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**DEVELOPMENT OF ATRIAL FIBRILLATION
DETECTION ALGORITHM BASED ON
EXTRACTED ECG FEATURES AND HYBRID
MULTILAYER PERCEPTRON NETWORK**

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**MASTER OF SCIENCE
(ELECTRICAL & ELECTRONIC ENGINEERING)**

**UNIVERSITI PERTAHANAN NASIONAL
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2019

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ALGORITHM BASED ON EXTRACTED ECG FEATURES AND
HYBRID MULTILAYER PERCEPTRON NETWORK**

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2019

ABSTRACT

Heart is made up by bundles of cardiac muscle. It has a pacemaker that generate electrical signal to escalate muscle for contraction and relax. However, when electrical signal undergoes internal or external disturbance, it may lead to cardiac abnormality. Cardiac abnormality refers to the capricious electrical activity of the cardiac muscles. It sometimes does not exhibit any symptom as it's still in the early stage or phase one, but which may lead to sudden end due to the heart cease functioning. In order to reduce the sudden death episode, a lot of research has been done to give early warning to the patient. In this research, a new approach has been developed which capable to detect atrial fibrillation (AF) activity based on electrocardiogram (ECG) signal using the Hybrid Multilayer Perceptron (HMLP) neural network. An intelligent system is designed to solve the problem at the earliest stage. A dataset of ECG signal is taken from the MIT-BIH database used in the research to train and generalize the HMLP network, as well as to test the network performance. Continuous ECG signal dataset needs to be segmented into a complex contains P, QRS and T waves, since information of cardiac abnormality depends on those waves. In this research, the R to R peak interval (RRI) is used to segment the ECG signal in a complex form. At this stage, rectangular pulses are overlapping with a complex ECG then the interception points are taken as fiducial point of the complex. The fiducial point contains the amplitude and duration at each intercept point. Furthermore, the amplitudes and durations are considered as the input vector to HMLP network. The HMLP network is trained by a number of training algorithms which are Levenberg Marquardt (LM), Bayesian Regularization (BR), Back- Propagation (BP) and Resilient (R). Then, it will come out with the prediction performance, including accuracy, sensitivity and specificity performances. The performances are divided into training and testing before overall performance is taken as the average (after 5 or more iterations). In the research, the performance of the classifier is measured by the mean square error (MSE) and regression (Reg) at each iteration. The lowest MSE performance and most approaching to 1 of regression performance may improve accuracy of the network. The Graphical User Interface (GUI) is designed to represent a whole research project with prediction performance of 98.61% accuracy.

ABSTRAK

Jantung terdiri daripada otot-otot kardiak. Ia mempunyai penentu rentak yang menjana isyarat elektrik untuk otot pengecutan dan berehat. Walau bagaimanapun, apabila isyarat elektrik menghadapi gangguan dalaman atau luaran, ia mungkin menyebabkan ketidakstabilan jantung. Ketidakstabilan jantung merujuk kepada aktiviti elektrik yang tidak menentu pada otot jantung. Ia selalunya tidak menunjukkan sebarang gejala seperti yang masih dalam peringkat awal atau peringkat satu, tetapi boleh mengakibatkan kematian secara tiba-tiba akibat jantung terhenti berfungsi. Untuk mengurangkan episod kematian secara tiba-tiba, banyak penyelidikan telah dilakukan untuk memberi amaran awal kepada pesakit. Dalam kajian ini, pendekatan baru telah dibangunkan untuk mengesan aktiviti atrial fibrillation (AF) berdasarkan isyarat elektrokardiogram (ECG) menggunakan rangkaian neural Multilayer Perceptron Berhibrid (HMLP). Satu sistem pintar direka untuk menyelesaikan masalah di peringkat awal. Dataset isyarat ECG diambil dari pangkalan data MIT-BIH yang digunakan dalam penyelidikan untuk melatih dan mengitlakkan rangkaian HMLP, serta untuk menguji prestasi rangkaian tersebut. Dataset isyarat ECG yang berterusan perlu disegmenkan kepada satu kompleks yang mengandungi gelombang P, QRS dan T yang lengkap kerana maklumat abnormaliti jantung bergantung kepada gelombang berkenaan. Dalam kajian ini, selang puncak R hingga R (RRI) digunakan untuk membentuk isyarat ECG dalam bentuk yang rumit. Pada peringkat ini, denyutan segiempat sama ditindihkan bersama kompleks ECG maka, setiap titik pemintasan diambil sebagai titik fisidual kompleks. Titik fisidual mengandungi amplitud dan durasi pada setiap titik pemintasan. Tambahan pula, amplitud dan durasi diambil sebagai vektor masukan kepada rangkaian HMLP. Rangkaian HMLP dilatih oleh beberapa algoritma latihan iaitu Levenberg Marquardt (LM), Bayesian Regularization (BR), Back-Propagation (BP) dan Resilient (R). Kemudian, ianya memberikan prestasi ramalan termasuklah keputusan ketepatan, sensitiviti dan kekhususan. Prestasi dibahagikan kepada latihan dan ujian sebelum prestasi keseluruhan diambil sebagai purata (selepas 5 atau lebih lelaran). Dalam penyelidikan ini, prestasi pengelasan diukur menggunakan min kuasa dua terkecil (MSE) dan regresi (Reg) pada setiap lelaran. Prestasi MSE terendah dan prestasi regrasi paling hampir dengan 1 dapat

meningkatkan ketepatan rangkaian. Antaramuka Pengguna (GUI) direkabentuk untuk mewakili keseluruhan projek penyelidikan dengan prestasi ramalan ketepatan 98.61%.

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TABLE OF CONTENTS

ABSTRACT	ii
ABSTRAK	iii
ACKNOWLEDGEMENTS	v
APPROVAL – EXAMINATION COMMITTEE	vi
APPROVAL – SUPERVISORY COMMITTEE	vii
DECLARATION OF THESIS	viii
TABLE OF CONTENTS	ix
LIST OF TABLES	xii
LIST OF FIGURES	xiii
LIST OF ABBREVIATIONS	xix
CHAPTER 1	1
INTRODUCTION	1
1.1 Overview	1
1.2 Problem Statement	2
1.3 Objective	3
1.4 Research Scope	3
1.5 Thesis Outline	4
CHAPTER 2	5
LITERATURE REVIEW	5
2.1 ECG Acquisition	5
2.2 The Cardiac Muscle	5
2.3 Basic of the ECG	9
2.3.1 ECG Signal Morphology	9
2.3.2 Fiducial Point Detection	11
2.3.3 ECG Lead Configuration	12
2.4 Holter Monitor	14
2.4.1 History of Development	15
2.4.2 Components of Holter Monitor	16
2.5 Atrial Fibrillation (AF)	19
2.5.1 AF Diagnosis	19
2.5.2 ECG Tracing	21

2.6	Neural Network (ANN)	22
2.6.1	Biological Neuron Networks	22
2.6.2	Artificial Neural Networks	23
2.7	Activation Functions of ANN	29
2.7.1	Learning Process	31
2.7.2	Application of ANN	32
2.8	Features Extraction	33
2.8.1	Characteristic Based Feature	33
2.8.2	Waveform Based Feature	35
2.8.3	AF Detection Algorithms	37
2.9	Characteristic and Architecture of Multilayer Perceptron Network	43
2.9.1	Weighting Network Connections	45
2.9.2	Back Propagation (BP) Algorithm	45
2.9.3	Levenberg-Marquardt (LM) Algorithm	47
2.9.4	Bayesian Regularization (BR) Algorithm	49
2.9.5	Resilient (R) Algorithm	52
2.10	Conclusion	52
	CHAPTER 3	53
	METHODOLOGY	53
3.1	Introduction	53
3.2	Activation Function	55
3.2.1	Role of Activation Function	56
3.2.2	Type of Activation Functions	56
3.3	Rectangular Pulse (RP) Feature Extraction Process	61
3.4	Mean Square Error (MSE)	62
3.5	ECG Pattern Recognition using Neural Network	63
3.5.1	Hybrid Multilayer Perceptron (HMLP)	64
3.5.2	The Structures and Architecture of HMLP	64
3.6	Conclusion	68
	CHAPTER 4	69
	RESULTS AND ANALYSIS	69
4.1	Introduction	69
4.2	Diagnostic performance analysis	69
4.3	Graphical User Interface (GUI)	110
4.3.1	Desinged GUI	110

4.4	Conclusion	115
	CHAPTER 5	116
	CONCLUSION AND RECOMMENDATIONS	116
5.1	Conclusion	116
5.2	Future Work and Recommendations	117
	REFERENCES	119
	BIODATA OF STUDENT	127

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 2. 1	ECG signal complex	10
Table 2. 2	The placement of 10 leads in the standard 12 Leads configuration.	13
Table 2. 3	The Einthoven's triangle configuration setting at the limb	14
Table 2. 4	Summary of waveform-based feature detection techniques	35
Table 2. 5	The comparative results of AF classification	38
Table 4. 1	Extracted ECG signal using Pulse Rectangular Domain	70
Table 4. 2	The HMLP classification performance by using extracted features from RRI morphology as the input vector	72
Table 4. 3	Accuracy performance of MLP network	87
Table 4. 4	MSE performance of MLP network	89
Table 4. 5	Accuracy performance of HMLP network	105
Table 4. 6	MSE performance of HMLP network	106
Table 4. 7	Overall Accuracy Performance of MLP and HMLP Network	107
Table 4. 8	Overall MSE Performance of MLP and HMLP Network	108

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2. 1	A closer look of Human Heart	6
Figure 2. 2	The cardiac cycle	7
Figure 2. 3	The control of heart rhythm	8
Figure 2. 4	ECG signal complex	10
Figure 2. 5	The fiducial points taken from a complex ECG signal	12
Figure 2. 6	The placement of 10 leads in the standard 12 Leads configuration	13
Figure 2. 7	The Einthoven's triangle configuration setting at the limb	14
Figure 2. 8	The Holter monitoring system	15
Figure 2. 9	The Holter system used to record ECG signals	17
Figure 2. 10	Holter monitor in use	17
Figure 2. 11	A screenshot of the Holter ECG	18
Figure 2. 12	The abnormal ECG signal in the heart	20
Figure 2. 13	The normal ECG signal in the heart	21
Figure 2. 14	Normal Sinus Rhythm	21
Figure 2. 15	Sinus Bradycardia	22
Figure 2. 16	Sinus Tachycardia	22
Figure 2. 17	Diagram of biological neurons	23
Figure 2. 18	Modeling of non-linear neurons	25
Figure 2. 19	Feed forward neural network	27
Figure 2. 20	Back Propagation Neural Network	27
Figure 2. 21	The linear activation function	30
Figure 2. 22	The Sigmoid Function graph	30
Figure 2. 23	PAR pulse generation	37
Figure 2. 24	The pattern recognition unit	43
Figure 2. 25	Architecture MLP network	44
Figure 3. 1	Flow Chart	54
Figure 3. 2	Binary Step Function	57
Figure 3. 3	Linear activation Function	58
Figure 3. 4	Logsig Activation Function	59

Figure 3. 5	Tansig Activation Function	60
Figure 3. 6	Rectified Linear Unit	60
Figure 3. 7	The flowchart of the RP based feature extraction process	61
Figure 3. 8	Nonlinear neuron model	63
Figure 3. 9	The MLP network	65
Figure 3. 10	Activation Curve of Sigmoid Function	66
Figure 3. 11	The HMLP network	67
Figure 4. 1	ECG Feature extraction based on RRI (AF signal)	71
Figure 4. 2	Feature extraction based on RRI (Normal signal)	71
Figure 4. 3	Training performance of MLP network trained by BP training algorithm and activated by Tansig activation function	73
Figure 4. 4	Testing performance of MLP network trained by BP training algorithm and activated by Tansig activation function	73
Figure 4. 5	Overall performance of MLP network trained by BP training algorithm and activated by Tansig activation function	73
Figure 4. 6	Training performance of MLP network trained by LM training algorithm and activated by Tansig activation function	74
Figure 4. 7	Testing performance of MLP network trained by LM training algorithm and activated by Tansig activation function	74
Figure 4. 8	Overall performance of MLP network trained by LM training algorithm and activated by Tansig activation function	74
Figure 4. 9	Training performance of MLP network trained by BR training algorithm and activated by Tansig activation function	75
Figure 4. 10	Testing performance of MLP network trained by BR training algorithm and activated by Tansig activation function	76
Figure 4. 11	Overall performance of MLP network trained by BR training algorithm and activated by Tansig activation function	76
Figure 4. 12	Training performance of MLP network trained by R training algorithm and activated by Tansig activation function	76
Figure 4. 13	Testing performance of MLP network trained by R training algorithm and activated by Tansig activation function	77
Figure 4. 14	Overall performance of MLP network trained by R training algorithm and activated by Tansig activation function	77

Figure 4. 15	Training performance of MLP network trained by BP training algorithm and activated by Logsig activation function	78
Figure 4. 16	Testing performance of MLP network trained by BP training algorithm and activated by Logsig activation function	78
Figure 4. 17	Overall performance of MLP network trained by BP training algorithm and activated by Logsig activation function	78
Figure 4. 18	Training performance of MLP network trained by LM training algorithm and activated by Logsig activation function	79
Figure 4. 19	Testing performance of MLP network trained by LM training algorithm and activated by Logsig activation function	79
Figure 4. 20	Overall performance of MLP network trained by LM training algorithm and activated by Logsig activation function	79
Figure 4. 21	Training performance of MLP network trained by BR training algorithm and activated by Logsig activation function	80
Figure 4. 22	Testing performance of MLP network trained by BR training algorithm and activated by Logsig activation function	80
Figure 4. 23	Overall performance of MLP network trained by BR training algorithm and activated by Logsig activation function	80
Figure 4. 24	Training performance of MLP network trained by R training algorithm and activated by Logsig activation function	81
Figure 4. 25	Testing performance of MLP network trained by R training algorithm and activated by Logsig activation function	81
Figure 4. 26	Overall performance of MLP network trained by R training algorithm and activated by Logsig activation function	81
Figure 4. 27	Training performance of MLP network trained by BP training algorithm and activated by Purelin activation function	82
Figure 4. 28	Testing performance of MLP network trained by BP training algorithm and activated by Purelin activation function	83
Figure 4. 29	Overall performance of MLP network trained by BP training algorithm and activated by Purelin activation function	83
Figure 4. 30	Training performance of MLP network trained by LM training algorithm and activated by Purelin activation function	83
Figure 4. 31	Testing performance of MLP network trained by LM training algorithm and activated by Purelin activation function	84

Figure 4. 32	Overall performance of MLP network trained by LM training algorithm and activated by Purelin activation function	84
Figure 4. 33	Training performance of MLP network trained by BR training algorithm and activated by Purelin activation function	85
Figure 4. 34	Testing performance of MLP network trained by BR training algorithm and activated by Purelin activation function	85
Figure 4. 35	Overall performance of MLP network trained by BR training algorithm and activated by Purelin activation function	86
Figure 4. 36	Training performance of MLP network trained by R training algorithm and activated by Purelin activation function	86
Figure 4. 37	Testing performance of MLP network trained by R training algorithm and activated by Purelin activation function	86
Figure 4. 38	Overall performance of MLP network trained by R training algorithm and activated by Purelin activation function	87
Figure 4. 39	Regression performance of MLP network	88
Figure 4. 40	MSE performance of MLP network	89
Figure 4. 41	Training performance of HMLP network trained by BP training algorithm and activated by Tansig activation function	90
Figure 4. 42	Testing performance of HMLP network trained by BP training algorithm and activated by Tansig activation function	90
Figure 4. 43	Overall performance of HMLP network trained by BP training algorithm and activated by Tansig activation function	91
Figure 4. 44	Training performance of HMLP network trained by LM training algorithm and activated by Tansig activation function	91
Figure 4. 45	Testing performance of HMLP network trained by LM training algorithm and activated by Tansig activation function	91
Figure 4. 46	Overall performance of HMLP network trained by LM training algorithm and activated by Tansig activation function	92
Figure 4. 47	Training performance of HMLP network trained by BR training algorithm and activated by Tansig activation function	93
Figure 4. 48	Testing performance of HMLP network trained by BR training algorithm and activated by Tansig activation function	93
Figure 4. 49	Overall performance of HMLP network trained by BR training algorithm and activated by Tansig activation function	93

Figure 4. 50	Training performance of HMLP network trained by R training algorithm and activated by Tansig activation function	94
Figure 4. 51	Testing performance of HMLP network trained by R training algorithm and activated by Tansig activation function	94
Figure 4. 52	Overall performance of HMLP network trained by R training algorithm and activated by Tansig activation function	94
Figure 4. 53	Training performance of HMLP network trained by BP training algorithm and activated by Logsig activation function	95
Figure 4. 54	Testing performance of HMLP network trained by BP training algorithm and activated by Logsig activation function	96
Figure 4. 55	Overall performance of HMLP network trained by BP training algorithm and activated by Logsig activation function	96
Figure 4. 56	Training performance of HMLP network trained by LM training algorithm and activated by Logsig activation function	96
Figure 4. 57	Testing performance of HMLP network trained by LM training algorithm and activated by Logsig activation function	97
Figure 4. 58	Overall performance of HMLP network trained by LM training algorithm and activated by Logsig activation function	97
Figure 4. 59	Training performance of HMLP network trained by BR training algorithm and activated by Logsig activation function	98
Figure 4. 60	Testing performance of HMLP network trained by BR training algorithm and activated by Logsig activation function	98
Figure 4. 61	Overall performance of HMLP network trained by BR training algorithm and activated by Logsig activation function	99
Figure 4. 62	Training performance of HMLP network trained by R training algorithm and activated by Logsig activation function	99
Figure 4. 63	Testing performance of HMLP network trained by R training algorithm and activated by Logsig activation function	99
Figure 4. 64	Overall performance of HMLP network trained by R training algorithm and activated by Logsig activation function	100
Figure 4. 65	Training performance of HMLP network trained by BP training algorithm and activated by Purelin activation function	101
Figure 4. 66	Testing performance of HMLP network trained by BP training algorithm and activated by Purelin activation function	101

Figure 4. 67	Overall performance of HMLP network trained by BP training algorithm and activated by Purelin activation function	101
Figure 4. 68	Training performance of HMLP network trained by LM training algorithm and activated by Purelin activation function	102
Figure 4. 69	Testing performance of HMLP network trained by LM training algorithm and activated by Purelin activation function	102
Figure 4. 70	Overall performance of HMLP network trained by LM training algorithm and activated by Purelin activation function	102
Figure 4. 71	Training performance of HMLP network trained by BR training algorithm and activated by Purelin activation function	103
Figure 4. 72	Testing performance of HMLP network trained by BR training algorithm and activated by Purelin activation function	103
Figure 4. 73	Overall performance of HMLP network trained by BR training algorithm and activated by Purelin activation function	103
Figure 4. 74	Training performance of HMLP network trained by R training algorithm and activated by Purelin activation function	104
Figure 4. 75	Testing performance of HMLP network trained by R training algorithm and activated by Purelin activation function	104
Figure 4. 76	Overall performance of HMLP network trained by R training algorithm and activated by Purelin activation function	104
Figure 4. 77	Regression performance HMLP network	105
Figure 4. 78	MSE performance of HMLP network	106
Figure 4. 79	Regression Performance of MLP and HMLP Network	107
Figure 4. 80	Regression Performance of Neural Network	109
Figure 4. 81	Graphical User Interface (GUI)	110
Figure 4. 82	GUI ECG sample selection	111
Figure 4. 83	Complete ECG signal sample	111
Figure 4. 84	Segmentation of ECG signal using RRI morphology	112
Figure 4. 85	ECG signal trimmed by segmentation selection	112
Figure 4. 86	Interception data seven features	113
Figure 4. 87	Normal ECG signal	113
Figure 4. 88	AF ECG signal	114

LIST OF ABBREVIATIONS

AV	Atrioventricular
SA	Sinoatrial
ECG	Electrocardiogram
MLP	Multilayer Perceptron
HMLP	Hybrid Multilayer Perceptron
BP	Backpropagation
LM	Levenberg-Marquardt
BR	Bayesian Regularization
R	Resilient
AI	Artificial Intelligent
ANN	Artificial Neural Network
MSE	Mean square Error
LDL	Low density lipoprotein
HDL	High density lipoprotein
CPR	Cardiopulmonary resuscitation
MIT-BIH	Massachusetts Institute of Technology Beth Israel Hospital
RPD	Rectangular Pulse Domain

CHAPTER 1

INTRODUCTION

1.1 Overview

The heart is an important organ in a human body, made up of cardiac muscle and it is myogenic which contracts without any signal from the nervous system. Unlike other organs in the human body, the nervous system will send an impulse that generates from our brain; Medulla oblongata but in heart pacemaker will generate waves of signal to contract and delay at the AV node. Then, the signal is given to the heart apex and spread throughout the ventricles. It is a process of the heart to pump oxygenated blood to whole of the body. Nevertheless, this organ still has its failure or abnormal activity due to certain causes. Cardiac abnormality will be occurred as the oxygenated blood or deoxygenated blood are failed pump to whole body at the normal heartbeat. This will be happening when a blood clot is blocking the artery, which are connected to the heart. The presence of blood clot will make the artery become narrow and disturbed the transport system in a human's body. In short time, the heart will become weak, and oxygenated blood pumped to whole body will be less than deoxygenated blood, causes cells in body lack of oxygen. This will contribute to heart attack.

Atrial fibrillation could be detected by using the electrocardiogram (ECG). The ECG is a test to show the electrical system in the heart working. During an ECG,

electrical leads placed on the chest, arms and legs. These leads detect small electrical signals and tracing on graph paper to illustrate the electrical signals throughout the cardiac muscle. Atrial fibrillation can be detected as the electrical signal illustrated is different from the normal one.

The data from the ECG will be extracted to detect the atrial fibrillation by using Hybrid Multilayer Perception (HMLP) neural network technique. The P, QRS and T peak amplitude will show the abnormality of the heart. A HMLP network consists of multiple layers with each layer are fully connected to each one. This project will train the HMLP neural network using learning algorithm to detect any abnormal activity of cardiac muscle by using P, Q, R, S and T amplitude and duration as the input parameter.

1.2 Problem Statement

The coronary atrial fibrillation or cardiovascular disease can be detected with the aid of the use of ECG test. By placing electrical leads to specific places on the body, an electrical signal that generated by the heart can be measured and recorded by the Holter monitor. ECG consists of P, QRS and T waves. Any abnormal or changes of these waves and segments doubtlessly display that the affected person may additionally have a coronary heart problem. However, an ECG signal may not show the patient has a heart disease, even though there is a serious heart problem. This project is to determine the atrial fibrillation activity by extracting features such as P-wave, QRS- waves and T- wave from the ECG signal to be used as input parameters for the HMLP network.

In this study, the duration and amplitude of the signal are put as high priority and ignored the other information. Most of ECG data are taken from the stationary patient (at rest) or while performing a constant movement (i.e. While on the treadmill with constant acceleration). ECG data collection on the non-stationary patient is performed at a minimum frequency whilst overlooks the high mortality rate during having sport or active activities. At this point, we will investigate best technique to extract the ECG features and try to solve the non-stationary issue. A lot of classifiers

are available to be used in the ECG pattern recognition process. The capability of classifiers to give high accuracy depends heavily on how the classifier is trained. The matched selection of the classifier structure and training algorithm allow good classification results to be produced. The complexity and stability of input parameter given also contributed to the performance of the classifier. In this research, we will try to improve the classification accuracy by doing some modification on the current neural network.

1.3 Objective

The objective of this project are:

1. To carry the performance analysis for training algorithm to train the HMLP network.
2. To determine the suitable ECG extraction technique for feature extraction as the input parameter for neural network.
3. To develop algorithm for detection of atrial fibrillation (AF) by using HMLP neural network.

1.4 Research Scope

The main of these researches is to get features extracted from the ECG signal. The noiseless ECG signals are taken from the MIT-BIH database. The data from normal sinus rhythm signal and Atrial Fibrillation (AF) signal make as a training and testing data of this research. Regardless of the noise, ECG signal taken from the MIT-BIH are clean signal.

The artificial intelligence will be basic for generating ECG features. Therefore, HMLP network, which is the improvement of MLP network is used as virtual brain. To develop the network, a few training algorithms undergoes an analysis process to get optimum accuracy. The Bayesian Regularization (BR), Levenberg-Marquardt (LM), Resilient (R) and Backpropagation (BP) act as the training algorithm to train the HMLP network. On the other hand, activation function is the other element that is involved in this network which will activate the network. The most efficient activation

function must be examined to be use of the network, which will be utilized for the growth of the research using MATLAB Toolbox.

1.5 Thesis Outline

The literature review described the structure and working principle of the heart. Then, continues by explanation of electrical signal of the heart itself which also known as electrocardiogram (ECG). The structure and features of these ECG signal explained as it have complex features that need to study. Finally, Artificial Intelligent (AI), which included Artificial Neural Network (ANN), which consist neural network structures such as Multilayer Perception (MLP), Hybrid Multilayer Perception (HMLP), and Mean Square Error (MSE). This chapter also explained a simple introduction about MLP and HMLP, including the design and architecture and equation.

Chapter 3 is more focus on the methodology of this project. A brief introduction and details about HMLP are explained, including the structure, equations, previous study on this field, and the training algorithm for this HMLP network which include the activation functions. It also explained how the input vector from the ECG signal is inserted into the network and how the performance is indicated.

Chapter 4 is the most necessary part of this thesis, which are analysis and result of this research. It consists of the application of Graphical User Interface (GUI) in detecting cardiac abnormality by inserting ECG data, the diagnostic performance analysis for both training and testing phase, and the overall performance of the HMLP Network. This chapter also incorporates a comparison of performance analysis between training and testing stage.

Finally, the overall discussion about the conclusion of this project. Some recommendations are also has been discussed in the future work of this project.

CHAPTER 2

LITERATURE REVIEW

2.1 ECG Acquisition

AF is an abnormality of cardiac rhythm, detected by ECG. The cardiac structure, anatomy and physiology, and associated abnormalities have to be understood before the arising of AF can be detected. Detailed explanation of electrocardiography and the use of the ECG in detecting and diagnosing cardiac rhythm abnormalities are present. The use of the Holter monitor allows continuous detection and recording of cardiac rhythm for several days. A review of Holter monitor development and its role in medical practice today is furnished. The latest technology used in the development of the Holter monitor in accordance with present modernization is also discussed.

2.2 The Cardiac Muscle

Located behind the sternum (breast bone), the human heart is about the size of a clenched fist and consists mostly of cardiac muscle. The two atria have relatively thin walls and serve as collection chambers for blood returning to the heart from the lungs or other body tissues. Much of the blood that enters the atria flows into the ventricles while all heart chambers are relaxed. The remainder is transferred by contraction of the atria before the ventricle begins to contract. The ventricles have thicker walls and contract much more forceful than the atria- especially the left ventricle, which pumps blood to all body organs through the systemic circuit.