the data for the (4097 x 8) matrix. According to Table , the duration of a brainwave wavelength is between ten and fifteen minutes.

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1/1/10	Send
10:43:04.964 -> LABEI, TIME, DELTA, THETA, LOW ALPHA, HIGH ALPH 10:43:04.964 -> RESETTIMER 10:43:36.403 -> 32805,19950,7982,12314,7075,4365,3420,1458 10:43:37.243 -> 29879,62982,7510,2665,8152,7647,1483,1006 10:43:38.255 -> 62612,8190,4289,5921,2202,3128,761,646 10:43:39.211 -> 40225,16165,2793,3830,1610,1597,224,180 10:43:40.223 -> 29722,32938,12284,4322,2284,3342,891,844 10:43:41.224 -> 57442,26628,8038,38836,25662,4294,1441,1151 10:43:41.224 -> 57442,26628,8038,38836,25662,4294,1441,1151 10:43:42.195 -> 19063,30239,1106,7367,2010,4152,749,882 10:43:43.188 -> 3927,58502,30180,2893,35746,59670,21417,6728 10:43:44.179 -> 12534,56798,7675,10128,7029,10092,3273,1919 10:43:48.204 -> 21106,3974,8896,6302,7401,6462,1655,1887 10:43:49,168 -> 43294,16646,28279,11415,2313,6841,5649,791 10:43:50.165 -> 61864,26175,13987,12621,2903,3911,2108,1973 10:43:51.194 -> 11399,39654,8093,8204,3443,1559,536,363 10:43:52.204 -> 20525,11984,2649,7198,3299,4009,2082,842 10:43:53.161 -> 55043,32400,50832,36270,20751,8280,8954,2113 10:43:54.162 -> 15448,9398,52355,9304,7186,9540,2568,4296 10:43:55.173 -> 4025,38457,15844,7136,25753,9506,1906,1853 10:43:55.174 -> 10023,33571,29086,38890,3064,7229,1949,806 10:43:55.139 -> 50221,46142,54563,6544,28587,10175,2983,2442	A, LOW BETA, HIGH BETA, LON GAMMA, HIGH GAMMA
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Figure 4.10: Data reading display from Serial COM Arduino Uno software

As illustrated in Figure 4.11 below, the baud rate is set to 57600 for both Arduino Coding and recovered interface data in PLX DAQ. The baud rate indicates how data is transmitted over a communication channel. In the context of the serial port, "57600 baud" refers to the serial port's maximum data transfer rate of 57600 bits per second.

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1	TIME	TIMER	DELTA	THETA	LOW ALPHA	HIGH AL PHA	LOW BETA	HIGH BETA	LOW GAMMA	HIGH GAMMA	r.	L IVI	N U	F	Q	-A
2	12:07:08 AM	0 100006	7893	8187	6433	3807	3449	8077	9706	4630						
3	12:07:09 AM	1 100006	8687	17661	453	6055	3906	4551	5017	1672	Open PLX D	DAQ UI				
4	12:07:10 AM	2 100006	7883	10517	8345	4942	2340	7522	5913	4412						
5	12:07:12 AM	3 860016	44877	26117	14021	10160	4372	11801	4961	1932						
6	12:07:12 AM	4.100006	23241	5921	46226	32648	6503	25262	13450	2467		PLX-DAO for Excel "V	ersion 2° by Net^Des	a ×		
7	12:07:13 AM	5.081024	16449	21397	10958	4066	6316	1999	1183	778				1		
8	12:07:14 AM	6.091003	3047	21587	12122	857	3197	2292	1625	1396		Ast Beach	Control	v. 2.11		
9	12:07:15 AM	7.091003	38255	36676	26087	19622	7987	7447	2911	1079		PL V_D00	Custom Check	cbox 1		
10	12:07:16 AM	8.081024	8957	45347	5780	6841	1536	2441	1419	621			Custom Check	cbox 2		
11	12:07:17 AM	9.081024	26348	43641	34067	19180	2816	4353	5496	3046		Settings	Custom Check	cbox 3		
12	12:07:18 AM	10.072020	23586	8245	1711	512	2020	2687	761	1134		Port: 4	Reset on Con	nect		
13	12:07:19 AM	11.079010	26068	21576	36523	17280	20588	6442	8811	4123		Baud: 57600	Reset Timer			
14	12:07:20 AM	12.071010	61622	20181	6855	19661	3733	5344	3076	1238		57000				
15	12:07:21 AM	13.062010	46084	40589	4731	6629	5405	3646	2906	1760		Disconnect	Clear Columns			
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18	12:07:24 AM	16.062010	22744	10021	5796	4340	1951	2150	3043	1441		Sheet name to port	to:	1 1		
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20	12:07:26 AM	18.052000	64361	27856	1798	5219	1989	1801	1929	885						
21	12:07:27 AM	19.052000	23994	12050	2714	1860	554	4697	738	1519		Contro	ller Messages:			
22	12:07:28 AM	20.043030	14131	4365	5794	1223	4037	3652	3067	2049		Accepting	data for Row 199			
23	12:07:29 AM	21.018010	21069	12350	10334	11486	8010	11036	3853	1521		Do not move this wi	ndow around while	logging !		
24	12:07:30 AM	22.013000	28183	10622	20122	15665	9898	2773	2942	1870		rnat mi	int crash txcel!			
25	12:07:31 AM	23.003020	58970	31461	6958	9344	5907	3728	1837	1093						
26	12:07:32 AM	24.013000	34026	50384	3424	3256	5840	5978	2278	1693						
27	12:07:33 AM	24.993010	55059	29099	3630	3690	1427	3715	1050	1554						
28	12:07:34 AM	25.999020	30861	24516	1680	7246	5573	5960	4073	3233						
29	12:07:35 AM	27.000000	14532	5448	9718	8944	1646	2663	1859	1667						
30	12:07:36 AM	27.995030	16817	32038	19423	5307	1596	3312	2555	1076						
31	12:07:37 AM	28.985020	5799	30410	3129	5791	8803	1500	3219	1244						
32	12:07:38 AM	29.985020	35357	50692	10259	8399	2940	14345	2782	2178						
33	12:07:39 AM	30.989010	10151	50117	5674	6996	2853	2889	4042	1798						
34	12:07:40 AM	31.987030	1548	2640	20310	9637	4455	3515	2825	1612						
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Figure 4.11 : Data Reading which display on serial monitor on Arduino Software

4.6 Analysis Using The App Designer in Matlab to Make the GUI

App Designer create a visual components to lay out the design of Graphical User Interface (GUI) and use integrated editor to quickly program its behavior. App Designer integrates the two primary tasks of app building – laying out the visual components of a graphical user interface (GUI) and programming app behavior. It is the recommended environment for building apps in MATLAB. Figure 4.12 show that the GUI of this project.



the waveform of Dataset Z. TEKNIKAL MALAYSIA MELAKA



4.7 Analysis by Testing the Real-Time EGG Brainwave Data.

To test the EEG MindLink Sensor's real-time data, the number of samples required for validation was established after training the EEG dataset using a Cascade -forward Neural Network identification system.

The standard deviation must be computed once again in this testing analysis. The sensor data has previously been classified into eight sub-bands: low alpha, high alpha, low beta, high beta, high gamma, low gamma, delta, and theta. Each sub-band wave obtains a total of (4097 x 8) matrix samples. The sub-band wave data is then partitioned into a (1 x 8)

matrix for the following frequencies: low alpha, high alpha, low beta, high beta, high gamma, low gamma, delta, and theta. As a result, determining the standard deviation for each subband would be much simpler.

After that, the data is uploaded to MATLAB. Thus, the standard deviations for each wave are combined and rearranged until a (8 x 1) matrix is obtained. Finally, the data is recreated using the same neural network as the EEG dataset, a Cascade-forward Neural Network. As is well known, the output that contains values between 1 and 2 is deemed normal, with 1 representing an average human with eyes open and 2 representing a normal individual with eyes closed.

The outcome of this testing analysis is only between numbers 1 and 2 since the data obtained from the volunteer is unique and in normal condition. We do not need to locate epilepsy sufferers since the findings indicate that the categorization is right. Thus, system investigations may be conducted on epileptic patients to yield findings in the range of 3, 4, or 5.

4.8 Discussion

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Development Of Computer Aided Design For EEG Signal Epilepsy Diagnosis Using Artificial Neural Network was successfully developed after so many research, trials and error that occurred during the process of completing it. This thesis required MindLink EEG Sensor to extract real-time raw dataset.

Nonetheless, this MindLink sensor must be configured before being linked to the Bluetooth Module HC-05 and transmitting data to the Arduino IDE. The code for this method is available on the Internet. However, certain modifications must be performed before uploading it to Arduino. Several mistakes occur throughout the data retrieval procedure from the MindLink Sensor, which is addressed in this thesis via error coding in the Arduino IDE. This occurred because the Bluetooth Module HC-05 required disconnecting from the Arduino board in order for the code to be uploaded correctly.

Arduino Uno's pins 0 (RX) and 1 (TX) are shared for serial connection with the computer. Bluetooth connection is required for the sensor. Additionally, these thesis need real-time brainwave data, which is 4097 rows by eight columns (4097 x 8) matrix. The data retrieval process takes one hour and eleven minutes. The data need 4097 samples since the raw EEG dataset from the University of Bonn utilized 4097 samples. After training, these two sets of data are used to determine if the real-time data can identify which set in the dataset it belongs to, namely Set A, Set B, Set C, Set D, or Set E.

Only one subject of a healthy person is utilized in this thesis since it would take more time to collect data from another subject. Additionally, obtaining epilepsy patients when they have a seizure is more difficult and time-consuming. As a result, just a single realtime dataset is required. According to the analytical test findings, the real-time data indicates that the outcomes are 1 and 2. The system is thus right since the healthy dataset is part of Set A and Set B, numbered 1 and 2.

Additionally, having different sample sizes for the input and target data sets can result in an error in MATLAB neural networks data training. In this system, the input target is a (4097 x 500) matrix, and the output target is (5 x 500). However, the EEG dataset is then subjected to DWT, which converts it to sub-band waves, followed by standard deviation. This system is then fed the standard deviation data matrix (8 x 500). Thus, the input and target data may have a different row count, but they must have the exact column count.

The most challenging sections of this thesis are those involving the analysis and testing of real-time brainwave data from an EEG sensor. MATLAB is unable to simulate a neural network using real-time data. This is because the size of the real-time dataset does not match the size of the EEG dataset's input data. This error occurred because the input data is

a matrix of size (8 x 500), but the data for testing analysis is 4097×8 . Additionally, the brainwave data must be comparable in size to the dataset in order to train the neural network using the same neural network.

Thus, to address this issue, each of the eight sub-bands of real-time data is divided into (4097 x 1), and then the standard deviation method is used to obtain a single value for each sub-bands. Following that, all eight standard deviations are collected and imported into Excel, yielding a matrix of (1 x 8). Finally, the test indices can be implemented using MATLAB code and output only 1 and 2. As a result, the output data is classified as belonging to Set A and Set B, which are composed of normal and healthy subjects.


CHAPTER 5

CONCLUSION

5.1 Overview

Chapter 5 concludes. This chapter will discuss the project's completion and also provide some recommendations. As summarized in this chapter, the project is complete, and the chapter concludes with a proposal on how to improve a system's performance based on the data.

5.2 Conclusion

In conclusion, this thesis accomplished all of its objectives. The first aim is achieved by constructing Computer Aided Design for EEG signals epilepsy diagnosis using Artificial Neural Network. This thesis proposes classifying EEG data into five categories using a Cascade-forward Neural Network. Additionally, depending on the research results, the number of neurons may be changed to achieve the highest level of accuracy. As a result, hidden neuron fifteen is picked as the classifier with the most outstanding overall accuracy of 76.2%. The second aim is to determine if the system can distinguish between healthy individuals and people living with epilepsy by analyzing its EEG parameter. The raw dataset is then transformed using the Discrete Wavelet Transform (DWT) to determine its standard deviation, allowing it to be utilized as input data for the following procedure. The dataset is capable of training and evaluating its output results by using a target dataset of the (5 x 500) matrix and input data (x) of the (8 x 500) matrix. Thus, data analysis can categorize healthy individuals and epilepsy sufferers based on the output obtained. The third aim, which may be accomplished, is to evaluate real-time brainwave data obtained from an EEG sensor using an Artificial Neural Network (ANN) to a dataset developed using the University of Bonn's

EEG dataset. The input and goal data are loaded into MATLAB's Neural Network Toolbox. Thus, the actual raw data collected from the University of Bonn and the raw data obtained from the EEG sensor are compared to determine which set corresponds to a healthy individual and corresponds to a person diagnosed with epilepsy. Finally, testing real-time data from an EEG sensor with a trained Artificial Neural Network (ANN) is successful because real-time data can be implemented using the same raw dataset processing method.

5.3 Future Work and Recommendation

In this future work of this thesis may train EEG data with different recognition approaches or algorithms to assess their accuracy for future investigations. Furthermore, this idea may be implemented by using an Artificial Immune Network (AIS). In terms of essential components, the Artificial Immune Network is equivalent to the neural network, but it has a class of computer-smart, rule-based machine learning systems inspired by the concepts and processes of the vertebrate immune system. Typically, the algorithms are modelled after the immune system's learning and memory capabilities in problem-solving. Artificial Immune Systems (AIS) were motivated by immunology theory and observable immune processes, ideas, and models, then applied to problem resolution. Furthermore, this study thesis may be used to determine whether data belongs to a normal person or patients with epilepsy by utilizing android applications linked to brainwave sensors to monitor when epilepsy occurs and provide notifications to the person in charge. Furthermore, this thesis research may be enhanced by using the IoT framework to communicate EEG sensor realtime brainwave data to the Cloud through the IoT platform. ThinkSpeak might conduct the research using various EEG devices to compare real-time brainwave data. ThingSpeak displays the data the computers have sent to ThingSpeak in real-time. The data obtained may be reviewed and understood utilizing an online interface to run MATLAB code in ThingSpeak. ThingSpeak may be used for prototyping and proof of concept IoT devices that need analytics. Finally, instead of utilizing the Arduino IDE and verifying the EEG sensor to gather diverse EEG signal data from multiple persons, this project expressly utilizes MATLAB to collect the EEG raw data signal from the EEG sensor.

5.4 **Project Potential**

Diagnosis of epilepsy patients is a challenging process that requires constant monitoring of a patient, which is time demanding and necessitates a lot of time to collect epileptic data with clinical information. With an ANN as a classifier to categorize epilepsy individuals during seizures, an EEG gadget may simplify a challenging process. As a result, this thesis gives crucial diagnostic information that medical researchers, such as physicians, may use to study and treat future epilepsy sufferers. Furthermore, seizure etiology results in various medications, which may aid in the management of future epilepsy.

Numerous domains may be implemented in this thesis, including medical fields, biological fields, physician studies, researchers, etc. This will enable them to study epilepsy and develop a better version of the Epilepsy Recognition System by incorporating and researching data from this thesis. As a result, superior performance of technology may be created. For example, this thesis might assist a doctor in confirming, detecting, or even studying a person suffering from an epileptic seizure with accuracy and precision in terms of the information presented. As a result, further therapy or surgery might be performed without hesitancy or lack of knowledge about epilepsy. Furthermore, additional medicine and treatment may spare an individual's epileptic sufferers' lives.

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APPENDICES

Appendix 1: Confusion Matrix Changes 10 until 15 Hidden Neuron in Cascade Forward Neural Network.



12 Hidden Neuron





Appendix 2 : Arduino Coding

```
+
 New_Coding§
int BAUDRATE = 57600;
// checksum variables
byte payloadChecksum = 0;
byte CalculatedChecksum;
byte checksum = 0; //data type byte stores an 8-bit unsigned number, from 0 to 255
int payloadLength = 0;
byte payloadData[64] = {0};
byte poorQuality = 0;
byte attention = 0;
byte meditation = 0;
// system variables
long lastReceivedPacket = 0;
boolean bigPacket = false;
boolean brainwave = false;
void setup() {
                         ALAYS/4
 Serial.begin(57600); // Bluetooth
                                      14.
 delay(500);
 Serial.begin(57600); //9600 // software serial
 delav(500);
 Serial.println("CLEARDATA");
 Serial.println("LABEL, TIME, TIMER, DELTA, THETA, LOW ALPHA, HIGH ALPHA, LOW BETA, HIGH BETA, LOW GAMMA, HIGH GAMMA");
 Serial.println("RESETTIMER");
/// Serial.print("Communicating...");
1
byte ReadOneByte() {
  int ByteRead;
  // Wait until there is data
 while(!Serial.available());
                                                                                     ه درو .
 //Get the number of bytes (characters) available for reading from the serial port. [/
 //This is data that's already arrived and stored in the serial receive buffer (which holds 64 bytes)
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```

```
ByteRead = Serial.read();
  return ByteRead; // read incoming serial data
  }
unsigned int delta_wave = 0;
unsigned int theta wave = 0;
unsigned int low_alpha_wave = 0;
unsigned int high alpha wave = 0;
unsigned int low beta wave = 0;
unsigned int high beta wave = 0;
unsigned int low gamma wave = 0;
unsigned int high gamma wave = 0;
void read waves(int i) {
 delta wave = read 3byte int(i);
  i+=3;
  theta wave = read 3byte int(i);
  i+=3;
  low_alpha_wave = read_3byte_int(i);
  i+=3;
 i+=3;
high_alpha_wave = read_3byte_int(i);
  i+=3;
  low beta wave = read 3byte int(i);
  i+=3;
 high_beta_wave = read_3byte_int(i);
  i+=3;
 low_gamma_wave = read_3byte_int(i);
                AIWN
  i+=3;
 mid_gamma_wave = read_3byte_int(i);
           ملسسا ملاك
}
int read 3byte int(int i) {
 return ((payloadData[i] << 16) + (payloadData[i+1] << 8) + payloadData[i+2]);
1
void loop() {
```

```
// Look for sync bytes
 // Byte order: 0xAA, 0xAA, payloadLength, payloadData,
  // Checksum (sum all the bytes of payload, take lowest 8 bits, then bit inverse on lowest
if(ReadOneByte() == 0xAA) {
if(ReadOneByte() == 0xAA) {
payloadLength = ReadOneByte();
if (payloadLength > 169) //Payload length can not be greater than 169
return;
payloadChecksum = 0;
     for(int i = 0; i < payloadLength; i++) {</pre>
                                                       //loop until payload length is complete
     payloadData[i] = ReadOneByte();
                                                        //Read payload
     payloadChecksum += payloadData[i];
   }
                                                       //Read checksum byte from stream
   checksum = ReadOneByte();
   payloadChecksum = 255 - payloadChecksum;
                                                       //Take ones compliment of generated checksum
    if(checksum == payloadChecksum) {
     poorQuality = 200;
     attention = 0;
     meditation = 0;
}
   brainwave = false;
   for(int i = 0; i < payloadLength; i++) { // Parse the payload</pre>
       switch (payloadData[i]) {
       case 02:
         i++;
         poorQuality = payloadData[i];
         bigPacket = true;
         break;
     case 04: 斗
         i++;
         attention = payloadData[i];
         break;
     case 05:
         i++;
         meditation = payloadData[i];
                   AINO
         break;
      case 0x80.
                                                 • 2
              5 N
             UNIVERSITI TEKNIKAL MALAYSIA MELAKA
```

```
case 0x80:
   i = i + 3;
   break;
case 0x83:
                                    // ASIC EEG POWER INT
  i++;
  brainwave = true;
  byte vlen = payloadData[i];
  // Serial.print(vlen, DEC);
  /// Serial.println();
    read waves(i+1);
    i += vlen; // i = i + vlen
    break;
}
                                   // switch
}
                                   // for loop
if(bigPacket) {
  if(poorQuality == 0){
  }
                                   // do nothing
  else{
  }
 }
    if (brainwave ss attention > 0 ss attention < 100) {
    Serial.print("DATA, TIME, TIMER, ");
     Serial.print(delta_wave, DEC);
      Serial.print(",");
    Serial.print(theta_wave, DEC);
      Serial.print(",");
    Serial.print(low_alpha_wave, DEC);
      Serial.print(",");
    Serial.print(high_alpha_wave, DEC);
      Serial.print(",");
    Serial.print(low_beta_wave, DEC);
      Serial print (",");
    Serial.print(high_beta_wave, DEC);
      INTO TEKNIKAL MALAYSIA MELAKA
 }
}
}
```

}

Appendix 3 : Coding Training Cascade Neural Network

```
x = x;
t = t;
trainFcn = 'trainscg'; % Scaled conjugate gradient backpropagation.
% Create a Pattern Recognition Network
hiddenLayerSize = 15;
net = cascadeforwardnet(hiddenLayerSize, trainFcn);
% Choose Input and Output Pre/Post-Processing Functions
net.input.processFcns = { 'removeconstantrows', 'mapminmax' };
% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivision
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = { 'plotperform', 'plottrainstate', 'ploterrhist', 'plotconfusion',
'plotroc'};
% Train the Network
[net,tr] = train(net,x,t);
% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform (net,t,y)
tind = vec2ind(t);
yind = vec2ind(y);
percentErrors = sum(tind ~= yind)/numel(tind);
% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1}; (AL_MALAYSIA MEL
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net, trainTargets, y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)
% View the Network
view(net)
if (false)
    genFunction(net, 'myNeuralNetworkFunction');
    y = myNeuralNetworkFunction(x);
end
if (false)
    genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    y = myNeuralNetworkFunction(x);
end
if (false)
   gensim(net);
end
```