Algorithms design for improving homecare using Electrocardiogram (ECG) signals and Internet of Things (IoT)

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Algorithms design for improving homecare using Electrocardiogram (ECG) signals and Internet of Things (IoT)

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Dedication

It is with genuine gratitude and warm regard that I dedicate this work to my beloved parents Sarah and Abdulrahman. Whose love for me knew no bounds and whose words of encouragement and push for tenacity ring in my ears. Along with help, constant support, and prayers where they are the reason why I am where I am today. My beloved brothers and sisters; particularly my dearest brother, Prof. Khalid, who encourage me to complete my postgraduate study abroad and always inspire me with research and knowledge. My beloved husband Bander who has encouraged me with light of hope and stands by me. All of you have been my best cheerleaders.

Abstract

Due to the fast growing of population, a lot of hospitals get crowded from the huge amount of patients visits. Moreover, during COVID-19 a lot of patients prefer staying at home to minimize the spread of the virus. The need for providing care to patients at home is essential. Internet of Things (IoT) is widely known and used by different fields. IoT based homecare will help in reducing the burden upon hospitals. IoT with homecare bring up several benefits such as minimizing human exertions, economical savings and improved efficiency and effectiveness. One of the important requirement on homecare system is the accuracy because those systems are dealing with human health which is sensitive and need high amount of accuracy. Moreover, those systems deal with huge amount of data due to the continues sensing that need to be processed well to provide fast response regarding the diagnosis with minimum cost requirements.

Heart is one of the most important organ in the human body that requires high level of caring. Monitoring heart status can diagnose disease from the early stage and find the best medication plan by health experts. Continues monitoring and diagnosis of heart could exhaust caregivers efforts. Having an IoT heart monitoring model at home is the solution to this problem. Electrocardiogram (ECG) signals are used to track heart condition using waves and peaks. Accurate and efficient IoT ECG monitoring at home can detect heart diseases and save human lives.

As a consequence, an IoT ECG homecare monitoring model is designed in this thesis for detecting Cardiac Arrhythmia and diagnosing heart diseases. Two databases of ECG signals are used; one online which is old and limited, and another huge, unique and special from real patients in hospital. The raw ECG signal for each patient is passed through the implemented Low Pass filter and Savitzky Golay filter signal processing techniques to remove the noise and any external interference. The clear signal in this model is passed through feature extraction stage to extract number of features based on some metrics and medical information along with feature extraction algorithm to find peaks and waves. Those features are saved in the local database to apply classification on them. For the diagnosis purpose a classification stage is made using three classification ways; threshold values, machine learning and deep learning to increase the accuracy. Threshold values classification technique worked based on medical values and boarder lines. In case any feature goes above or beyond these ranges, a warning message appeared with expected heart disease. The second type of classification is by using machine learning to minimize the human efforts. A Support Vector Machine (SVM) algorithm is proposed by running the algorithm on the features extracted from both databases. The classification accuracy for online and hospital databases was 91.67% and 94% respectively. Due to the non-linearity of the decision boundary, a third way of classification using deep learning is presented. A full Multilayer Perceptron (MLP) Neural Network is implemented to improve the accuracy and reduce the errors. The number of errors reduced to 0.019 and 0.006 using online and hospital databases.

While using hospital database which is huge, there is a need for a technique to reduce the amount of data. Furthermore, a novel adaptive amplitude threshold compression algorithm is proposed. This algorithm is able to make diagnosis of heart disease from the reduced size using compressed ECG signals with high level of accuracy and low cost. The extracted features from compressed and original are similar with only slight differences of 1%, 2% and 3% with no effects on machine learning and deep learning classification accuracy without the need for any reconstructions. The throughput is improved by 43% with reduced storage space of 57% when using data compression.

Moreover, to achieve fast response, the amount of data should be reduced further to provide fast data transmission. A compressive sensing based cardiac homecare system is presented. It gives the channel between sender and receiver the ability to carry small amount of data. Experiment results reveal that the proposed models are more accurate in the classification of Cardiac Arrhythmia and in the diagnosis of heart diseases. The proposed models ensure fast diagnosis and minimum cost requirements. Based on the experiments on classification accuracy, number of errors and false alarms, the dictionary of the compressive sensing selected to be 900.

As a result, this thesis provided three different scenarios that achieved IoT homecare Cardiac monitoring to assist in further research for designing homecare Cardiac monitoring systems. The

experiment results reveal that those scenarios produced better results with high level of accuracy in addition to minimizing data and cost requirements.

Declaration

Hereby declare that this thesis has been genuinely carried out by myself and has not been used in any previous application for a degree. Chapters 3 to 5 describe work performed by me in the present of guides and support of my supervisors, Prof. Hongjian Sun and Dr. Qing Wang. These chapters have been published or submitted for publication (as shown in the publication list - Chapter 1).

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List of Algorithms

List of Acronyms

MQTT Message Queuing Telemetry Transport 16

MSE Mean Square Error ix

NMSE Normalized Mean Square Error ix

NoS Number of Samples 72

RFI Radio Frequency Identification 38

RFID Radio Frequency Identification 13

SSD solid-state drive 36

SVM Support Vector Machine ix

TCP Transmission Control Protocol 15

WBAN Wireless Body Area Network 13

WSN Wireless Sensor Network 8

Chapter 1

Introduction

This chapter introduces the work conducted by this thesis in terms of explaining the motivation behind the research, aims and objectives. The chapter also explores the contributions made by the research work and lists the instances of previous publication of the results and outcomes. Furthermore, a brief description of the organisation of the thesis is provided to explore the content of subsequent chapters.

1.1 Introduction

As a result of the huge expansion of the Internet, a new concept has emerged which converts static objects to smart objects and links them together, known as Internet of Things (IoT). The term IoT generally refers to the network of objects and sensors that communicate over the Internet and exchanging data with other devices and systems with minimal human intervention. The sensors can sense and detect changes in their surrounding environment and send these data to systems using wireless communications. IoT has been widely applied in diverse domains such as healthcare and smart homes. During the lockdown of COVID-19, the usage of Internet services increases by 40% to 100% [1]. The normal life of the whole world is changed during the pandemic. A lot of governments, organizations, institutions and companies moved their work from on-site to on-line to reduce the spread of the virus and minimize the pandemic losses and damages. The pandemic has affected most people in consuming the Internet and Internet services to carry on their life at home. Homecaring of patients and elderly is highly important. The importance of that field is clearly gets the consciousness of caregivers and caretakers during the pandemic.

The number of elderly people living alone is increasing and they require smart caring. Healthcare monitoring by health experts and home monitoring and control are considered crucial to them. The increasing number of patients in hospitals forming a burden that requires more need for caring patients while they are at home. Homecare management systems are increasingly important nowadays. Integrating homecare systems with IoT technologies will provide more caring functionalities. Using IoT sensors and actuators inside the home with the assistance of communication technologies will help caregivers monitor their patients remotely. Moreover, decision makings can be achieved using the sensor data to reduce the burden on caregivers. In addition, IoT based homecare will provide more convenience for living. People can monitor and automate devices without movement which will help the handicapped and/or elderly people living alone. Providing reliable and comfortable living along with accurate health caring is the main objective of the research in this area.

Monitoring health conditions can be achieved by focusing on the most diseases that cause death to take care of the human body and monitor the condition before any harm can be produced for reduce loosing of lives. The heart considered a crucial organ in the human body located in the left behind of the chest bone. It pumps blood throughout the whole body using the network of veins and arteries. Any abnormal heart condition leads to heart disease. According to the Centers for Disease Control and Prevention (CDC), the main cause of death in the United States is by heart disease. Around one to four people both male and female die because of multiple kinds of heart conditions [2].

Nowaday it is possible for the doctor to monitor the heart status for a patient without interrupting his or her day by advanced technology. Monitoring heart conditions are very essential to detect abnormalities. Sometimes, heart disease can be discovered with no symptoms. Moreover, cardiac monitoring assist in defining the best treatment and minimizing heart diseases. Therefore, having homecare cardiac monitoring system is required especially these days during the pandemic of COVID-19. However, high level of accuracy is needed because those systems are dealing with human health where any mistakes could lead to wrong diagnosis and treatments that my destroy the human life. Moreover, real time monitoring is important to get the fast response and diagnosis required with low cost.

As a result, this thesis proposes novel cardiac monitoring models which can be used to realize IoT homecare management systems. The three different models are built to address different issues with homecaring. The first model worked by taking the raw ECG signals from online and hospital databases after applying two different filters to remove the noise. Number of features are extracted and saved using an implemented feature extraction algorithm. Based on the saved features, the classification is made in three different ways to increase the accuracy. Threshold value is used to classify and diagnose heart disease based on medical measurements. Machine learning using an implemented SVM algorithm to define the classification accuracy without any human exertion. Deep learning using an implemented MLP algorithm to increase the classification accuracy and minimize the number of errors along with solving the drawbacks of SVM algorithm. Due to the huge number of ECG signals, data compression is used in the second model to reduce the storage needs and minimize the transfer time. An adaptive amplitude threshold algorithm is implemented to transfer compressed ECG signals to receiver and the receiver can extract features and classify the signals from the compressed domain without affecting the real data. On the other hand, a compressive sensing algorithm is implemented to transfer compressed signals between sender and receiver and then the receiver can make feature extraction and classification from the reconstructed signals. The three models are evaluated by considering accuracy, data and cost of homecare systems and they proved efficiency and effectiveness.

1.2 Statement of aim

This thesis aims to design models that achieve IoT management system for improving homecare using ECG signals. The proposed models address some of the current research issues in the accuracy, data and cost of homecare technology.

1.3 Research Objectives

- **Objective 1:** To design an ECG monitoring model for the diagnosis of heart abnormality that based on ECG signals from two different databases online and hospital. Apply signal processing using two filters to remove the noise and any external interference. Extract number of features from the clear signals and save them to apply classification on them. Classify using three different ways; threshold value, machine learning and deep learning to improve the accuracy of diagnosing and minimize the number of errors. (Achieved in Chapter 3)

- **Objective 2:** To design a novel Adaptive Amplitude Threshold ECG Compression Algorithm for homecare Cardiac system using data compression technique to reduce the data storage size of ECG signals and minimize the transmission time between sender and receiver by diagnosing heart diseases from the compressed domain. (Achieved in Chapter 4)

- **Objective 3:** To design a novel Compressive Sensing algorithm for homecare Cardiac system for the diagnosis of heart disease from the reconstructed signal using compressive sensing to reduce the data storage size and ensure fast transmission for fast response homecaring. (Achieved in Chapter 5)

1.4 Publications

The work in this thesis has been published and presented at several international conferences. A list of publications is provided based on the category of international conferences and journals as follows.

- **Journals**

  1. A. Almazroa, H. Sun,"Homecare Management System", published in Journal of Computer Methods and Programs in BioMedicine, 2019.
  2. A. Almazroa, H. Sun, "Review of Internet of Things (IoT) based Smart Homecare Technologies: Challenges and Opportunities", submitted to *IEEE Access.* (Chapter 2)
  3. A. Almazroa, H. Sun, Homecare Cardio Management System Using Adaptive Amplitude Threshold Compression Algorithm, submitted to *Bioelectronic Materials and Systems for Smart Healthcare, Micromachines, MDPI.* (Chapter 4)
  4. A. Almazroa, H. Sun, Homecare Cardio Management System Using Compressive Sensing, submitted to *IEEE Transactions on Biomedical Engineering.* (Chapter 5)
  5. A. Almazroa, H. Sun, Homecare Management System Using Cardiac Arrhythmia Classification and Artificial Intelligence, submitted to *IEEE Journal of Translational Engineering in Health and Medicine.* (Chapter 3)

- **Conferences**

  1. A. Almazroa, H. Sun, "An Internet of Things (IoT) Management System for Improving Homecare - A Case Study," in *International Symposium on Networks, Computers and Communications (ISNCC'19)*, Istanbul, Turkey, IEEE, 2019. (Chapter 3)
  2. A. Almazroa, H. Sun, "An Internet of Things (IoT) Homecare Management System Using Cardiac Arrhythmia Classification", in *11th IFIP International Conference on New Technologies, Mobility & Security*, Paris, France, IEEE, 2021. (Chapter 3)

1.5 Overview of Thesis Structure and Research Contributions

This thesis is structured as follows: first, this chapter (**Chapter 1**) introduces the work and explains the motivation behind it, and also presents the research contributions.

Chapter 2 Based on the submitted survey paper listed in section 1.4, the basic concept of Homecare technology is introduced, exploring various systems that were proposed for healthcare and home automations. Moreover, detailed background on ECG data compression and compressive sensing used in homecare systems. Also, various solutions for ensuring reliable homecare systems are discussed. Then, the open research issues for homecare technology are presented.

Chapter 3 Based on the submitted journal and published conference papers in section 1.4, a Cardiac Arrhythmia feature extraction and classification model is presented. The raw ECG signal is passed through signal processing stage using two filter techniques to clear it from noise and any external interference. Then the cleared signal is passed through the feature extraction stage to extract a number of features that are used in the classification stage. After that, a classification stage to detect Cardiac Arrhythmia is made in three models: threshold values, machine learning and deep learning to improve the accuracy.

The main contributions are:

1. A novel Cardiac Arrhythmia feature extraction algorithm to extract the most important features for diagnosing and then save them to apply classification stage for improving homecare using two different databases.

2. The accuracy of the model is improved using SVM machine learning algorithm. The proposed model achieves high accuracy rate and minimum number of errors based on the simulation results that overcome existing work in [3].

3. The accuracy of the model is further improved using MLP deep learning algorithm that overcome the SVM decision boundary limitation. The proposed model achieves high accuracy rate and minimum number of errors in comparison to SVM and based on the simulation results that overcome previous work in [4].

4. The use of huge and real ECG signals from hospital that improves the decision making regarding the Cardiac Arrhythmia based on the classification accuracy results and the comparison made between online and hospital databases.

Chapter 4 Based on the submitted journal in section 1.4, a novel Adaptive Amplitude Threshold ECG Compression Algorithm for homecare Cardiac system for the diagnosis of heart disease from the compressed domain is proposed. The raw ECG signal is passed through signal pre-processing stage for filtering and scaling. The threshold value is calculated and the signal is compressed using the calculated threshold. Then the compressed signal is pushed through the feature extraction stage to extract a number of features that are required in the classification stage. After that, a classification stage based on the feature values to detect ECG abnormalities is made using machine learning and deep learning. In addition, analytical and simulation models are proposed. The main contributions are:

1. A novel Adaptive Amplitude Threshold ECG Compression Algorithm is proposed.
2. Applying SVM machine learning algorithm and MLP deep learning algorithm in the compressed domain for the classification stage to preserve the accuracy of ECG diagnosis and reduce the data storage needs in a short transfer time with less errors.

Chapter 5 Based on the submitted journal paper in section 1.4, a novel Compressive Sensing algorithm for homecare Cardiac system for the diagnosis of heart disease from the reconstructed signal is presented. The raw ECG signal is passed through signal pre-processing stage for filtering and scaling. Then, the compressive sensing algorithm is applied on the filtered signal to produce the compressed signal and transfer it to the receiver. The receiver will reconstruct the signal using the shared key and make feature extraction, classification and diagnosis on the reconstructed signal. The main contributions are:

1. A novel Compressive Sensing algorithm based Cardiac Homecare system model is proposed. Different from Chapter 4, the diagnosis of heart disease is from the reconstructed signal in the receiver.
2. The algorithm is able to make accurate and true decisions with small amount of data to be carried between sender and receiver to preserve fast transmission.

Chapter 6 presents a summary of the proposed research and summarises the key findings. Also, it makes some recommendations for future work.

Chapter 2

Literature Review

This chapter provides a review of the literature to examine various existing homecare management systems and models. These systems are classified into healthcare, home automation, and hybrid healthcare/home automation. Then, discussions and comparisons considering hardware and software criteria are provided. Moreover, a background of methods and algorithms of ECG signals and literature are provided. Details are explained for ECG signal processing and filtering. Furthermore, background on ECG data compression and compressive sensing are provided. Finally, the research challenges, and some future opportunities are pointed out.

2.1 Background of homecare technology

Due to the ageing population, the number of elderly people living alone is increasing and they require smart caring. Healthcare monitoring by health experts, and home monitoring and control are considered crucial to them. The increasing number of patients in hospitals forming a burden that requires more need for caring patients while they are at home. Homecare management systems are increasingly important nowadays. Integrating homecare systems with

IoT technologies will provide more caring functionalities. Using IoT sensors and actuators inside the home with the assistance of communication technologies will help caregivers monitor their patients remotely. Moreover, decision makings can be achieved using the sensor data to reduce the burden on caregivers. In addition, IoT based homecare will provide more convenience for living. People can monitor and automate devices without movement which will help the handicapped and/or elderly people living alone. Providing reliable and comfort living along with accurate health caring is the main objective of the research in this area.

Many research works have been done on homecare management systems with the innovation of IoT technologies. In this chapter, we aim to provide a comprehensive review in this area and study the challenges for all types of such systems. We believe that this literature review will guide future research for addressing challenges of the future homecare system.

There are several published review papers that cover various aspects of smart home and healthcare systems. For example, the survey by Biljana *et al.* [5] investigated the-state-of-the-art in Wireless Sensor Network (WSN) solutions and IoT concepts for smart home applications with a summary of their architectures and frameworks. Moreover, the most relevant smart home systems for supporting elderly and disabled people were investigated in [6]. Additionally, the authors in [7] overviewed the latest approaches in smart home environment and tele-medicine systems. Also, they investigated emergency managements for smart homes. Moreover, a semantic review in smart homes and healthcare monitoring systems was presented in [8]. Furthermore, the survey paper in [9] introduced several healthcare systems in smart homes. Different from [8] and [9], this literature review makes the following contributions in relation to the recent literature:

- Compared to other survey papers in the field, this review is the first one that combines healthcare systems with smart home systems without customization and the first one that classifies homecare management systems into healthcare and home automation with several scenarios.
- Key challenges of homecare management systems are provided along with our suggested solutions.

2.2 Methodology

We focus on three important keywords: homecare, healthcare and smart home. Detailed steps can be found in Figure 2.1. First of all, all papers including these keywords were investigated to find their advantages and limitations. Then, several research papers were grouped under each keyword. For each research paper, a summary of the methodology and results were presented. Moreover, the used network, software and hardware were highlighted. Furthermore, a clear focus on sensor type and usage for each research paper were investigated. All the research papers were found while searching for the three keywords on IEEE, ACM, Springer, Science Direct and Web of Science.

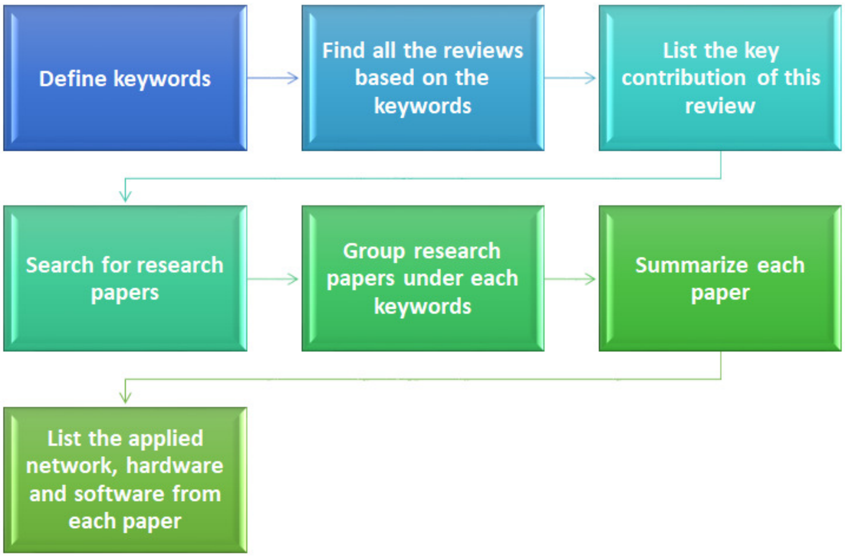


Figure 2.1: Review methodology

2.3 Homecare management systems and literature

Smart Homecare aims at integrating the home with smart technologies for caring purposes on patients and elderly people. Homecare management systems can be classified into three main parts as shown in Figure 2.2.

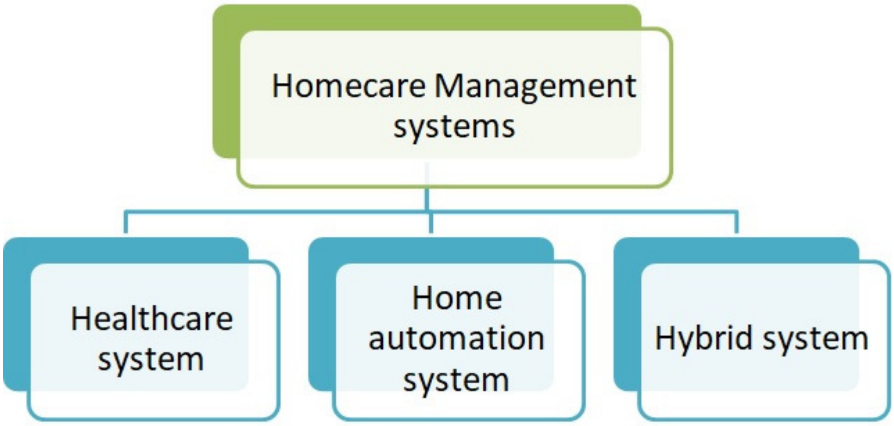


Figure 2.2: Classification of homecare management systems

2.3.1 Healthcare System

Healthcare systems are systems that provide medical solutions to caretakers using several techniques managed by caregivers. Caregivers are individuals or institutions supplying healthcare services such as doctors or hospitals while caretakers are patients or elderly people who require caring. The following subsections provide an investigation on several applications of available healthcare systems grouped by considering their main purpose.

Health Monitoring Systems

Nowadays, health monitoring system inside home become a focus of many researches. Monitoring caretakers at homes and outside of traditional clinics or hospitals will decrease healthcare delivery costs. To allow patients stay comfortable at their homes while monitoring their health conditions, Pham *et al.* [10] proposed a cloud based smart home environment for providing healthcare. The system gathered vital signs data using wearable sensors. It provided daily information about activities, motions and locations in home using smart home environment sensors. The caretaker can stay at home while the health information monitored in real-time by caregivers via Internet-connected devices. The data from the wearable sensors and the environmental sensors were processed on the smart home gateway using preprocessing, localization and activity recognition algorithms. Then, the data sent to the private cloud server to provide caretakers and caregivers with comprehensive real-time vital data with contextual information.

Moreover, Ou *et al.* [11] proposed a homecare system to elderly people for making several comfortable services. One of these services is a real-time remote monitoring for taking care of elderly people through web services using a web-based central camera management. Another interesting service is behavior recognition and interaction along with camera managing using audio and visual cognitive methods to provide multi-modal human to machine interaction service. Vital sign measurement, remote controlling, emergency calling and scheduling of hospital appointments can be achieved in this system using smart human to machine interface to provide user management service.

In addition, Sung and Chang [12] implemented an Android IoT healthcare system. This system uses cloud computing to perform storage, processing, collection and analysis of data. In this research, vital sign data processing fusion algorithms and evidence theory were used. The system focused on measuring blood pressure, ECG, oxygen saturation, respiration rate and body temperature through Bluetooth communication using portable device. The vital signs were transmitted to the Android mobile phone using Wi-Fi and Bluetooth modules then uploaded to the cloud to be downloaded by caregivers for monitoring. In advance, this system sent SMS notification to caregivers when the data is ready in the cloud and also provided video chatting with caretakers if needed.

Emergency Systems

Emergency systems aim to provide home healthcare systems with alarming and warning features for serious health conditions for monitoring and taking actions from caregivers. Smart home health emergency systems track the attention of many researches. One of these researches proposed a wearable health monitoring system for sensing temperature and heart beat rate for babies in real-time using smart phone [13]. The system can issue health status report and notify in case of emergency situations. The system consisted of wearable hardware device, middleware, cloud server and smart phone application that can act as a microcontroller between body sensors and middle-ware. The communication protocol used in this system was Bluetooth. The battery used in hand glove was coin cell. Raspberry Pi used as a middle-ware device with Wi-Fi and Bluetooth interface that can transfer vital sign data to the cloud server for processing using Microsoft Azure platform in addition to storing them in the local storage. The application was built on .net platform using $C\#$ programming language and Windows phone device. In addition, the system sent notification and alarms using the mobile application based on real-time monitoring.

Moreover, Rajkumar *et al.* [14] proposed a health monitoring system project to monitor biological parameters such as body temperature and heart rate. The system used Fitbit connected to Raspberry Pi to monitor heart rate. A Temperature sensor was used to monitor body temperature. SMS messaging was used for alerting in abnormal situations were vital signs went beyond or above the normal ranges. The system also emphasized the patient to take medicines at time by sending reminders through SMS. The Raspberry Pi was used as a server to store the medicines of the patient. This system can be used in home or hospitals and able to collect a large amount of data as well. The objective of this system was to cut down the costs produced by healthcare and also to provide a quick action to catch an issue.

Another system for detection of abnormal vital signs of bodies in real-time was proposed in [15]. The hardware used were Raspberry Pi, heart beat sensor and temperature sensor. Two servers were used, one for deployment and one for storing data. The vital signs were sensed using the sensors and the sensing result sent to the server. The server processed these data and compared them with the normal range. In case of any abnormalities, the system sent an alert message to the doctor's mobile registered in the system within one minute for diagnosis purposes. The main objective of this system was to shorten the power consumption and to increase the communication coverage.

Furthermore, an intelligent sensing framework for real-time healthcare monitoring in home for elderly and disabled people was proposed in [16]. The system provided health monitoring services in addition to emergency response services in case of any emergency health situations happened. The aim of this paper was to explore IoT facilities in monitoring health status in home. The system contained of two sides. The remote side used for saving and transmitting data to caregivers and the local side used for gathering the biological data from body sensors. Arduino was used for data aggregation and processing from body sensors to caregivers and remote servers. The hardware used in this system were smart phone, Arduino, oxygen sensor, ECG sensor, Electromyogram (EMG) sensor, body temperature sensor, pulse sensor and blood sugar sensor. The data gathered from those sensors were processed to check for any abnormalities and an alarming feature was used in case of any emergency. The sensors were connected to the smart phone using Bluetooth communication. The smart phone was used as a gateway for sending data between sensors and Internet and used as an interface. Each room contained a Radio Frequency Identification (RFID) reader and each user carried an RFID tag attached to the smart phone which used to configure the person for monitoring and to record the location. Fuzzy logic was used as decision making technique and RESTful as a web service. Remote monitoring and controlling were handled by caregivers using this system. The distinguishing feature of this research was the efficient used of biomedical sensors to produce real-time response in case of urgent situation. The healthcare proposed system was efficient and cost effectiveness.

Falling Detection Systems

Falling Detection System is an assistant system for alarming and alerting when a falling event happened. Particularly, the advantages of falling detection systems are eliminating the panic of falling and fast assisting after falling. Falling detection systems in home are important for elderly and disabled people living alone. Several researches proposed such systems. Yang *et al.* [17] investigated an IoT mobile healthcare system inside home for disabled people who used wheelchair. Wireless Body Area Network (WBAN) was used for the architecture and design of this system. The WBAN nodes contained heart rate, ECG sensors, pressure detecting cushion, temperature sensor, humidity sensor and control actuators. A watch at wrist was used to monitor heart rate with ECG and the sink node located at the belt. The wheelchair held the pressure cushion for detecting whether the user falling from the wheelchair or not. The accelerator sensor used to detect the falling of wheelchair itself. The system architecture contained three layers.

The WBANs and smart objects layer, the smart phone layer, and the data center layer in the cloud. The communication protocols used were Zigbee and Bluetooth. The smart phone was used as a gateway and a server. This system satisfied the mobility of data collection, healthcare monitoring based on the environment and remote interaction with surroundings.

Moreover, Rakhman *et al.* [18] proposed a prototype of ubiquitous fall detection system with alert feature in home using smart phone. The prototype contained special features in sensing data that was gathered from the accelerometer and gyroscope and embedded inside the smart phones. The prototype provided real-time alert feature using mobile alarm, SMS notification and automatic calling. It showed the falls history with time, position of body, and fall location using the smart phone.

Furthermore, an IoT based mobile gateway using intelligent personal assistants for health monitoring was proposed in [19]. The intelligent personal assistant had the ability to communicate with IoT devices. The mobile gateway can collect heart rate from user along with location and fall detection anywhere and send them in real-time to caregiver for taking actions and alerting using intelligent personal assistant platform called AMBRO. The mobile gateway was used in the mobility environment to establish a connection between IoT devices and the Internet and its application deployed in smart phone. A prototype of this scenario using Android smart phone was demonstrated and evaluated in terms of power consumption and accuracy. The body sensor network contained shimmer sensor for fall detection, smart watch with optical heart rate sensor and a Global Positioning System (GPS) sensor embedded in the smart phone for location detection. The Body Area Network (BAN) communication was controlled by AMBRO mobile gateway application using Bluetooth communication.

In addition, Lee *et al.* [20] demonstrated a smart home monitoring system for elderly people to let them stay independently in a safe manner. Fall detection technique was implemented using Android smart phone with accelerometer. Detecting falling was implemented by comparing the acceleration value with the threshold saved. When the system detected falling, the smart phone graphical user interface examined the fall and the user can respond with denying the fall option. If this option was clicked in case everything was normal, the detection cancelled and the system returned back to its initial state. Otherwise, the falling was confirmed and an emergency alarm sent to the monitoring system. Wi-Fi communication was established between the smart phone and the monitoring system using Transmission Control Protocol (TCP)/ Internet Protocol (IP). The monitoring system was implemented on a computer and connected using wireless communication with a remote panic button implemented in the Android smart phone in case of any emergency happened. The remote panic button worked as follows; once the help button on the smart phone is pressed, the emergency signal is sent to the monitoring system requesting for caregiver's assistant. The caregivers can access the monitoring system in case of any needed information and the system can answer the call automatically after alerting. By using this system, elderly people can stay independently at home with remote care and monitoring services.

In Hospital Systems

Similar monitoring and emergency health systems can be found in hospitals. A hospital monitoring and measuring system was proposed in [21] for several vital signs measuring that were implemented with the help of Raspberry Pi. The hardware used were temperature sensor, wireless blood pressure, and heart beat sensor. The measuring results were sent to the server. Authorized caregivers used the website to monitor the patients for diagnosis purposes. Moreover, the patient can view his biological data on the website. A mobile application was developed in advance to the website for showing the results to patients and caregivers. The application can be accessed using user name and password. The server updated the vital sign data every 60 seconds. A red color in the mobile application showed in case the temperature, blood pressure or heart rate reaches abnormal values.

Another monitoring system for Intensive Care Unit (ICU) patients was proposed in [22] for checking vital signs. Raspberry Pi was used to gather data using wireless connection. After making some processing, the data sent to the server. The data gathered can be displayed in the website for authorized access accounts only. Additionally, the system captured real-time video streaming using webcam located in patient's room. These video streams were sent to doctors for monitoring the patient from anywhere along with the vital signs' values taken from the website. The Raspberry Pi was connected with the webcam. In case of any abnormality in the vital signs, alert message sent to doctor. The used sensors were heartbeat sensor, pulse rate sensor, temperature sensor and blood pressure sensor.

ECG Systems

Heart is one of the most important organs in human body that requires monitoring and caring. Any problem with that organ can destroy the human life. ECG monitoring homecare systems were rarely used due to the accuracy limitation . Several IoT systems were demonstrated in this review. Yang *et al.* [23] proposed an IoT wearable ECG monitoring system. In this system, a new ECG monitoring method was demonstrated which based on IoT and cloud techniques. The ECG data were collected using wearable sensors and sent to the cloud using Wi-Fi communication to visualize and store data for future analysis. Hyper Text Transfer Protocol (HTTP) and Message Queuing Telemetry Transport (MQTT) protocols were applied in the cloud for giving ECG data to users in short time using a web-based Graphical User Interface (GUI) to be accessed anywhere. This system was evaluated in terms of reliability using a healthy body of a volunteer person. The system was reliable for real-time ECG data in terms of collecting and displaying.

Another IoT monitoring framework was proposed in [3]. ECG and other biomedical data were gathered using sensors and sent using Bluetooth technology to the cloud for accessibility. Several signal processing techniques were used for ECG signals. Watermarking was used to enhance the security in the client side before send it to the cloud. Spectral and temporal features were extracted in the cloud and then classified using machine learning classifier. The classification result was sent to health experts then the final decision sent to the cloud to notify the patient. Experimental evaluation and simulation were used for system validation. The simulation was applied by installing IoT ECG monitoring service in the cloud. The accuracy for the classification was 83% which is still low and need to be enhanced.

Moreover, Mahdy et al. [24] presented an IoT system for detecting Arrhythmias using an ECG Holter device. The system used an ECG sensor located on the patient's chest for taking real time

ECG signals. The data was sent to a smart phone with the assist of Bluetooth communication technique. A machine learning algorithm called K-Nearest Neighbors (KNN) was used to classify the data into normal and abnormal. The evaluation result of the classification accuracy using 303 patients was 70% which is very low.

Some tele-monitoring systems were studied in this research. A real time ECG tele-monitoring system was presented in [25]. A novel approach was described to prevent sudden cardiac arrests using an advanced alarm system. The device that monitored the ECG was placed on the chest and connected to a mobile phone using Bluetooth. The ECG signals were transferred in a real time to the Cloud server using cellular network. The system was evaluated on five volunteers in a marathon. Three out of them showed sensible measurement of ECG with a full centralized monitoring.

Another wireless ECG monitoring system was developed in [26]. The system used a tiny dry capacitive electrode for long-term monitoring of cardiovascular health. This electrode was able to measure ECG signals over a textile-based interface material between the skin and electrodes. The raw ECG signals were received from the electrodes and transmitted through Bluetooth communication technology. An application was developed to process, store, and display the ECG signals in real time and in the presence of body movements to detect abnormal ECGs. The system consumed small amount of power using a coin cell battery for long-term monitoring.

Moreover, a wearable ECG tele-monitoring system was proposed in [27]. The purpose of that system was to detect atrial fibrillation which is the most common sustained cardiac arrhythmia that affecting about millions of people worldwide [28]. Based on studies atrial fibrillation is correlating with sudden cardiac death, stroke, and heart failure [29], [30]. The system was based on Android smartphone and cloud computing. The ECG signals were collected using a wearable ECG patch and sent to the smartphone using Bluetooth. The ECG waveforms were displayed using a developed Android App. Every 30 seconds the ECG data was transmitted to the cloud. Atrial fibrillation was detected in the cloud using a Cat Boost machine learning classification method. When atrial fibrillation detected, the ECG data and the classification result pushed to the web browser of the doctor for diagnosis that displayed in the App.

2.3.2 Home Automation System

Home automation system is a system for controlling home appliances and electrical devices remotely using wireless connections. Centralized controlling of lighting, climate, entertainment systems, security and safety systems, kitchen and bathroom appliances to make them more favorable and to save the energy. Home automation systems are very important nowadays for disabled and elderly people for controlling home appliances and alerting them in emergency status especially for seniors living alone.

Android Systems

There are many Android systems for home automation. Shingate *et al.* [31] investigated an automation system using Android Development Kit (ADK) to control and monitor home appliances using Android phone or tablet. Home appliances were connected to the ADK and there was a communication between the ADK and the Android phone or tablet. The system design contained of Android phone with home automation application installed and Arduino Mega ADK. Using android phone, the user can send control signal to the Arduino ADK. Then the ADK can control other devices and sensors. The system can check for the authentication of the user at the beginning. It can monitor home main functions such as light and door controlling, smoke detection and room temperature sensing. The system was intelligent; it can switch lights on/off during night for saving energy. Furthermore, the system can adjust fan or air conditioning based on room temperature. Moreover, it can activate smart alarming when smoke detected and can call the home owner. The system was suitable for blinded people where there was a voice navigation feature.

Another system investigated a home control and monitoring for low cost and flexible to use proposed in [32]. An Android smart phone application was made to achieve remote accessing and controlling for devices and appliances using micro-web server on Arduino Ethernet with IP connectivity and without using a server. RESTful web-based services were used in the application layer to integrate with healthcare services. Using Wi-Fi or 3G/4G, home owners can control and monitor their homes remotely using the application in their smart phones through server real

IP. The architecture of this system contains three layers: home environment, home gateway and remote environment. Remote environment layer showed the eligible users to access the system using their smart phone application through the Internet. The used communication techniques were Wi-Fi or 3G/4G network. Home environment layer contained home gateway and a module for hardware interface. The functionality of this layer was to monitor home environment using environmental sensors. Home gateway layer was responsible for providing the translation of the data through the Internet. The micro web server embedded inside the home gateway is for managing, controlling and monitoring system components. The system was implemented in JAVA programming language using ADK.

Raspberry Pi Systems

Raspberry Pi was used as well in-home automation systems. Agarwal *et al.* [33] developed an IoT enabled home automation system. NodeRed, an open source platform, was used as flow-based programming tool for building IoT systems. In this system each part in the home was connected to WSN which enabled the data to be sent to the web server. The WSN was connected through MQTT protocol for the communication between various devices. Each sensor and appliances contained a threshold value. In case a reading went below this value, notifications using email or twitter will be sent to users. For security, the web server interacted with the system using Ngrok which is a webhook development tool. The central unit of the system was connected using Wi-Fi and communicated with WSN using MQTT protocol. The central unit consisted of Raspberry Pi that was connected to the home Wi-Fi using Wi-Fi enabled microcontroller. The web server sent the sensor data to Raspberry Pi then uploaded them to the web server. After uploading, users can monitor their home whenever they are.

Other Systems

Using cloud computing and big data techniques, an energy efficient cyber physical smart monitoring system in home for elderly people was proposed in [34]. A smart middleware assistant that support multimedia was presented to allow elderly people to control home appliances. The controlling was made by hand and body gestures and the status received using sharing multimedia messages. The data taken from sensors and multimedia were processed in the server. On the other side, events were classified to help caregivers in taking decisions. For energy awareness, voice commands and gestures were used in this system for switching devices on and off while needed without any need for movements. The voice and gestures of the elderly person were captured by the system then sent to the interpretation tool to find the keywords. The system worked in noisy situations by focusing on lip region of the video streams to get the keywords. After that, a suitable action was taken for controlling the electrical devices. Image and audio sensors were used to support this system along with a huge amount of user events stored in the cloud. The response time of the system in controlling the electrical devices was very fast due to the assistant of the cloud platform and data centers along with maximizing physical resources such as disks.

A home automation system was proposed in [35] which helped elderly, disabled and blinded people in controlling their devices inside their homes without any need for movements. XBee was used as a communication transceiver with radio frequency signals. Laser buttons were used for controlling in addition to Braille interface for blinded people. The remote control contained supported command buttons and propped by alert messages. Moreover, an energy saving option along with power consumption feature were provided in this system.

2.3.3 Hybrid System

Hybrid system is a combination of healthcare and home automation system. It is the way of controlling the health status along with the smart home management. This kind of systems make the home more convenient and luxury. Hybrid system is a more comfort home and health management particularly for elderly living independently.

IoT Systems

Hybrid system of healthcare and home automation are widely known. Several IoT systems were proposed. Kang *et al.* [36] demonstrate an IoT-based monitoring system using a tri-level context making model for services in smart homes. A real prototype and service scenario for the coming IoT environments were investigated using context-based smart home service. The proposed work was to demonstrate the future of IoT technology and show the direction of smart home technology. The tri-level context making model worked as follows; each level of the model contained different types of services. Those services were simple monitoring service, automatic control service, and user-centric service. The implementation of the tri-level context aware model was tested in two scenarios. The first one was a disaster management service such as fires and gas leakage while happened and informed users by using alarms of LED lights, beep buzzers, and remote notifications. The second scenario was a smart home healthcare assistance such as deep sleeping and comfort home management. This service makes the information analysis required for the monitoring of comfortable living environments and health performance, and give services that need quick actions.

Another research on home automation system was proposed in [37]. The system helped users with mobility restrictions who faced difficulties in using smart phones or remote-control devices to control their appliances. It solved the problem through IoT technique by using only the voice to control and monitor home appliances. The system allowed users to deal with messages to enable remote monitoring with caregivers. Speech recognition techniques were used to configure and deal with the voice. This system satisfied that it was low in consuming cost and bandwidth. The system recognized voices even in a noisy area. It used Raspberry Pi as a single board computer which acted as an IoT gateway. For the communication protocol Zigbee was used along with Xbee wireless unit in controlling sensors and home appliances. The system-controlled appliances by switching them on/off using voice. Based on the speech command, the system sent an alarm and generated a load audio. The system monitored health status such as temperature, humidity and cardiac frequency. The system performance was high in accuracy that was evaluated based on the latency and voice recognition performance in a dedicated language.

Another prototype using IoT technology with images and emotions to help elderly people living in smart home and providing treatment services was demonstrated in [38]. Images were used to identify users and match them with individual treatment. On the other hand, emotions were used for providing monitoring services by caregivers to recover users from diseases. The proposed system contained two parts sensors and decision-making system. The sensors were used to collect health information and send them to the decision making for recognizing the patient and knowing his/her emotions. The decision-making acting as an interface between the caretakers and caregivers. It was responsible for making the treatment decision based on the information received. When the local server overloaded with images an extra cloud was used. The hardware used in this system were Raspberry Pi with wireless interface module, a smart phone with a front camera to capture faces and an accelerometer in addition to a gyroscope for detecting any accidents happened. Moreover, rooms were equipped with web cameras to recognize patient entering and identifying his/her record. In addition, smart watch along with wearable sensors on clothes were used to gather health information. The software contained Raspbian operating system for Raspberry, face tracker for monitoring videos from web camera and Python to read sensor data from Raspberry. The proposed system was able to recognize facial expression for identifying patients and understanding their feeling based on the images taken. All the patients' records were stored in a local database in addition to the web services that can be accessed using HTTP. An evaluation procedure was taken in terms of performance and accuracy.

Another IoT smart homecare system was proposed in [39]. The home gateway played the major role in the architecture of this system. A comprehensive functional home gateway was designed which combined methods of several system strategies on the middle-ware. After the aggregation process in the gateway, data was sent to the cloud through web services. The proposed framework contained three parts; front-end sensors, gateway and back-end servers. All of the three parts of devices deployed a middle-ware for providing functionalities such as; access and control, web services and cloud storage. The front-end sensor devices contained; Raspberry Pi for gathering sensor data, camera lens sensors for capturing images and Wi-Fi module for communication. The backend devices used for saving handled images in a perfect way. Congestion may happen due to the flow of the data from front-end devices to the home gateway and from the gateway to the back-end devices. This problem was solved using comprehensive functional home gateway middleware which cleaning the unwanted data and accommodating several data throughput on the images stream.

WBAN Systems

Several WBAN systems available as well. The U-Health smart home in [40], investigated the population with a huge range of healthcare services that can be improved by time. WBAN contained body sensors that were used to gather vital sign data from the patient body to monitor the health status and provide some medicines if needed. In this system, a WBAN along with a Home Communication Network (HCN) and U-Health autonomic decision-making system were deployed. Body sensors communicate using wireless connection for sending vital signs data directly or via the HCN to the U-Health smart home automatic decision-making system. Detecting health status was achieved by the analysis and the correlation of the vital signs data and with some data from the surrounding environment such as localization and appliance status.

Gnanavel *et al.* [41] as well proposed a smart home monitoring system based on WSN for elderly people. The aim of this system was to monitor health status of those people and provide them with comfortable and secure living. Several body sensors were used such as temperature, heartbeat and blood pressure. Those sensors were placed on the waist of an elderly man. Temperature sensor was used for measuring human temperature and heartbeat sensor for counting heartbeat. This system also monitors falling actions. Accelerometer and gyroscope were used for this purpose. For security reasons, the doors were equipped with magnetic contact to monitor the door status open/close. The data in this system transmitted using wireless communication. It was processed using LabVIEW and implemented using Arduino. SMS messaging to caregivers and hospital were used in case of any emergency. The system appeared to be efficient in power consuming.

Other Systems

There are several hybrid systems available for providing comfort and luxury living. Basanta *et al.* [42] built a platform to control appliances using voice and gesture. This platform helped people to live in their home in a comfort way based on their health conditions. The data gathered from the body vital signs and the environmental sensors in room were used to control lights and air conditioning based on the comfortable level and health status of person living in such a home. The system provided real-time health monitoring. For the monitoring of the heart rate an alarm buzzer with emergency light was available in the room. In case of any emergent abnormal heart condition happened, the system pushed alarms and the emergency lights switched on. The authors built an Android application system to allow users to deal with the data from the gesture and voice recognition systems. Users can control their home appliances using the Android application as well.

Another home appliances system was proposed in [43] for providing smart home entertainment, remote monitoring and assisting systems. This system integrated between body sensors and smart home entertainment devices and applying remote controlling on them. They have used a home server to implement a link between home entertainment devices, remote assistance, such as hospital, and monitoring components. The home server used Wi-Fi to connect with the smart entertainment devices. The home server was used to coordinate the monitoring network produced from body sensors. In case of any emergency situations, all data stored and updated on the hospital server with a minimum latency.

The integration of BAN with smart monitoring system in home was proposed in [44]. This paper combined BAN, Home Area Network (HAN) and intelligent agents to make a smart monitoring system using context aware technique. The system processed environmental data along with vital sign data to enable an early detection of emergency situations and support healthcare in smart homes. Body sensors gathered health information such as heart rate, body temperature, blood pressure and oxygen saturation using Bluetooth module connected with Arduino. Environmental sensors collected the location of person, occupancy, falling, flood detecting, temperature measuring and smoke detection. The system reaction time produced a delay of three seconds for sending the data from sensors.

Another multi-platform control system in smart home was presented in [45]. The platform contained home automation, remote monitoring, environmental monitoring and health monitoring.

Environmental monitoring focused on room humidity and temperature and, fault tracking and management. The system was tested and it was flexible and reliable. Moreover, it was classified as a secure and safe system. The system controlled by microcontroller software and supported by remote control feature. Bluetooth technique was used as a communication to monitor and control electrical home appliances using Arduino. For security, the system used infra-red sensor for detecting human body movement to check for intruders. It worked by sensing the temperature and applied even in darkness.

Several hybrid systems available for providing safely living. A homecare monitoring system of vital signs for elderly people was presented in [46] to allow them to live safely in their homes. By using a tele-operated robot, virtual visits for patients were applied to gather vital signs data and activities. Vital signs contained; body temperature, blood pressure, pulse oximeter and glucose. While activities collected were bed and chair occupancy, door and electrical usage. The system produced alarms in case of emergency such as falling. Furthermore, a number of emergency detection sensors were used such as, gas detector, smoke detector and heat detector. This system was implemented, tested and deployed in six different homes for one year. The middle-ware was used to combine the system components and to be able to make any further addition or deletion.

Another smart collaborative mobile system was proposed in [47, 48] for elderly and handicapped people. The sensors installed inside the smart phone were used to monitor the status of the user. Furthermore, monitoring the surrounded environment of that person helped in determining his/her status as well. Furthermore, fixing what happened to the neighbors helped in taking decisions. The system in [47] was implemented in a group of elderly and disabled people. Each person held a smart device that contained many sensors such as light, magnetic and acoustic sensors, compass, gyroscope, accelerometer and GPS. A collaborative algorithm was presented to gather the data from sensors and shared these data with neighboring devices to be ready for any alarm. A simulation to show how to initiate a warning signal was provided using MATLAB. The warning message was activated based on the sensor values and neighbors replies. The system was able to monitor the person's activity to find the best way to solve accidents. A reinforcement

Table 2.1: The most used sensors by literature.

Sensors	***Biological***	Body Temperature	[11], [12], [13], [14], [15], [23], [21], [22], [37], [41], [44], [46]
		Heart rate	[13], [14], [15], [23], [19], [21], [22], [41], [42], [44]
		Pulse rate	[16], [22], [46]
		ECG	[12], [16], [23], [3], [24], [27]
		Blood pressure	[12], [49], [22], [41], [44], [46]
		Oxygen saturation	[12], [16], [44]
	Environmental	Temperature	[31], [44], [45]
		Humidity	[45]
		Pressure	[23]
		Accelerator	[23]
		Gyroscope	[38], [41], [47]

learning concept was added in [48] to decrease the percentage of false positive and to increase the accuracy to anticipate an alarm before happening. Also, there was an increase in the number of devices. More simulations were built to show the system performance as well. Four of the most used ad-hoc networks were compared and discussed to select the suitable one for this system.

2.3.4 Remarks

Several systems were demonstrated in the sections above. The most common network, software and hardware are shown in Figure 2.3. Based on the literature, Table 2.1 surveyed the most applied sensors by existing research. Moreover, Table 2.2 observed the most utilized microcontroller or special computer by research studies. A comparison of the most used network technologies can be found in Table 2.3. For the systems applied in real world, Arduino and Raspberry Pi were mostly used. The comparison between them can be found in Table 2.4. The most used simulation application and programming language summarized in Table 2.5.

2.4 Methods and algorithms of ECG signal processing

Working with ECG signals need some methods and algorithms to process each signal and to take the most important information from them in an efficient way. Some preprocessing techniques

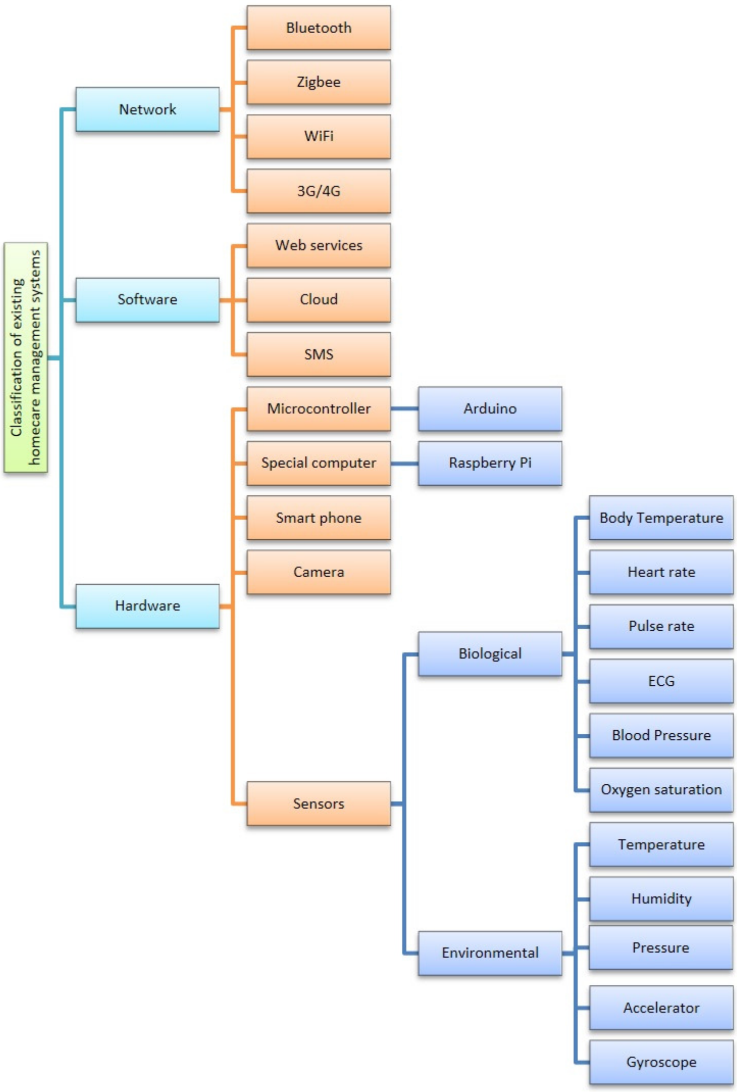


Figure 2.3: Classification of existing homecare management systems techniques.

Table 2.2: The most used microcontroller or special computer by literature.

Microcontroller / Special Computer	**References**
Arduino	[16], [31], [32], [41], [44], [45], [27]
Raspberry Pi	[13], [14], [15], [21], [22], [33], [37], [38], [39]

Table 2.3: Network Technologies.

Network Technology	**Range**	**Data Rate**	**Cost**
Bluetooth	10 m	1 Mbps	Medium
Zigbee	10 m - 100 m	250 Kbps	Low
WiFi	100 m	54 Mbps	High
3G/4G	30 km	50 Mbps	High

Table 2.4: Comparison between Arduino and Raspberry Pi.

Specification	**Arduino**	**Raspberry Pi**
Size	7.6 x 1.9 x 6.4 cm	8.6 x 5.4 x 1.7 cm
Memory	0.002MB	512MB
Speed	16 MHz	700 MHz
Operating system	none	Linux
Environment	Arduino	anything with Linux

Table 2.5: Simulation applications and programming languages.

Simulation and/or Programming Language	**References**
MATLAB	[47]
C#	[13]
JAVA	[32]
ADK	[12], [20], [31], [32], [41]
NodeRed	[33]

are needed to remove the noise and any external interference and to have clear ECG signals. The most used signal filtering techniques are explained below. Moreover, algorithms for ECG data compression and compressive sensing are explained with literature.

2.4.1 Signal processing and filtering

Signal processing techniques are required for ECG signals to reduce the noise. This processing step is critical for accurately finding the waves in the ECG signal that is very important in the monitoring and diagnosing.

- Low-Pass filter: A low-pass filter is a signal enhancement technique to reduce the noise by reducing high frequency components from the signal to make it much clearer. Also, it is used to remove external interference from the signal to avoid artifacts. However, the inappropriate use of that filter may lead to misdiagnosis. Low-pass filter is worked by putting the signal in lower frequency then attenuating the signal with higher frequency.
- Savitzky Golay filter: It is a digital filter that is used for scaling the signal, smoothing and differentiation. This filter is applied by using least squares technique. It is applied to increase the signal-to-noise ratio without distorting the signal. The signal after that filter becomes much clearer and wider.

2.4.2 Background of ECG data compression and compressive sensing

Heart disease is still a considerable anxiety and one of the popular reasons of patients death. ECG is the most important tool that measures patient heart health for the diagnosis of cardiac diseases. The shape and wave of that signal are closely linked with the healthy of the human cardiac system. Every patient with cardiac disease needs extra caring and intensive monitoring. Some of those patients live in rural countries that far away from the main hospitals. Some of them live in crowded population that puts a burden on hospital. It turns out that wireless data transmission is more effective for processing ECG signals [50]. Homecare management systems bring the attention of many governments, companies and researchers to work in that field to support the patients. Storing ECG signals requires long monitoring periods that could exhaust computing system and needs a huge amount of data storage space. Homecare cardiac system requires transmission of data from sensors to mobile application or hospitals in a quick and accurate manner to support real time monitoring. There is a need for a technique to compress this huge amount of data. Data compression and compressive sensing help in reducing the amount of ECG data and therefore minimizing the storage needs for more efficient ECG monitoring system for analysing and diagnosis of cardiac diseases [51].

Data compression

Data compression in signal processing is the way of encoding or converting data using fewer bits than the original size. Moreover, it is called source coding because encoding is done at the source or sender before storing or transmitting in such a way that it produces less storage space, speed up file transfer, and decrease costs for storage hardware and network bandwidth [52].

There are two methods of data compression as shown in Figure 2.4:

- Lossless compression: The way of reducing data by eliminating redundancy without loosing any information.
- Lossy compression: The way of reducing data by removing unnecessary or less important information but does lose some information [53]. This loss of information is acceptable if some loss of accuracy is acceptable.

Data compression is beneficial because it minimizes the resources required for storage and transmission of data. To design a data compression scheme, several trade offs under multiple factors should be considered. Those trade offs include the amount of compression ratio, the amount of deformation when using lossy compression, and the resources needed for data compression [54] [55].

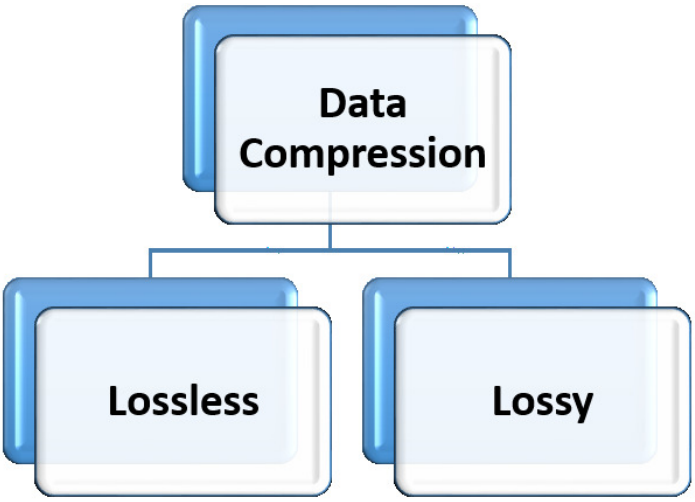


Figure 2.4: Data compression methods.

Data compression could improve the spectral efficiency of communication systems [56]. Data compression is used in many areas as well as in medical field [57]. ECG data compression algorithms with a greater compression ratio and lower loss of data are needed.

In recent years, many techniques were developed for ECG data compression [58] and [59]. Hakkak and Azarnoosh [60] analysed several ECG data compression techniques. A comparison between these techniques were evaluated and compared using three databases.

ECG data compression using lossy methods

Abo-Zahhad *et al.*[61] proposed an ECG compression technique using QRS detection and wavelet transform techniques. First, the QRS complex was detected from the ECG signal and compared between the preprocessed ECG signal. Using 2D matrix wavelet transform, the error signal was aligned to form the matrix. The resulting coefficients from wavelet transform were split into groups and thresholded. The algorithm was tested in 24 different records from MIT-BIH Arrhythmia Database and performed high compression ratio. However, the detection of the QRS complex in ECG is hard because it has a time varying morphology and it is based on variations of patient and can be corrupted by noise.

ECG data compression using lossless methods

In [62], an ECG data compression algorithm for cardiac patients lived in rural area was proposed. This algorithm was based on a combination between two encoding techniques; run length encoding and Huffman encoding with discrete cosine transform. Discrete cosine transform converts the signal from time to frequency domain. The ECG signals were taken from MIT-BIH arrhythmia database. Sahoo *et al.* [63] presented an algorithm based on empirical mode decomposition, discrete cosine transform, downsampling, window filtering and Huffman encoding. A compression algorithm based on adaptive bit encoding of discrete furrier transform coefficients was proposed in [64].

A good performance achieved from data compression based on vector quantization technique but has a drawback from high computational complexity [65]. However, many other algorithms were developed using effective and very soft techniques based on thresholding [66] and [67]. A combination of empirical analysis and wavelet transform to form a compression method was presented in [68]. The suggested method compresses the inherent state functions into two groups and compresses each group separately to fully utilize the data properties. Swarnkar *et al.* [69] proposed an ECG compression technique based on threshold functions and linear flow filters. Multiple threshold functions were applied such as hardness, soft, combination, soft-soft and thresholding techniques. At the receiver the original signal was recovered using the reverse method. Another algorithm applied for ECG compression was Length Encryption [70]. It worked by dividing the ECG signal into different frequency bands then threshold and apply Run length encryption to enhance the compression ratio.

Compressive sensing

Compressive sensing theory was introduced in 2004 given knowledge about a signal's sparsity by Candès, Romberg, and Tao in [71] and Donoho in [72]. It asserts that efficiently reconstructing or recovering a signal from fewer samples by finding solutions to linear systems based on the sparsity of the signal. Sparsity means that the continuous time signal should be smaller in size than described by its original bandwidth and can be reconstructed with even fewer samples than the sampling theorem requires [73]. This concept is the backbone of compressive sensing as many kind of signals are sparse in some domain and can be reconstructed.

The structure and processes of compressive sensing can be found in Figure 2.5 and Figure 2.6. Consider x is the original signal of dimensions N x 1; $x \in R^N$. To gain non-adaptive linear measurements from x, x is multiplied by matrix φ represented based on eq(2.1):

$$y = \varphi x \tag{2.1}$$

where, φ is the measurement matrix which is a selection matrix with dimensions M x N that randomly chooses M columns of the size N identity matrix. y is the compressed vector of dimension M x 1 where $M > 1$. When x is K sparse where ($K \ll N$) that means K out of N values in x are not neglectable. The theory explains that if the shape of the sparse signal is protected during measurements, the sparse signal can be recovered by reconstruction methods from only some few measurements. The performance of reconstruction is specified by three factors; the sparsity K of the signal x, the properties of the measurement matrix φ, and the recovery algorithm.

An early background of compressive sensing was based on Nyquist–Shannon sampling theorem [75][74]. It declares that if the highest frequency of a signal is fewer than half of the sampling rate, then the reconstruction can be achieved well by means of sinc insertion. Consequently, fewer samples are required to reconstruct the signal based on the prior knowledge about signal's frequencies bands. So, minimizing the number of data to be sampled reduces the amount of data to be transmitted. This indeed, will raise the energy efficiency and minimize the battery consumption.

Applying compressive sensing in ECG signal is essential for providing continuous heart monitoring in less storage needs as shown in Figure 2.7. The earlier the diagnosis is performed, the

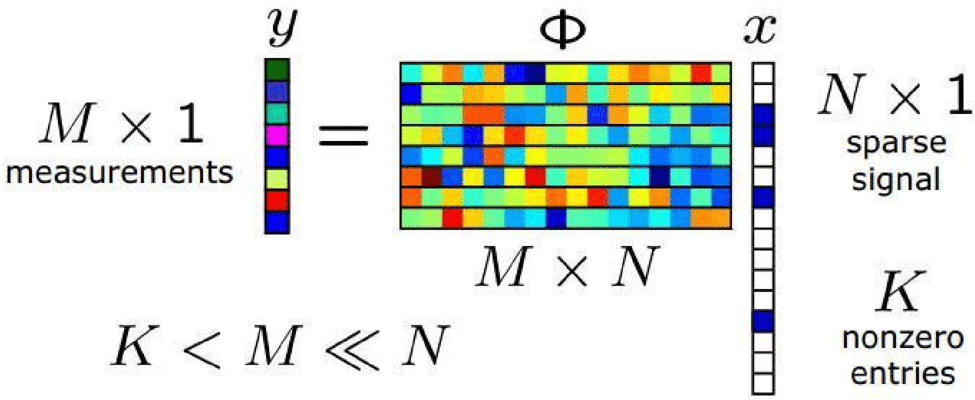


Figure 2.5: Compressive sensing structure [74].

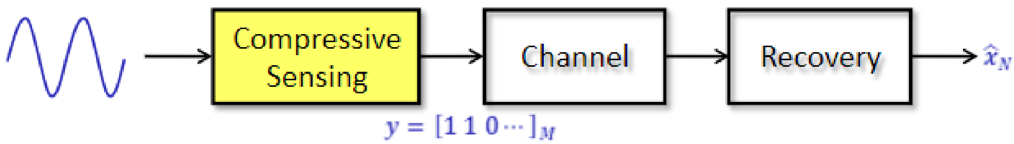


Figure 2.6: Compressive sensing processes.

higher the likelihood of survival. The whole record of ECG signal monitoring of one patient contains two parts; low activity region with no important information and high activity region with full of information that is crucial in the diagnosis of heart disease as shown in Figure 2.8.

In recent years, many techniques were developed for ECG compressive sensing. Dias *et al.*[76] presented the current state-of-the-art for the applications of compressive sensing in the usage of ECG signal. Furthermore, the importance of continuance ECG monitoring and data processing was asserted. They concluded that applying compressive sensing on ECG signals proposes to minimize the data size for sampling in order to consumed the energy by reducing the amount of data before transmitting.

ZHANG *et al.*[77] achieved a compressive sensing method to deal with ECG and electroencephalography (EEG) signals. A collective scheme was proposed by using wavelet transform and iterative threshold method to make sparse data before compressing. After that, compressive

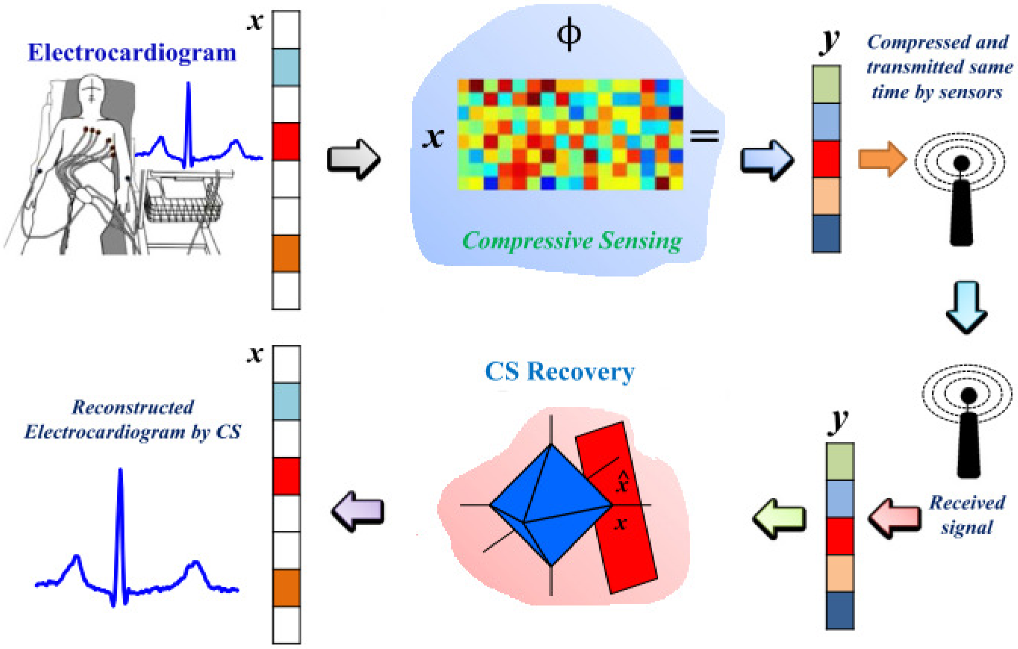


Figure 2.7: Applying compressive sensing in ECG signal.

sensing model is executed to produce the data compressed. For reconstructing after compressing, Bayesian compressive sensing (BCS) was used to return the original signal. The results prove that compressive sensing is an efficient way to compress the data and reduce the data size with best quality of reconstruction and effective minimization of noise.

Izadi *et al.*[78] proposed a system architecture using linear method that can produce compressed ECG samples with Compression Ratio (CR) reached 75%. The sparsity of the ECG signal was used with the compressive sensing theory to compress the ECG signals in real time. The size of the ECG samples are reduced in order to consume the energy. For reconstruction, Kronecker technique was applied to produce high quality recovered ECG signal.

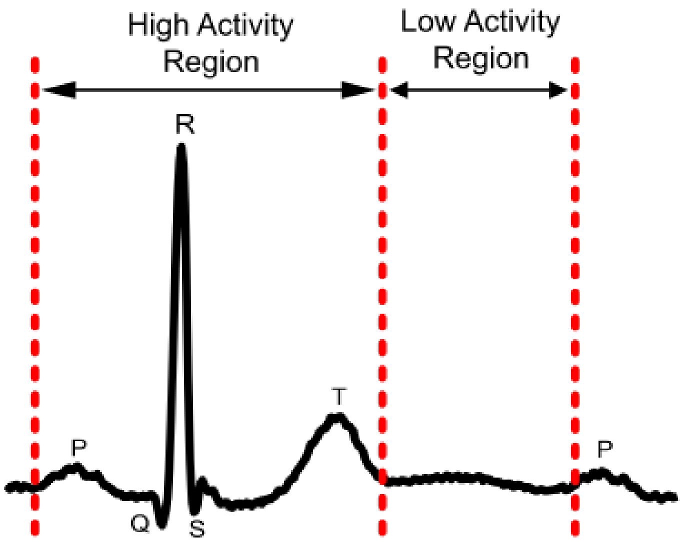


Figure 2.8: Information regions in ECG signal.

2.5 Open Challenges and Opportunities

IoT Homecare management system is still considered as a recent open research field. Several challenges and limitations are encountered.

Major efforts have been made; however, several open issues are still needing more consideration to achieve a robust Homecare management system. Some of these issues are discussed in the following sections.

2.5.1 Gap 1: Accuracy

Accuracy is one of the main challenges that needs to be studied and improved. Such systems need to give accurate results for best caring. Having accurate results make the system more reliable and can be used confidently. Any mistakes in the results of those systems can lead to wrong diagnosing, inappropriate caring or false alarming which may lead to destroy the person's life. Several researches in the literature described above encountered this limitation. Moreover, Zhu *et al.* [79] mentioned that machine learning can perform better than clinic protocols in the rehabilitation for homecare patients. Charles *et al.* [80] deduced that applying deep learning algorithm in fall detection performed accurate results. On the other hand, Feng *et al.* [81] concluded that combining two deep learning algorithms performed better accuracy in fall detection and adding more training data will improve the accuracy of the system. Machine learning and deep learning can help in solving accuracy problem by using huge training data. These techniques will let the machine learn from previous evaluated data to examine and predict the output of new data using decision making process. To increase the accuracy using machine learning, a huge training data is used to let the machine learn well from the trained data to provide accurate decisions on the test data. One of the limitations of machine learning is the linear decision boundary that leaves some data unfitted correctly between the two classes. To solve this issue, deep learning algorithm is used where the data are fitted accurately between the two classes using non linear decision boundary. This gab is addressed in Chapter 3.

2.5.2 Gap 2: Data

The data used in those systems need to be perfectly collected, stored and ready for processing.

Data Collection: For example, the collection of health data needs to access patient data in hospital which is private and unable to access. Due to this limitation, the researches focused only on online databases which are limited and old. Other researches deal with a volunteer person. This way is more specific and cannot gather all the diagnosis situations. The solution to this problem is to collaborate with data providers to get permission to access the private data. This gab is addressed in Chapter 3.

Data Processing: After the collection step, data need to be processed. The processing of the data needs to be efficient and fast to produce critical information and/or to make decisions in real-time. This issue can be solved by using high processor Personal Computer with high capacity solid-state drive (SSD) to store persistent data while processing.

Data Analysis: Data analysis process is critical in those systems for decision making step. The quality of this process depends on the storage and middleware technologies. It is important that the data entered to those systems are validated and in high quality which are both correct and useful to reduce any noise and to produce better and faster results.

Data Storage: Most existing IoT homecare management systems produce huge amount of data especially healthcare data. The flood of those data may cause unforeseen problems if the developers did not manage it perfectly. Cloud computing technique is the one of the suggested way to handle this issue without affecting the real time feature of such systems. However, there is a need to minimize the data size itself without destroying its features. Data compression helped in reducing the storage needs for data. Moreover, compressive sensing sampling data at much lower rate that results in less memory storage. This gab is addressed in Chapter 4 and Chapter 5.

2.5.3 Gap 3: Cost Effectiveness

There are a limited number of low-cost homecare systems. Several systems must use Internet technology for data transmission and emergency response by using high cost technologies such as 3G/4G which is unavailable in poor countries. Where on the other hand, there are some low-cost technologies for connection such as Bluetooth and Zigbee but have some limitations regarding the coverage area. Furthermore, several systems required the use of smart phone or expensive devices that are not affordable to everyone. Typically, there is a tradeoff between high quality and low cost in sensors and sensing devices [82]. The software developers should use the minimum required low price techniques in designing homecare systems to solve this issue. Minimizing the cost is not just in equipments, sending less data is one of the ways to reduce the cost. One of the techniques is compressive sensing; it produces effective data sampling at a much lower rate than required. Compressive sensing possesses several interests, such as much less storage need, higher data transmission rate, much less power consumption and much smaller need for sensory devices. Moreover, data compression produces several advantages in minimizing the cost. After applying this technique there is a reduction in the storage hardware needs, the data transmission time and the channel bandwidth. This result in considerable savings of the required costs for IoT Homecare management systems. This gab is addressed in Chapter 4 and Chapter 5.

2.5.4 Gap 4: Connectivity

Achieving connectivity at any place on any time is one of the challenges. For real time systems the connection should be reliable without interrupts. Communication using 3G/4G services may have signal problems. Radio Frequency Identification (RFI) sometimes is used whilst a problem of interference may appear. Wireless technologies make homecare management systems achievable. However, such networks that operate in outdoor environment have many connectivity issues especially in rural countries. There are many aspects that can influence the reliability of homecare system networks such as, real obstacles, atmospheric absorption and system failure. The solution to solve this problem is to have a strategy of several communication networks to navigate between them in case any interrupts happened.

2.5.5 Gap 5: Reliability

Some of the key research issues of using sensors are energy efficiency, responsiveness and robustness. The need for having sensors operate all the time in homecare systems require the need for low-power consumption and high energy efficiency techniques to satisfy high performance system. Those sensors as well require the need to report their data to the microcontroller, robust and energy-efficient protocols are needed to ensure that monitoring events are not missed. The overall performance of the system should not be sensitive to individual sensor failures. Therefore, robust data fusion technology for extracting information are very important to solve this issue in homecare systems.

2.5.6 Gap 6: Security and Privacy

Security and privacy are considered as the major concern of homecare management systems. Focusing on the integrity of the data transmitted and the authorization of access to those data.

Furthermore, highlighting on which information each person should receive and deal with are considered important. Kotz *et al.* [83] discussed the available privacy frameworks with limitations and therefore extracted a number of rules to solve the privacy demand in mobile healthcare and smart home systems based on the privacy principles. Most homecare management system data are private and sensitive and requires a high level of security. Many research studies attempted to solve the security issues. For authentication, Catuogno and Galdi [84] used video camera for event recognition. The authentication protocol performed well but required a huge amount of energy and capacity that are not preferred in IoT homecare systems. Moreover, Zuniga *et al.* [85] used biometric technologies to solve the authentication in healthcare. However, biometric technology usually is not accurate 100% and can be affected by the environment and users. Alsaadi, I. M. [86] recommended a combination of several biometric methods to produce accurate and reliable authentication for best level of security. Having IoT devices may increase the risk of having vulnerabilities. As the number of devices increase, the number of ways the attacker break into the system could rise. It is highly important to make sure the user's data are confidential and the connection is private and secure to solve this issue. Not securing the system could lead an attacker to get access to confidential information and could break the system or produce incorrect results. Securing IoT homecare systems are still need further investigations.

2.6 Summary

Various IoT based smart homecare technologies are available for providing comfort living. In this chapter, the state-of-the-art homecare management systems were first investigated and classified into healthcare, home automation and hybrid of healthcare/home automation. Based on the literature the most applied network, hardware and software were explained. Moreover, the type of the sensors used in the literature were pointed out and classified into biological and environmental. Also, a comparison of the most used microcontroller and special computer is provided. Furthermore, the comparisons and discussions of various network technologies were presented. Then, detailed background of data compression and compressive sensing were investigated. Finally, the main challenges and future research directions were discussed for novel contributions to this research area.

Chapter 3

Cardiac Arrhythmia Feature Extraction and Classification

This chapter achieves the thesis aim by proposing a Cardiac Arrhythmia Feature Extraction and Classification model for homecare systems. The proposed model for homecare systems achieves Objective 1 in Chapter 1. Thus, it addresses various research gaps in Chapter 2, which are Gap 1 and Gap 2.

The most important challenge in homecare system is the accuracy because those systems are dealing with human health which is sensitive and need high accuracy. The trusted homecare system by health experts should be able to detect abnormalities and make decisions in an accurate way. To overcome the accuracy challenge, this chapter presents a Cardiac Arrhythmia monitoring framework that is able to diagnose patient and classify ECG signal into normal and arrhythmia. Cardiac Arrhythmia happen when the ECG signal contains irregularity in their features. The raw ECG signal is passed through signal processing stage for denoising using Low-pass filter and Savitzky Golay filter. Then the denoised signal is passed through the feature extraction stage to

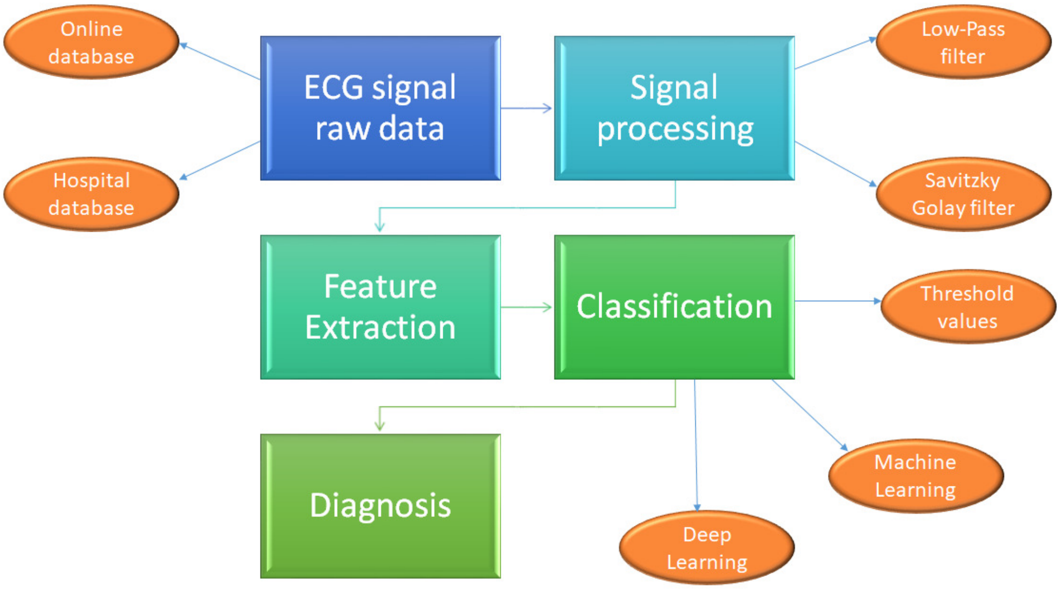


Figure 3.1: Cardiac Arrhythmia Feature Extraction and Classification Model Processes

extract a number of features that are used in the classification stage. After that, a classification stage to detect Cardiac Arrhythmia and classify ECG signal to normal and arrhythmia is made in three ways; threshold values using medical measurements, machine learning using SVM and deep learning using MLP to improve the accuracy. Finally, the performance of the proposed model is assessed by comparing it with two existing model to examine the machine learning and deep learning results. Experiment results reveal that the proposed model is more accurate in the classification of Cardiac Arrhythmia and more reliant from caregivers point of view in comparison with other researches.

3.1 Proposed Model

The proposed model is focus on implementing an ECG monitoring model. Figure. 3.1 summarizes the main model processes of the proposed work. The uniqueness of this model is by using raw ECG signals taken from two databases; online that is limited and old, and from hospital that is exclusive and new. Each signal is passed through signal processing stage for denoising using Low-Pass filter and Savitzky Golay filter. Combining these two filters provide better results different than existing works. Low-Pass is used to remove the noise from the signal and Savitzky Golay filter to scale the signal and make it much clearer to accurately extract the peaks. Then the denoised signal is passed through the novel algorithm for feature extraction to find the peaks and waves of the signal and extract a number of features that are important in the classification stage. After that, a classification stage to detect Cardiac Arrhythmia is made in three different ways to increase the accuracy where no other existing work did the same thing. First, classify using threshold values where there are strict medical values in case any feature value goes above or beyond those values an alarm message is shown with the specified diagnosis. Second, classify using machine learning to get the machine learn from the trained data using SVM machine learning algorithm and then classify new patient based on the trained data to normal or arrhythmia. Third, due to the SVM drawback in linearity of decision boundary, there is a need to use MLP deep learning method to increase the accuracy and overcome the SVM limitation using non linear decision boundary and then classify new patient based on the trained data to normal or arrhythmia. Finally, the performance of the proposed model using machine learning and deep learning are assessed by comparing them with two existing model. Experiment results reveal that the proposed model is more accurate in the classification of Cardiac Arrhythmia and more reliant from caregivers point of view in comparison with other works. Moreover, the hospital database results are compared to the online database in terms of classification accuracy and number of errors and they achieve better results due to the huge number of patients for training.

3.1.1 ECG Signal

Each ECG signal has a standard shape which consists of five main waves [87] as shown in Figure 3.2:

- P wave (Q-pre): the atrial systole contraction pulse.
- Q wave: the downward deflection immediately preceding the ventricular contraction.

- R wave: the peak of the ventricular contraction.
- S wave: the downward deflection immediately after the ventricular contraction.
- T wave (S-post): the recovery of the ventricles.

Each wave represents a vital health process in the heart. Any abnormalities or irregular activities are called arrhythmias. Cardiac arrhythmias are indication of a cardiac health or heart diseases where heart beat irregular, too slowly, or too quickly. Several heart diseases discovered from abnormal ECG signal such as:

- Severe hyperkalaemia: considered as a dangerous heart disease that can cause lethal arrhythmias such as ventricular fibrillation or asystole, leading to cardiac arrest [88], [89]. It therefore requires high level of caring, ECG monitoring, and immediate remedy [90]. It is associated with abnormal ECG signal, including wide QRS complexes.

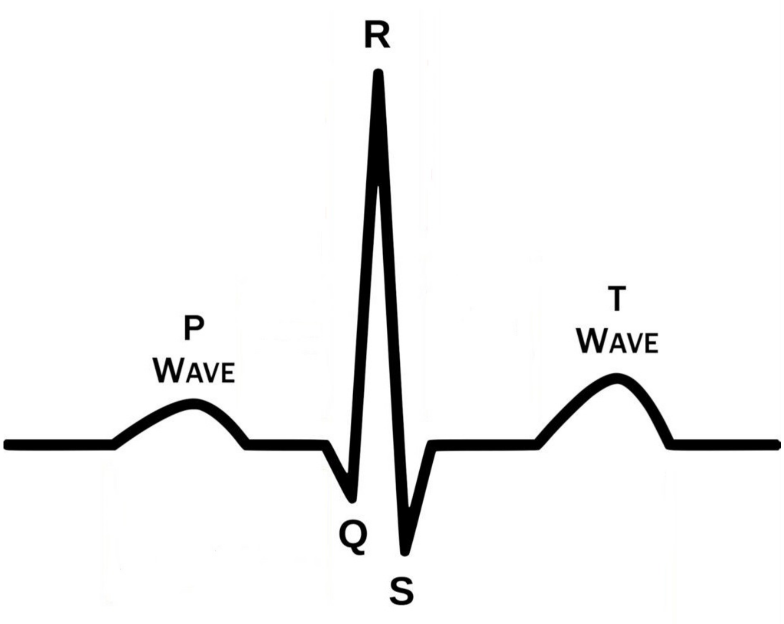


Figure 3.2: ECG signal components

- Wolff parkinson white syndrome: one of the common heart diseases that forces the heart to beat fast for periods of time in an abnormal way. The reason for this problem is an extra electrical connection in the heart that present at birth. However, symptoms may not appear until later in life [91].

- First degree of atrioventricular block: a condition of abnormal ECG signal where there is a long interval without disruption of atrial to ventricular conduction. There are no symptoms in this heart disease and discovered only on routine ECG monitoring.

- Ventricular tachyarrhythmia: a heart disease where ECG signal act abnormal with fast heart rate. It starts in lower chambers of patient's heart, called the ventricles. Ventricular tachyarrhythmia is configured where three or more heart rate of more than 100 beats per minute.

3.1.2 Feature Extraction

The clean and clear signals arrived from the signal processing stage and ready for the feature extraction. The peaks and waves can be marked clearly based on medical measurements and the interval between those waves are important in detecting abnormality. Using the marked waves and peaks, several features of ECG signal can be extracted based on medical standards [92] as shown in Figure 3.3:

- QRS Complex: the time interval between Q and S waves in milliseconds.

- RR interval: the time interval between two adjacent R waves in milliseconds.

- Heart Rate: calculated by dividing 60 over the RR interval in beat per minute as expressed by eq(3.1).

$$HR(bpm) = \frac{60}{RRinterval} \tag{3.1}$$

- QT interval: the time interval between the start of Q wave and the end of T wave in milliseconds.

- Corrected QT interval (QTc): the QT interval normalized by the square root of RR interval in milliseconds as expressed by eq(3.2). (Bazett formula)[49].

$$QTc = \frac{QT}{\sqrt{RRinterval}} \tag{3.2}$$

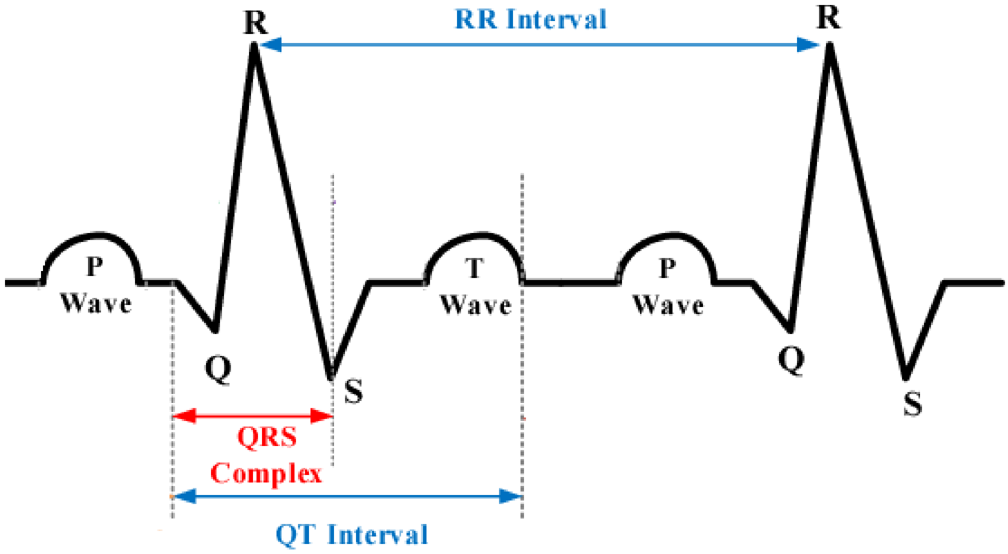


Figure 3.3: ECG signal interval and features

The algorithm to extract features is built based on deep research on how to read the important information from the ECG signal itself and in collaboration of health expert in that field. The details can be found in Algorithm 3.1:

1. Find and mark R peaks that hold the highest peak for each 500 samples and then save the value and location of those peaks.
2. Remove the outer edges that contain incomplete waves.
3. Find and mark Q and S waves that are adjacent to each R peaks by using a window size of 80 samples and shift it based on R peaks location.

Algorithm 3.1: Feature extraction algorithm

for $i \in (1, ..., NoS/500)$ **do**
  Find R peaks: $(t, Rpeaks(t, i))$
end for
Remove outer edges
for $j \in (1, ..., NoS/80)$ **do**
  Find Q based on R: $(t, Q(t, j))$
  Find S based on R: $(t, S(t, j))$
  Calculate $QRS = loc(Q) - loc(S)$
  Find P based on QRS: $(t, QRS(t, j))$
  Find T based on QRS: $(t, QRS(t, j))$
end for
Calculate and save $QRScomplex = median(QRS)$
Calculate and save RR, QT, QTc

4. Calculate QRS by counting the difference between each locations of S and Q waves in milliseconds during the whole number of samples then calculate QRS complex by taking the median of all the QRS in the signal.

5. Find and mark P and T waves that are adjacent to each QRS by using a window size of 80 samples and shift it before the starting of Q wave for P wave and after the ending of S wave for the T wave.

6. After finding all the waves RR interval, heart rate, QT interval and QTc interval are extracted and saved.

The normal ranges for each feature based on medical measurements can be found in Table 3.1 [23]. Using this table, we can guarantee that the features values are within the standard ranges.

3.1.3 Classification & Diagnosis

The classification and diagnosis of our model are made in three ways: threshold values, machine learning and deep learning.

Table 3.1: ECG features threshold values.

ECG Feature	**Threshold value**
QRS	< 120 ms
RR interval	600-1000 ms
QT interval	320-440 ms
Heart Rate	40-105 or 60-105 bpm (40 minimum normal for athletes at rest)

Threshold values

Several diseases can be figured out from the feature extraction step using the threshold values method. If the feature value goes beyond or above the threshold value, a disease can be discovered as shown in Table 3.2 [3].

Table 3.2: Diseases discovered from abnormal ECG feature values.

ECG Feature	**Abnormal value**	**Disease**
QRS	> 120	Disruption of the heart's conduction system, or severe Hyperkalaemia
RR interval	< 120 > 200	Wolff Parkinson White syndrome First degree of Atrioventricular block
QTc	> 440	Ventricular Tachyarrhythmia
Heart Rate	< 40 or > 105	Abnormal Heart Beat

Machine Learning

Machine learning algorithms can be used to increase the accuracy of the diagnosis and to reduce human exertions. It is the field of artificial intelligence that gives the computer the ability to learn from data to make decisions without being fixed programmed. This is achieved by building a model based on some sampling data, those data known as training data, in order to predict a value or make a decision. Machine learning algorithms are applied in a large set of applications, such as medical field, where it is hard or unable to build traditional algorithms to perform the required tasks.

Machine learning are split into three groups, based on the data nature to the learning system:

- Supervised learning: finding a rule to map inputs to outputs based on training data. Supervised learning algorithms worked by building a mathematical model of a set of training data that contains inputs and desired outputs [93]. Supervised learning algorithms are used for active learning, classification and regression [94]. Classification algorithms are used when the outputs are limited to a set of values.
- Unsupervised learning: take a set of input data only and find matching in the data, such as grouping or clustering.
- Reinforcement learning: a training method based on remunerative a required conducts and/or penalizing undesired ones.

The most common supervised linear classification algorithm for best classifying the data using a segregate hyperplane is SVM. Hyperplane means a decision boundary that provides two sides. Data landing on one of the two sides of the hyperplane can be assigned to different classes. To separate two classes of data, there are many possible hyperplanes that can be used. The most important thing is to find a hyperplane with maximum margin. Which means the maximum distance between data in the two classes. Maximizing the margin distance perfectly produces some confidence for future data to be classified optimally as cleared in Figure 3.4.

Data that are closer to the hyperplane are called Support vectors as shown in Figure 3.5. Those support vectors are used to maximize the margin of the hyperplane.

SVM is one of the most powerful prediction methods. Two types of data are used; training and testing. The training data used to build up the model and define the classes of the classifier. Testing data used to validated and evaluate the performance of the model. Using a set of training

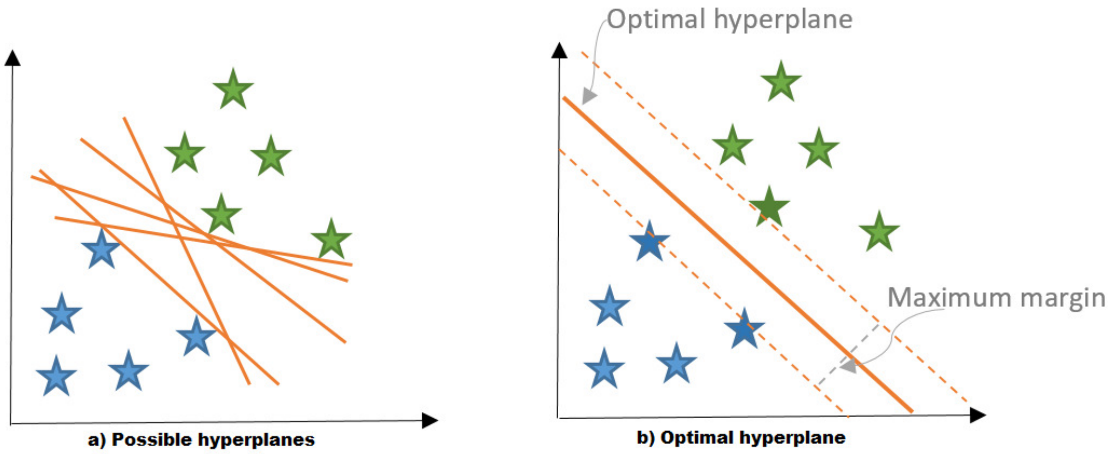


Figure 3.4: Hyperplane to classify data in two classes: a) Possible hyperplanes, b) Optimal hyperplane

data each marked to one of two classes. SVM algorithm assigns new testing data to one of the two classes as a binary linear classifier. For ECG classification and based on the literature, SVM produced much better than other machine learning algorithms.

There are several other supervised machine learning algorithms. Decision tree [95] used for regression and classification problems by creating a training model to predict the desired output by learning simple decision rules from the training data. Starting from the root of the tree by comparing the values and jumping to the next node.

Moreover, k-nearest neighbors KNN algorithm [96] is one of the supervised machine learning algorithm that can be applied for solving classification and regression problems. For classification, the input consists of the k nearest training data of the total data set. The output is a class where it is worked by voting of the neighbors for each node. It is simple and easy algorithm but has a drawback of slowness with growing number of data.

Furthermore, Linear Discriminant or Discriminant Analysis [97] is an algorithm used for supervised classification problems. This algorithm worked by finding a linear combination of features for separating two or more classes of data as a linear classification.

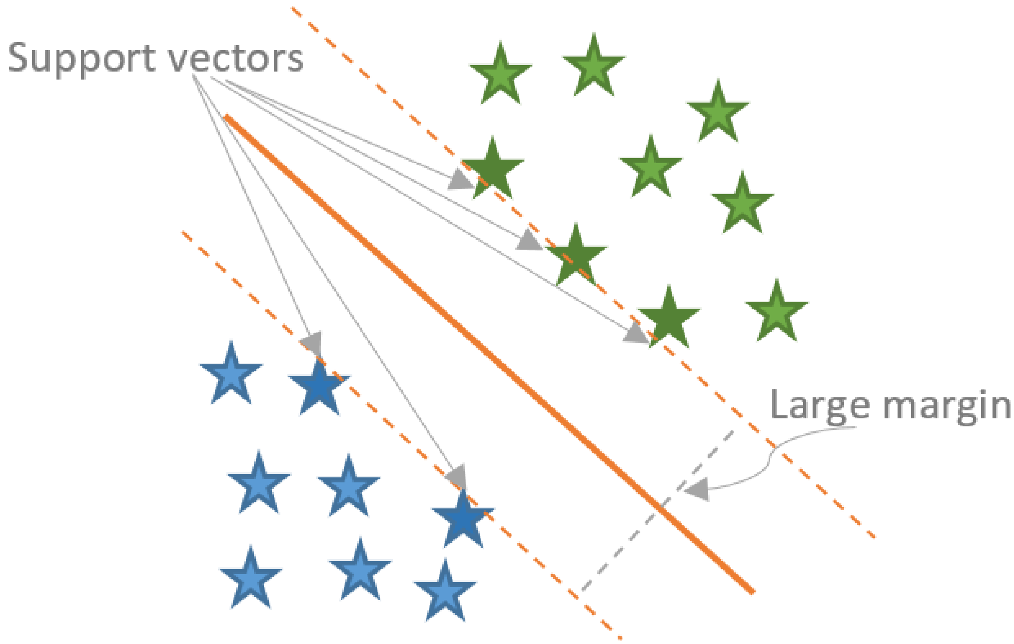


Figure 3.5: Support vectors between two classes

Deep Learning

Deep learning algorithms are part of the machine learning that belonges to Artificial Intelligence technique. In our model it is used in raising the accuracy of arrhythmia detection and minimizing the human efforts. Deep learning is different from machine learning in the presentation of data. It depends on number of layers of Artificial Neural Network (ANN). ANN is a connected nodes called artificial neurons based on the biological brain neurons. However, neurons in ANN are static and symbolic. A feedforward neural network is a type of ANN where the connection between neurons do not support any backward results as an input so they don't form a cycle. An MLP neural network is a class of feedforward artificial neural network that contains multiple layers of perceptrons. Each node except the input node is a neuron that uses a nonlinear activation function. Activation function of a node worked by defining the output of that node by given an input or set of inputs. Three types of activation/loss functions can be applied on neurons:

- Piecewise linear: a function of unbounded interval and real variable with straight line segments graph [98].
- Sigmoid: a function of bounded interval and real variables and has a non negative derivative at each point [99].
- Signum: an odd function for extracting the sign of a real number. The signum of a number is known as its sign.

MLP used in this framework as a classifier for best cardiac arrhythmia detection. MLP can differentiate data that are not separated linearly. The structure of MLP consists of four components as shown in Figure 3.6:

1. Input layer to receive the signal;
2. Hidden layers the true computational engine of the MLP;
3. Output layer to make a decision or prediction about the input;
4. Weights between them.

Weights can be found using derivative, partial derivative or chain rule. When chain rule is applied to find and update the weight, this is called backpropagation. The algorithm consists of two stages forward pass and backward pass. In the forward pass, the activation function is used to find the outputs of the given inputs. However, partial derivatives of the cost function is used in the backward pass and propagated back through the network. The weights then can be applied using any gradient optimisation algorithm. The entire process is repeated until the weights collected [100]. MLP can be trained using epochs by keeping all parameters fixed and calculate the weights using all the training data then accumulate them and update the parameters once.

The detailed steps on how MLP is working are as follows:

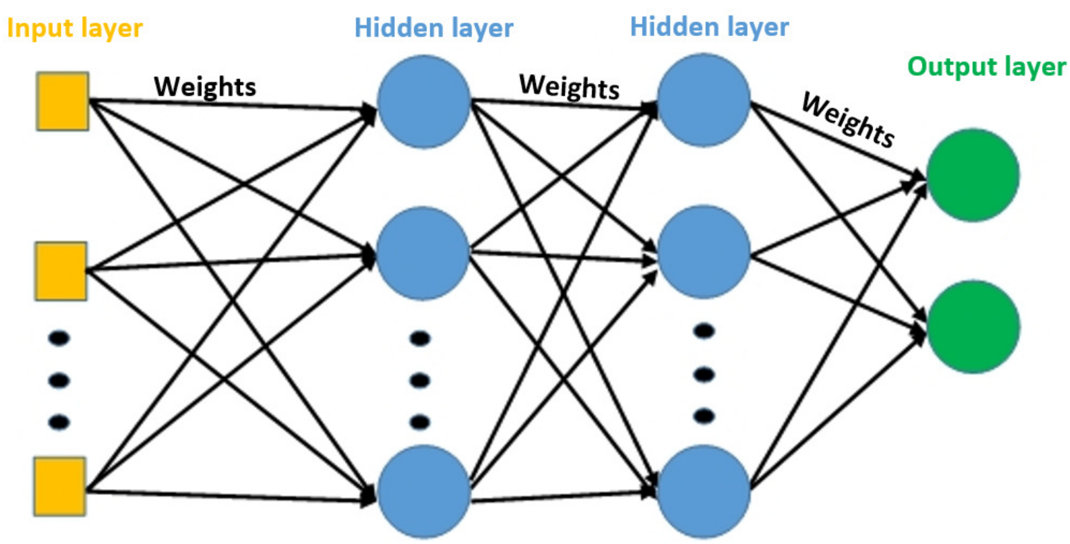


Figure 3.6: MLP structure

1. Weight initialization V and W with random numbers from a suitable interval lets say (-1 to 1)

2. Inputs application with a random one pair (x,t) of the training set for the coming steps and mark it as used.

3. Sum of inputs - weight product by doing a forward calculation. The notation x' is the input vector x multiplied by the bias.

4. Backward calculation by applying the activation function.

5. Weight adaption by calculating the weight changes and update them.

6. Back to step 2 and repeat it until using all the pairs in the training.

The training set consists of pairs where x is the input vector and t is the output vector.

3.2 Experiment Results

3.2.1 Simulation Setup

The platform used for this simulation model was built using MATLAB simulation environment version R2019a. The device used is a desktop personal computer with Intel Core i7 processor.

3.2.2 ECG Data

The data used in this simulation was downloaded from online database. However, this database is limited and old that requires the need to have new and real time one from real patients. The second part of data were taken from a hospital with a large number of real patients to test the algorithm and to update the accuracy in terms of artificial intelligence.

Online Database

For simulation parameters, the ECG data was downloaded from PhysioBank.com [101]. PhysioBank.com is a large archive of digital recordings for biomedical signals and all the related data for use by the researchers.

The first 48 ECG signals were taken from MIT-BIH Arrhythmia database [102]. The signals were taken between the years 1975 and 1979. They were related to patients in and out the hospital. The last 18 signals were taken from MIT-BIH Normal Sinus Rhythm database. No arrhythmias were found in this database that was taken from 5 men and 13 women. The signals in those databases were made of half an hour recording from Holter device in labs [103, 104]. The raw signals in both database were digitized in the hospital at 360 samples per second per channel.

Hospital Database

Real ECG signals included in this study were collected from King Abdulaziz Medical City, Ministry of National Guard- Health Affairs in collaboration with Dr. Haitham Alanazi, Head of the Cardiac Electricity Department and Professor at King Saud University for Health Sciences.

The database includes ECG signals recorded from in hospital patients using Holter device. The collected ECG signals stored in 62 CDs. The total number of corrected ECG signals used in this study is 946 signals from both male and female patients. Around 51% of the total data belongs to male and 49% to female. The ages for male ranged from two days to 88 years old and for female ranged from one day to 100 years old.

Each CD contains number of patients records organized by measuring dates. For each patient there are two records FULL for 24 hours recording and CFR for short recording. The short signal is more informative and suitable to the considered model.

3.2.3 Simulation Results

First, each ECG signal is plotted in samples per amplitude to show the waves of the signal. Figure 3.7 represent the raw ECG signal of the first patient. The signal of all patients contains 3600 samples. The ECG waves can be configured however, some noise are recognised that require the need for some signal enhancement techniques.

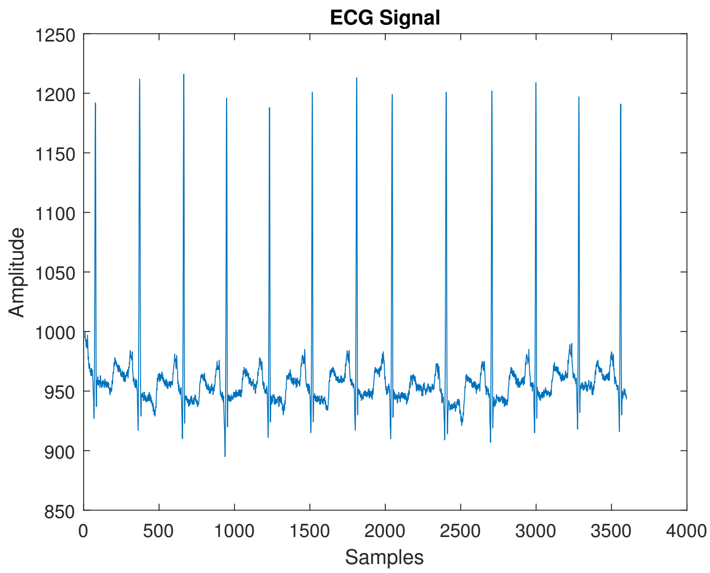
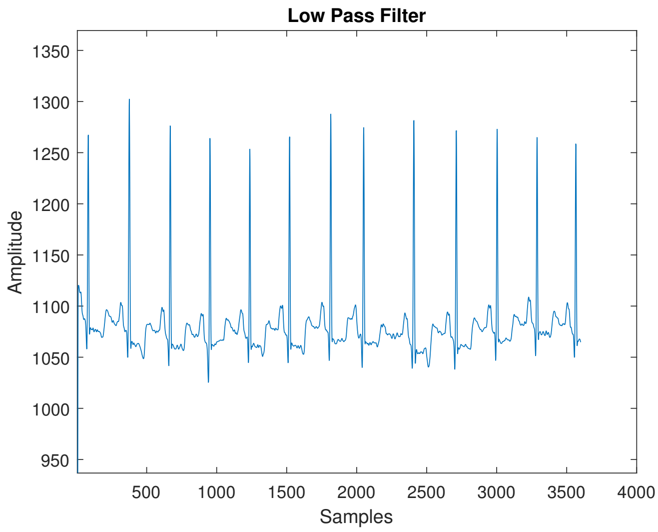


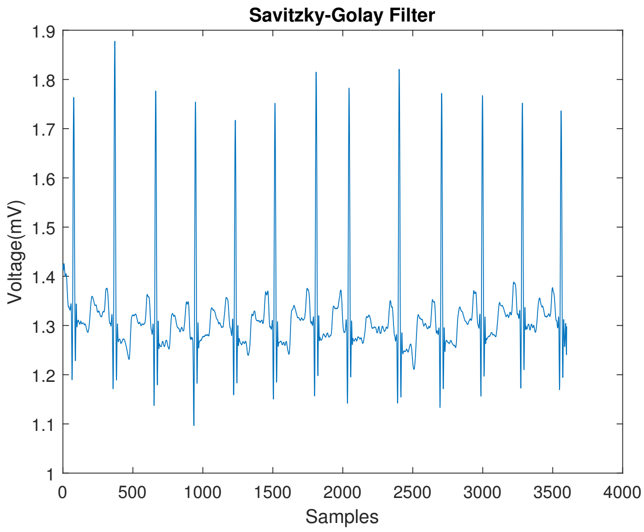
Figure 3.7: The raw ECG signal of the first patient

The impact of signal processing on ECG signals

For the reason of noise, two signal processing techniques were applied on the first patient. A low-pass filter was implemented to reduce the noise of the signal as shown in Figure 3.8(a). The



(a) Low-Pass filter



(b) Savitzky-Golay filter

Figure 3.8: Signal processing techniques on ECG signal: a) Low-Pass filter, b)Savitzky-Golay filter

x-axis represents the number of samples and the y-axis shows the amplitude reached. The edges of the signal are clearly configured and the noise are removed compared to the raw ECG signal.

Before extracting the feature, the signal needs to be scaled. A Savitzky Golay filter was implemented as shown in Figure 3.8(b). The x-axis represents the number of samples and the y-axis shows the amplitude in voltage that is normalized for eliminating and regulating peak levels. The small details of the waves can be seen clearly and the signal is ready now for the feature extraction stage.

The impact of feature extraction on ECG signals

In the feature extraction method, five main waves are found Q, R, S, P and T waves. Those waves and peaks are marked as shown in Figure. 3.9. R peaks represent the highest peak in Red

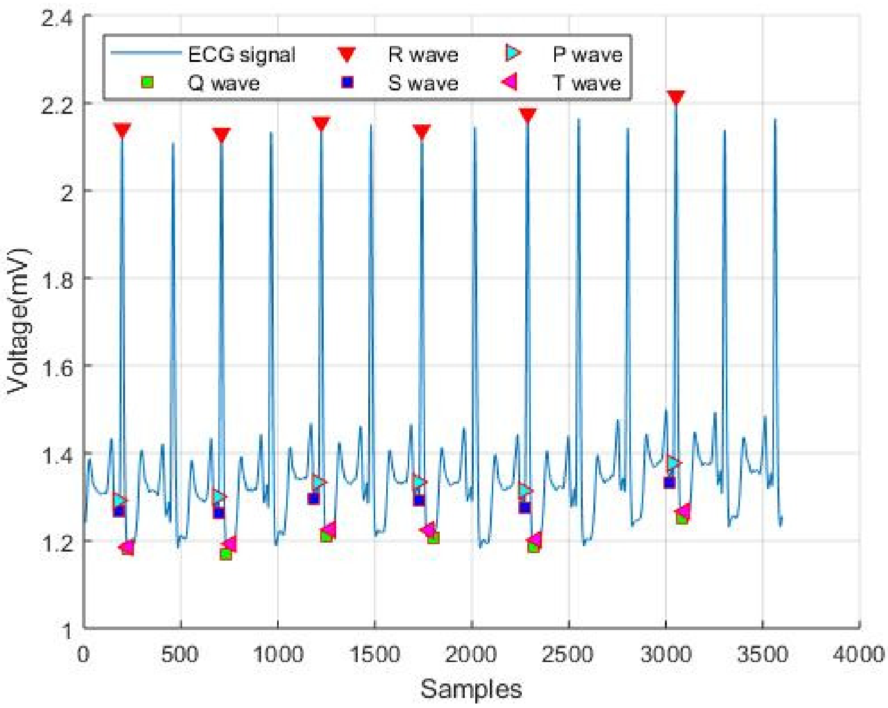


Figure 3.9: ECG signal peaks and waves: Q, R, S, P and T waves

triangle, where the other waves are in low amplitudes. The other peaks are marked based on the beginning of each wave. The starting of Q waves represented in Green squares and S waves in Blue squares. The starting of P and T waves represented in Turquoise and Pink triangles.

Several features are extracted using the waves and peaks marked. The values of the features for the first patient from online database are:

- QRS= 38.00 ms
- Heart rate= 101.01 beat/min
- RR interval= 594.00 ms
- QT interval= 237.60 ms
- QTc interval= 308.29 ms

All the remaining feature values for online database are clearly shown in Figure 3.10. Each coloured shape represents a feature value in five different shapes. Light Blue diamond for QRS, Orange square for heart rate, Gray triangle for RR interval, Yellow x-shape for QT interval and Blue special x-shape for QTc. The x-axis represents the ECG signal for each patient in online database. The y-axis represents the range for all the features values. In this figure, the range for each feature can be clearly segmented or grouped. Starting from QRS, the values ranged from 35 to 100. Then heart rate, the values ranged from 62.76 to 117.19. Then some overlapped between QT and QTc with ranges 170.67 to 478 for QT values and 238.5 to 488.87 for QTc values. Then finally, a spread look to Gray dots for RR interval with values ranged from 512 to 956.

However, the values of the features for the first patient in hospital are:

- QRS= 35.00 ms

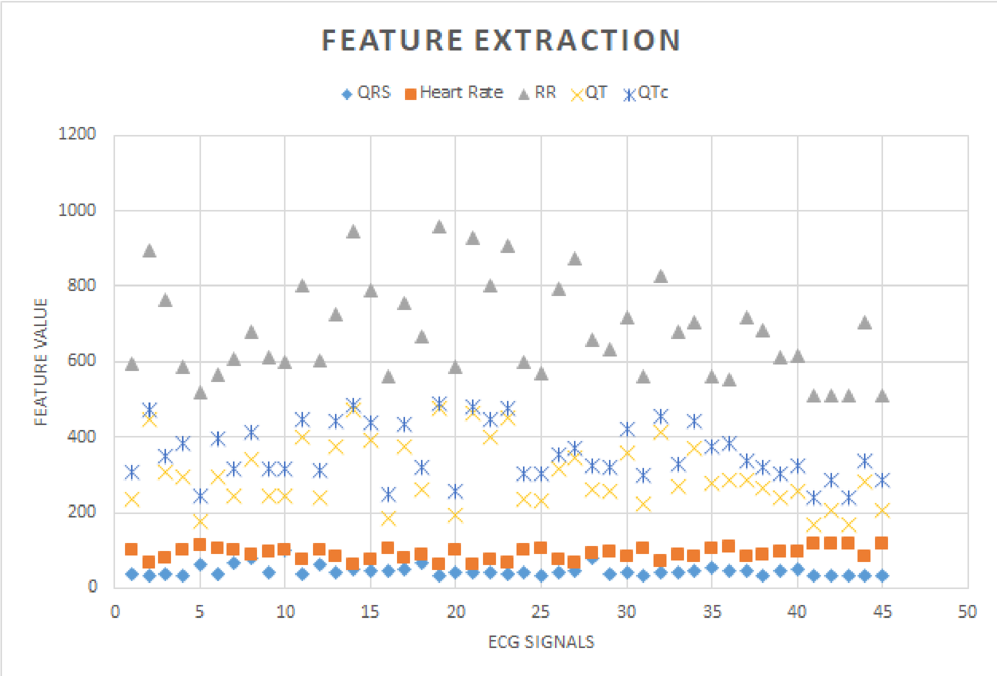


Figure 3.10: Extracted features values of online database: QRS, heart rate, RR interval, QT interval and QTc

- Heart rate= 89.087 beat/min
- RR interval= 673.5 ms
- QT interval= 271.3 ms
- QTc interval= 330.58 ms

All the remaining feature values for hospital database are clearly shown in Figure 3.11. In this figure, there are a huge number of coloured shapes that can clearly differentiate the areas of the same colours. For QRS, the values ranged from 26 to 49 with some overlapping with heart rate that ranged from 20.08 to 118.11. Then another overlapping configured between QT and QTc with values ranged from 174.17 to 667.95 for QT and 235 to 649.66 for QTc. Finally, RR

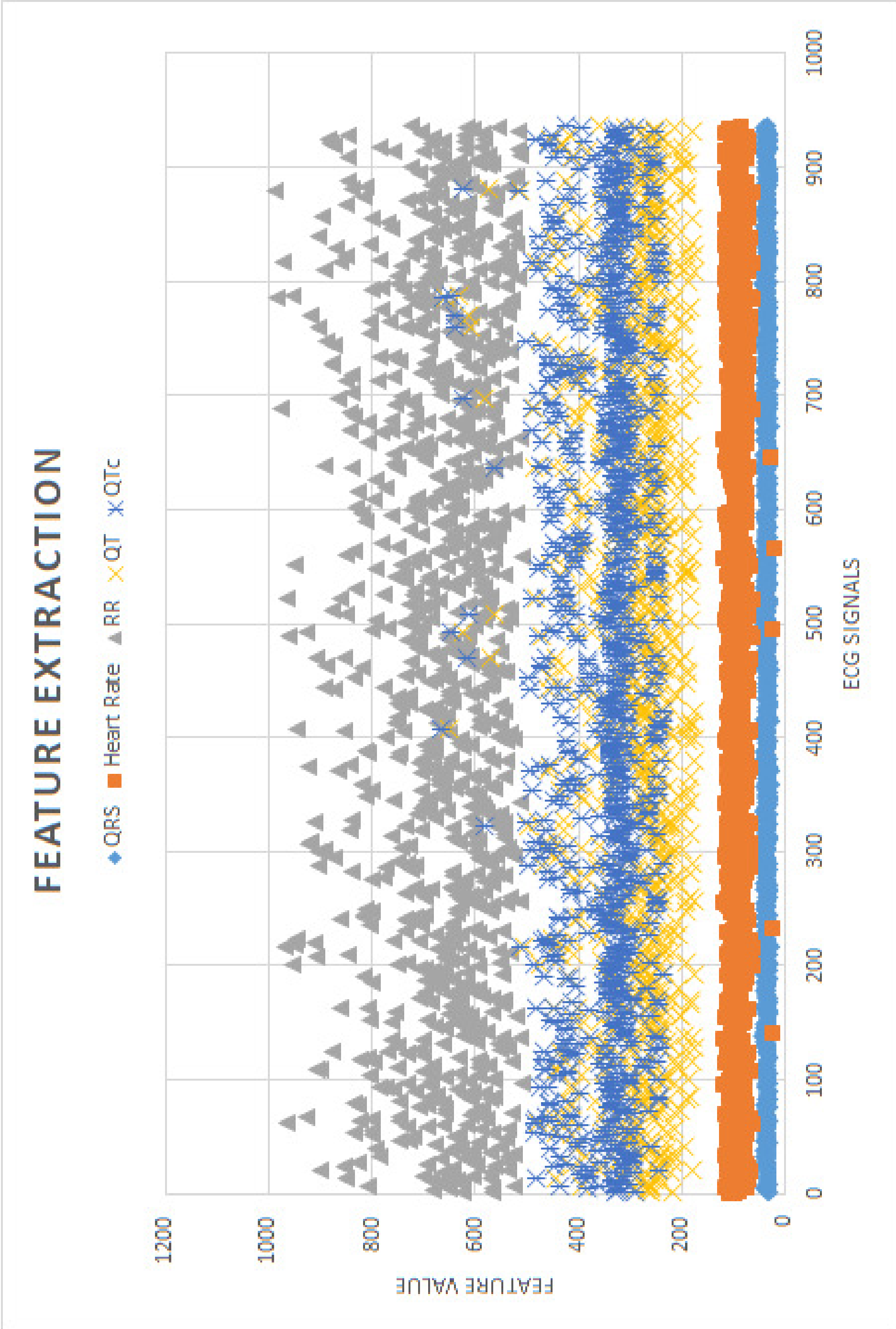


Figure 3.11: Extracted features values of hospital database: QRS, heart rate, RR interval, QT interval and QTc

Table 3.3: The accuracy of machine learning algorithms.

Machine learning method	**Accuracy**
Decision Tree	83.3%
K-Nearest Neighbours	86.7%
Linear Discriminant	90.0%
Support Vector Machine	96.7%

coloured shapes are holding the highest range from 508 to 990. All these features are stored in the local database to apply classification methods.

The impact of threshold value on ECG signals classification

For the classification step based on the threshold value strategy, a warning message is shown with the diagnosis specified. For the first patient case, the warning message was: *This patient may have first degree of Atrioventricular Block.* Several diagnosis messages are displayed based on the feature values:

- This patient may have: Abnormal Heart Beats.
- This patient may have: Wolff Parkinson White syndrome.
- This patient may have: A disruption of the heart's conduction system, or severe Hyperkalemia.
- This patient may have: Ventricular Tachyarrhythmia.

The impact of machine learning on ECG signals classification

Several machine learning classification methods were applied in our model. By using classification learner tool in Matlab, SVM was selected as the best classification method for our scenario. The accuracy of SVM was very high 96.7% in a short time training as shown in Table 3.3.

Table 3.4: Comparison of existing work and our work in using SVM.

Characteristics	**Existing work[3]**	**Proposed work**
Signal processing techniques	low-pass filter and moving average filter	low-pass filter and Savitzky Golay filter
Classification techniques	SVM	Threshold values and SVM
Machine learning classification accuracy	83% for 7 features	91.67%
Database	MIT-BIH arrhythmia and private database	MIT-BIH arrhythmia
Classification of data	10% training 90% testing	80% training 20% testing

A full SVM algorithm is implemented in Matlab for our model. After the feature extraction step, the values of features for the 48 patients from online database are stored in the local database. The data then is divided into two sets: the first set is for training and used 80% of data while the second set contains 20% of data for testing. All the extracted features are fed into the classification model to find the decision boundary between normal and abnormal classes. Based on the overlapping between the features (QRS, Heart rate) and (QT, QTc), (QRS, Heart rate) are selected to represent the results because they are much important in the diagnosis of heart diseases than (QT, QTc).

The implemented SVM was able to classify the signals and draw a hyperplane between normal and abnormal cases as shown in Figure. 3.12. The green plus sign and the red dots represent the normal and abnormal data respectively. The hyperplane in the figure was able to differentiate between normal and abnormal classes using yellow and blue colours respectively. The data was fitted correctly between the classes. The accuracy was 91.67% which is high in comparison with previous research in [3]. The comparison is accomplished using SVM algorithm on MIT-BIH database and with the same features as shown in Table 3.4. The classification accuracy is calculated by computing the true positive (TP), false positive (FP), true negative (TN) and false negative (FN) as expressed by eq(3.3).

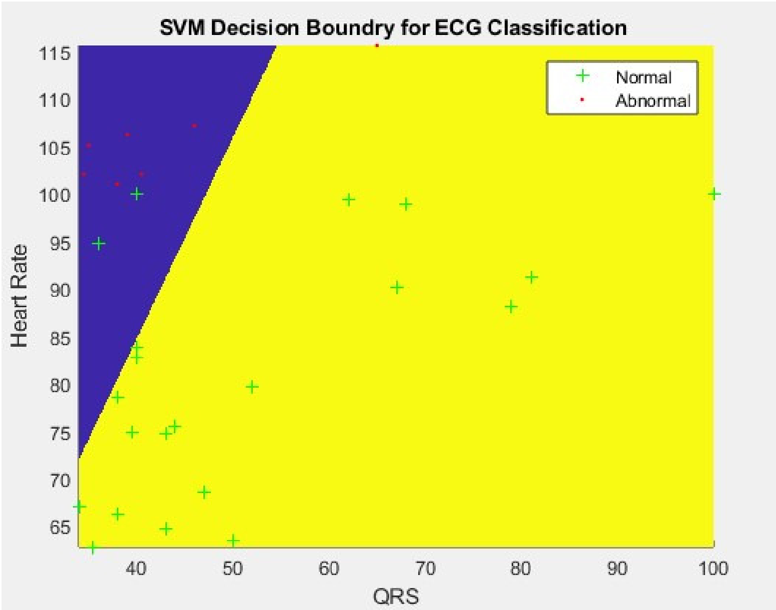


Figure 3.12: SVM classification using ECG signals from online database into normal class in yellow and abnormal class in blue colour

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.3}$$

To improve the accuracy for the classification, the same SVM algorithm is implemented in Matlab for our model. After the feature extraction step, the values of features for the 946 patients from hospital database are stored in the local database. The data then is divided into two sets: the first set is for training and used 80% of data while the second set contains 20% of data for testing. All the extracted features are fed into the classification model to find the decision boundary between normal and abnormal classes. QRS and Heart rate are selected to represent the results. The implemented SVM was able to classify the signals and draw a hyperplane between normal and abnormal cases as shown in Figure. 3.13. The green plus sign and the red dots represent the normal and abnormal data respectively. The hyperplane in the figure was able to differentiate between normal and abnormal classes using yellow and blue colours respectively. The blue area for abnormal values was narrowed in comparison to online database in Figure 3.12 to special part

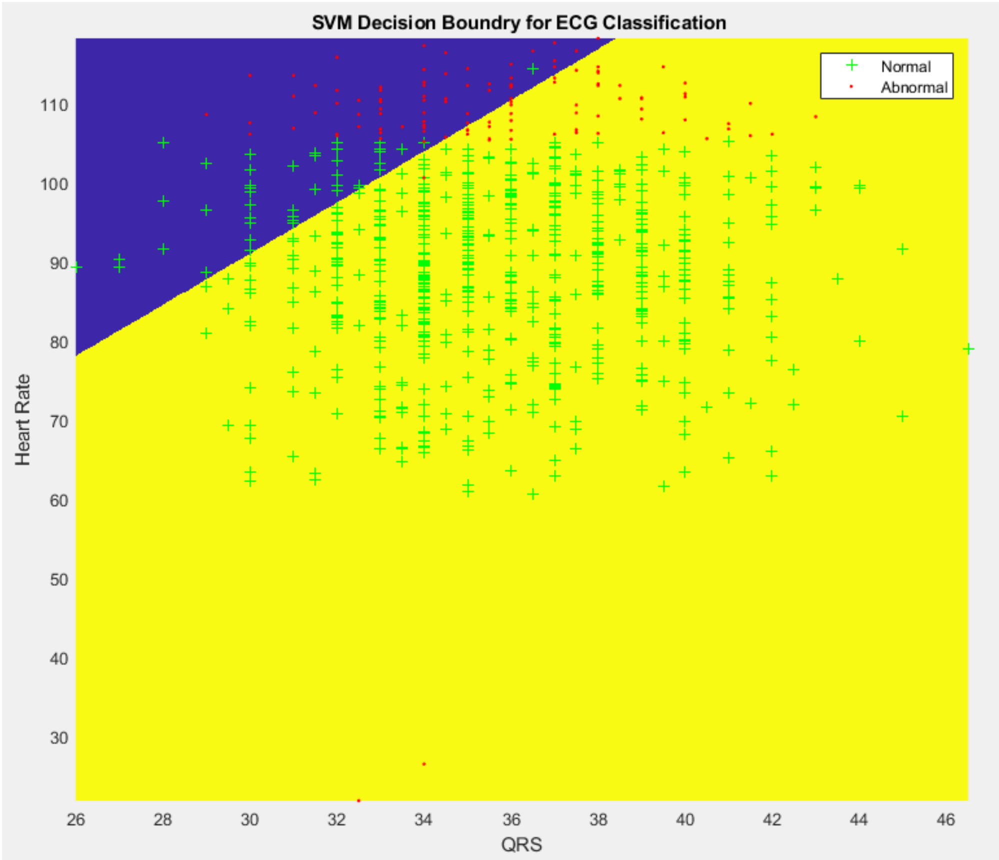


Figure 3.13: SVM classification using ECG signals from Hospital database into normal class in yellow and abnormal class in blue colour

only that classify accurately abnormal values as abnormal with minimal errors. The data was fitted correctly between the classes that reduced the number of false positive and false negative. The accuracy was 94% which is high in comparison with online database. However, some data are fitted wrongly the green pluses in the blue or abnormal class, and the red dots in the yellow or normal class. This is happened due to the linear hyperplane of SVM algorithm which means only single striate line is used to classify two classes. Based on the results, the data used are not linearly separable data which require the need to classify using non-linear classification algorithm. SVM is very good when we have no idea on the data at the beginning. But after the results there is a need for non linear classification algorithm with high level of accuracy. Moreover, SVM required long training time for large datasets. The need for non linear, fast and accurate classification algorithm is required for the proposed model that is solved in the following sub section.

The impact of deep learning on ECG signals classification

For cardiac arrhythmia classification a deep learning MLP feedforward artificial neural network was implemented to learn the mapping between inputs to predict output. This type of deep learning algorithm is able to determine the data that are not separated linearly. A sigmoid was used as an activation function because it gives clear prediction with smooth gradient using output values bound between 0 and 1. It is expressed by eq(3.4), where x is the weighted sum of inputs.

$$Sigmoid(x) = \frac{1}{(1 + e^{-}x)} \tag{3.4}$$

Backpropagation algorithm was implemented for training with a gradient descent to find the best weight as expressed by eq(3.5), where K is the training iteration, C is the learning rate and E is the loss function.

$$w_{l_j}^{k+1} = w_{l_j}^{k} - C\frac{\partial E}{\partial w_{l_j}} \tag{3.5}$$

The loss function can be expressed by eq(3.6), where t is the target output, y is the actual output and n is the training data.

$$E = \frac{1}{2n}\Sigma_{i=1}^{n}(t - y)^2 \tag{3.6}$$

Train by Epoch was used to keep all the parameters fixed and calculate the weight using all the

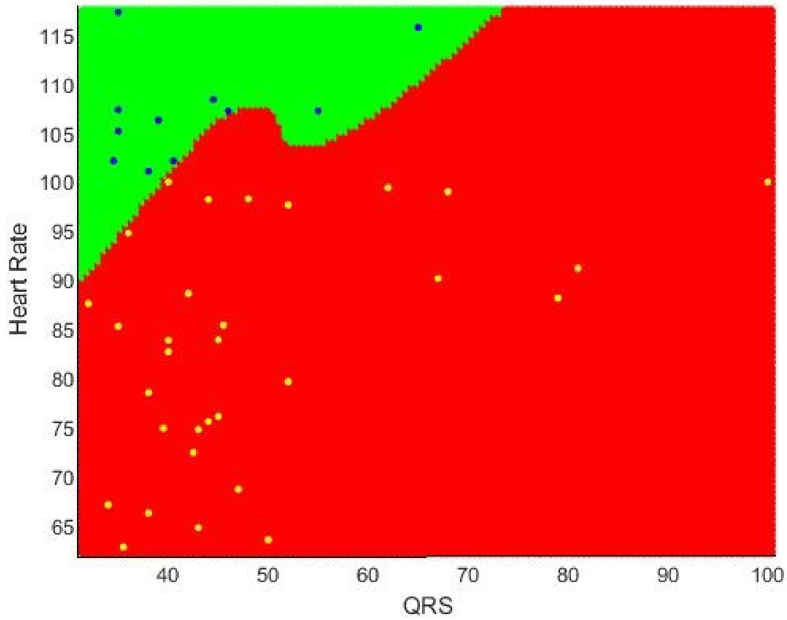


Figure 3.14: MLP Decision boundary for online database in two classes: normal class in red and arrhythmia class in green colour

training data then accumulate them and update the parameters once. For training, 80% of total data was used while the remaining 20% for testing. Two features were selected as input; heart rate and QRS and two outputs; normal and Arrhythmia. The number of hidden layers in the neural network were two each one of them contains 10 neurons. The learning rate selected to be 0.15 and the maximum number of epoch is 500. MSE was selected as an evaluation metric to measure the average squares classification errors and can be expressed by eq(3.7).

$$MSE = |\frac{\Sigma_{i=1}^{n}(t-y)^2}{n}| \tag{3.7}$$

The decision boundary for the values of the two features QRS and Heart rate are displayed in Figure 3.14. In this figure four colours are used. Yellow dots represent the normal values while

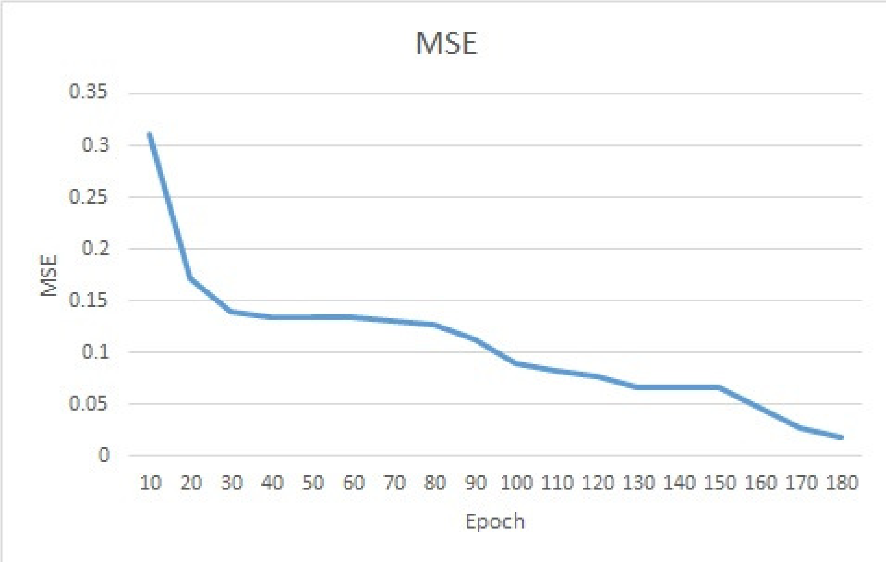


Figure 3.15: MSE of online database

blue represent the abnormal values. Red and green are clearly differentiate between the two classes by drawing a wave decision boundary. The MLP algorithm was able to classify the data into normal and Arrhythmia and draw a non linear decision boundary between them after 176 epochs done out of 500 with a MSE reaches 0.019 which is very close to zero.

The MSE is calculated and displayed based on the number of epochs reached as shown in Figure 3.15. The x-axis displays the number of epochs and the y-axis shows the number of errors reached. For the first 10 epochs it was 0.31 and then 0.09 after 100 epochs. Finally it reaches 0.019 after 176 epochs which means very high accuracy.

To improve the accuracy of the decision, MLP algorithm is applied with Backpropagation technique using the hospital database. For training, 80% of total data used while the remaining 20% is for testing. To represent the results, two features are selected as input; heart rate and QRS and two outputs; normal and Arrhythmia. The number of hidden layers in the neural network are two each one of them contains 10 neurons. The learning rate selected to be 0.15 and the maximum number of epoch is 500. The decision boundary for the values of the two features

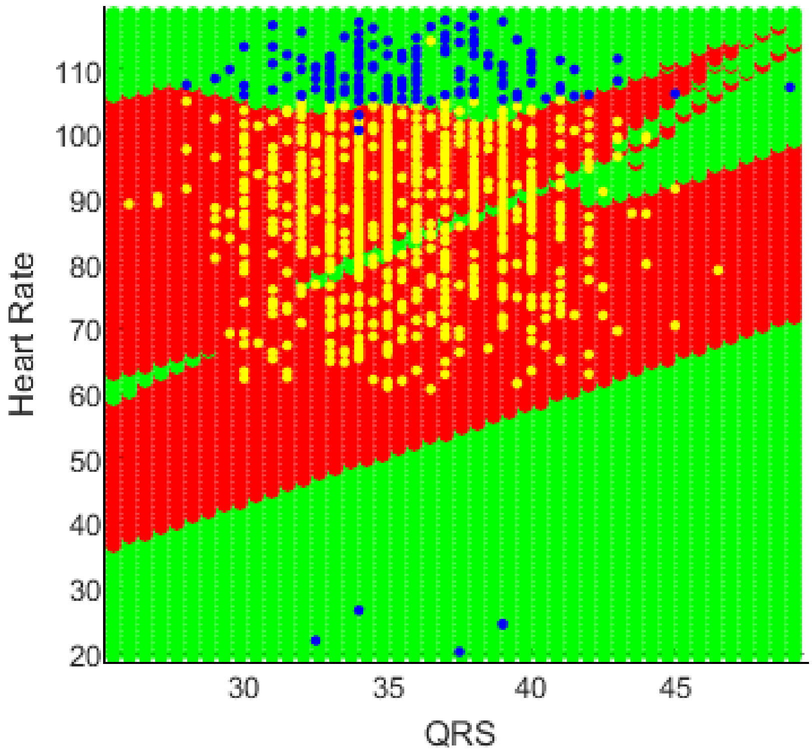


Figure 3.16: MLP decision boundary for hospital database in two classes: normal class in red and Arrhythmia class in green colour using non linear decision boundary

QRS and Heart rate are displayed in Figure 3.16. The MLP algorithm was able to classify the data into normal and Arrhythmia and draw a non linear decision boundary between them. The decision boundary is much better than online database with more non linear areas of normal and Arrhythmia for best diagnosis. There are two non linear areas for Arrhythmia ECG signals highlighted in red which means any future data fed into these areas classified as Arrhythmia ECG signal. Furthermore, three different areas for normal values in green colour so any future data fed into these areas classified as normal ECG signal. However, in online database only one area for each class configured.

The MSE is calculated and displayed based on the number of epochs reached as shown in

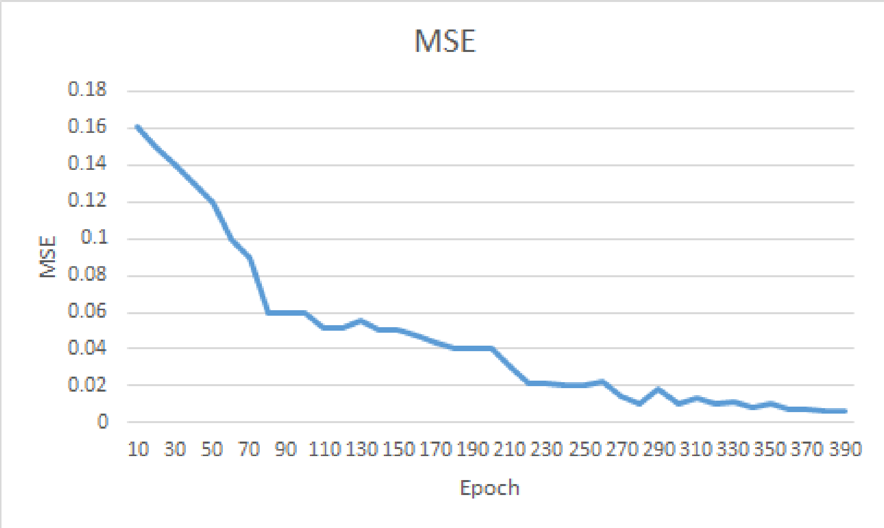


Figure 3.17: MSE of hospital database

Figure 3.17. The x-axis displays the number of epochs and the y-axis shows the number of errors reached. For the first 10 epochs it was 0.16 and then 0.05 after 100 epochs. Finally it reaches 0.006 after 390 epochs which means very high accuracy in compassion to online database due to the huge number of patients.

To compare the results with previous work, MLP algorithm was applied with Backpropagation technique using the same database from PhysioBank.net and details can be found in Table 3.5. The parameter values were taken from the research paper in [4]. The learning rate selected to be 0.002 and the maximum number of epochs was 1000. Four hidden layers were used with 60 neurons in each one of them. NMSE and accuracy were used as evaluation metrics as expressed by eq(3.8) and eq(3.9).

$$NMSE = |\frac{1}{2n}\Sigma_{i=1}^{n}(t-y)^2| \tag{3.8}$$

$$Accuracy = 1 - \sqrt{MSE} \tag{3.9}$$

Table 3.5: Comparison of previous work and proposed work in using MLP.

Characteristics	**Previous work[4]**	**Proposed work**
Training techniques	TensorFlow library on Python	Matlab code
Classification techniques	MLP and CNN	MLP
Hidden layers	4 with 60 neurons	4 with 60 neurons
Activation function	Sigmoid	Sigmoid
Classification accuracy	69% for 100 epochs	87% for 100 epochs
Database	MIT-BIH arrhythmia and kaggle.com	MIT-BIH arrhythmia
Classification of data	80% training 20% testing	80% training 20% testing

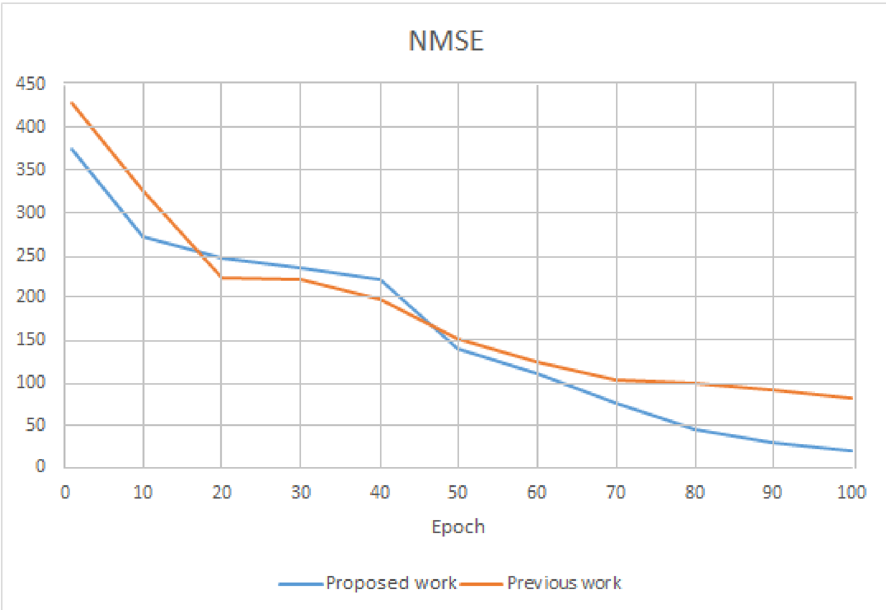


Figure 3.18: NMSE of previous work [4] and proposed work

For comparison, the first 100 epochs were selected from previous work and our proposed work to check the NMSE and the accuracy. Figure 3.18 shows two different colour lines blue for the proposed work and orange for the previous exciting work by other researchers[4]. The x-axis

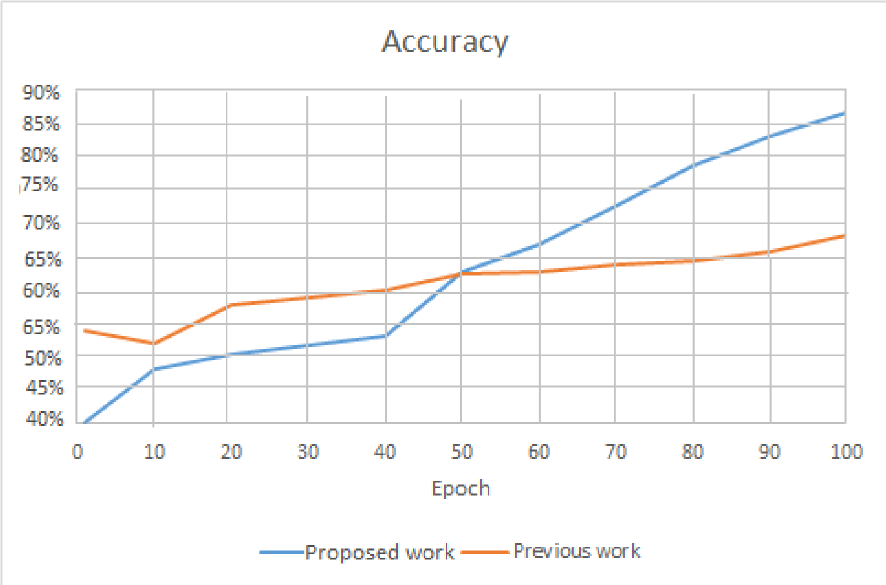


Figure 3.19: Accuracy of previous work [4] and proposed work

shows the number of epochs reached and the y-axis shows the number of classification errors using NMSE equation eq(3.8). The NMSE of the previous work reaches 430 errors in the first epoch while it reaches 375 errors in our work. Then it decreases slightly until it reaches 83 for previous work and 20 for our work. Which means our work performs better and achieves minimum number of errors comparing to previous work and using the same simulation setup.

Accuracy was compared in the same way. The first 100 epochs were taken from the previous work and our work as shown in Figure 3.19. In this figure, two different colour lines appeared blue for our proposed work and orange for the previous existing work by other researchers[4]. The x-axis shows the number of epochs reached and the y-axis shows the percentage of classification accuracy using Accuracy equation eq(3.9). From the first epoch the accuracy reaches 54% in previous work while it reaches 40% in our work. After that, the accuracy increases slightly until it reaches 87% for our work and 69% for previous work after 100 epochs. Those results prove that our work outperformed previous work in accuracy.

3.3 Summary

In this chapter, a Cardiac Arrhythmia model on ECG signals for feature extraction and classification was proposed. This model includes signal enhancement, feature extraction and classification. For signal filtering, two filters were applied Low-Pass filter and Savitzky Golay filter. An implemented algorithm for extracting features was discussed. The classification was applied in three ways: fixed threshold values, machine learning and deep learning. The fixed threshold value classification was based on medical ranges for each feature with the diagnosis for each patient based on the features values in comparison with medical ranges. To improve the accuracy, machine learning algorithm using an implemented SVM algorithm was applied. Then a deep learning algorithm using an implemented MLP algorithm was proposed to better improve the accuracy. Then, several experiments were conducted to evaluate the performance of the proposed model. Two databases were used, an online one that is limited and old, and an exclusive hospital database with huge number of real patients. The main conclusions are:

- The proposed model benefit from the exclusive hospital database more than online database with new, real, huge and existing patients in hospital rather than other existing works that worked on online database or limited volunteer patients.
- Applying two kind of filters produced clear ECG signal with no noise to extract the features accurately.
- The proposed model outperform the other researches in the cardiac arrhythmia classification purpose with higher accuracy of 91.67% for SVM and 87% for MLP with minimum number of errors.
- Huge number of data used leads to higher classification accuracy with less errors that is essential for healthcare sector.
- The SVM decision boundary using hospital database is much accurate than online database with accuracy reached 94% and the two classes are narrowed with specific ranges for normal and abnormal to get precise diagnosis.

- The MLP decision boundary using hospital database is much precise than online database with multiple non linear lines that clearly differentiate between normal and Arrhythmia areas with MSE reduced to 0.006 which is very close to zero that means high level of accuracy.

Chapter 4

Adaptive Amplitude Threshold Compression Algorithm

ECG monitoring is playing a crucial function of taking care of patients having cardiac diseases. But huge amount of signals need to be stored, processed and transmitted. To solve this issue, data compression must be applied in an effective way to reduce the storage demands and minimize the cost. Having an efficient cardio system for analysing and diagnosing the condition of heart is our goal. Therefore, this chapter addresses Gap 2 and Gap 3 in Chapter 2 and achieves Objective 2 in Chapter 1 by designing a novel adaptive amplitude threshold compression algorithm.

In this chapter, an adaptive amplitude threshold compression algorithm is proposed for effective cardio management system. The raw ECG signal is passed through signal preprocessing stage for filtering and scaling using Savitzky-Golay filter. After that, R peaks are marked and saved as the signal sparsity. Then the threshold value is calculated using adaptive amplitude threshold equation. Then, the signal is compressed by comparing left and right neighbour of each sample with the calculated threshold value. If it is higher, the sample is stored to form the compressed

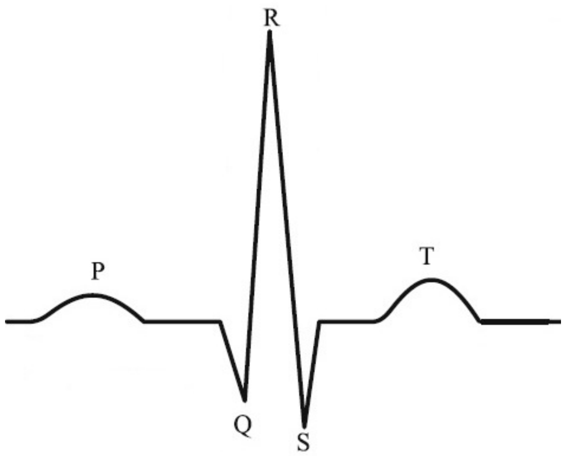


Figure 4.1: ECG signal waves

signal. Otherwise, the sample is rejected. After that, the whole compressed signal is transmitted to the receiver. The receiver receives the compressed signal as it is and start extracting the features. After saving all the features values, a classification stage is started based on the feature values to detect ECG abnormalities. This stage is made using machine learning and deep learning. Experiment results show that the proposed algorithm is more efficient and fast in the classification of ECG signals in low cost.

4.1 Proposed algorithm

This algorithm deals with the whole ECG signal. It works by comparing the amplitude difference between left and right neighbours of each sample with the adaptive threshold (AT). AT is a novel algorithm that is based on the ECG signal sparsity. Each ECG signal has a standard shape which consists of five main waves as shown in Figure 4.1:

- P wave: the atrial systole contraction pulse.

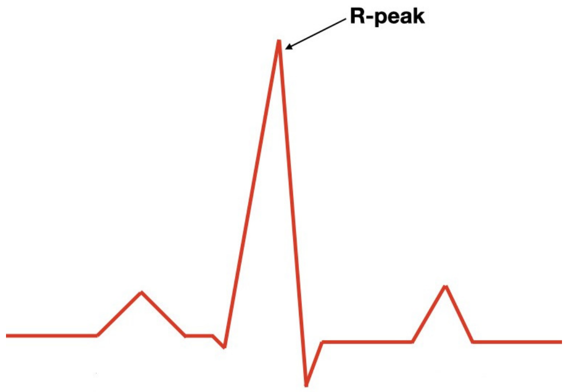


Figure 4.2: R peak in ECG signal

- Q wave: the downward deflection immediately preceding the ventricular contraction.
- R wave: the peak of the ventricular contraction.
- S wave: the downward deflection immediately after the ventricular contraction.
- T wave: the recovery of the ventricles.

The sparsity of the signal defined by the number of significant amplitude in signal. ECG signals checked to be sparse in frequency domain. After running several simulations on different ECG signals, the key finding is that R peaks are selected as a signal sparsity. R peaks are holding the maximum amplitude value in the wave. The shape of that peak can be found in Figure 4.2. The amplitude of this peak is much higher than others and easily can be recognised by eyes. The detection of those peaks are very essential for the diagnosis of heart disease. The novelty here is that there is relation between the marked R peaks (signal sparsity) and the Number of Samples (NoS) to calculate the AT. This relation is found after running different simulations to find relevant information. If the difference between left and right neighbour of each sample is higher than the AT, the sample is stored. Otherwise, the sample is rejected. The compressed signal is formed by the stored samples after comparing with the AT. The first sample of the

Algorithm 4.1: Adaptive threshold algorithm

1: Get the ECG signal: $(t, sig(t))$
2: Filter the signal: $(t, flt(t))$
3: Scale the filtered signal: $(t, scl(t))$
4: Count number of R peaks $\Rightarrow \#Rpeaks_{original}$
5: Calculate $AT \leftarrow \frac{2 \times \#Rpeaks_{original}}{NoS}$
6: **for** $i \in (1, ..., NoS - 2)$ **do**
7:     **if** $abs(scl(t_i) - scl(t_{i+2})) > AT$ **then**
8:         $(t_{i+1}, scl(t_{i+1})) \leftarrow stored$
9:     **else**
10:         $(t_{i+1}, scl(t_{i+1})) \leftarrow rejected$
11:     **end if**
12: **end for**
13: Count number of R peaks in stored signal $\Rightarrow \#Rpeaks_{compressed}$
14: **if** $\#Rpeaks_{original} == \#Rpeaks_{compressed}$ **then**
15:     Extract features and save
16: **else**
17:     Reject compressed signal
18: **end if**

signal is automatically stored because it has only right neighbour. The detailed algorithm can be found in Algorithm 4.1.

In step 1, the ECG signal on time domain is displayed. In step 2, The same signal is filtered on time domain. In step 3, the filtered signal is scaled in time domain. In step 4, the number of R peaks are counted. In step 5, the threshold value AT is calculated based on the number of R peaks and NoS. In step 6, loop throughout the number of samples of the scaled signal and then find the difference between left and right neighbour of each sample if the difference is higher than the calculated AT value, then this sampled is stored otherwise it is rejected. After the loop is terminated in step 12, the compressed signal is formed from the stored samples then move to step 13. In this step, count the number of R peaks in the compressed signal. In step 14, compare between the number of R peaks before and after compression. In step 15, if the number of R peaks are the same before and after compression then start extracting the features. Otherwise, reject the compressed signal and try again. And finally after compressing all the signals, the classification is made based on the saved features from the compressed signals.

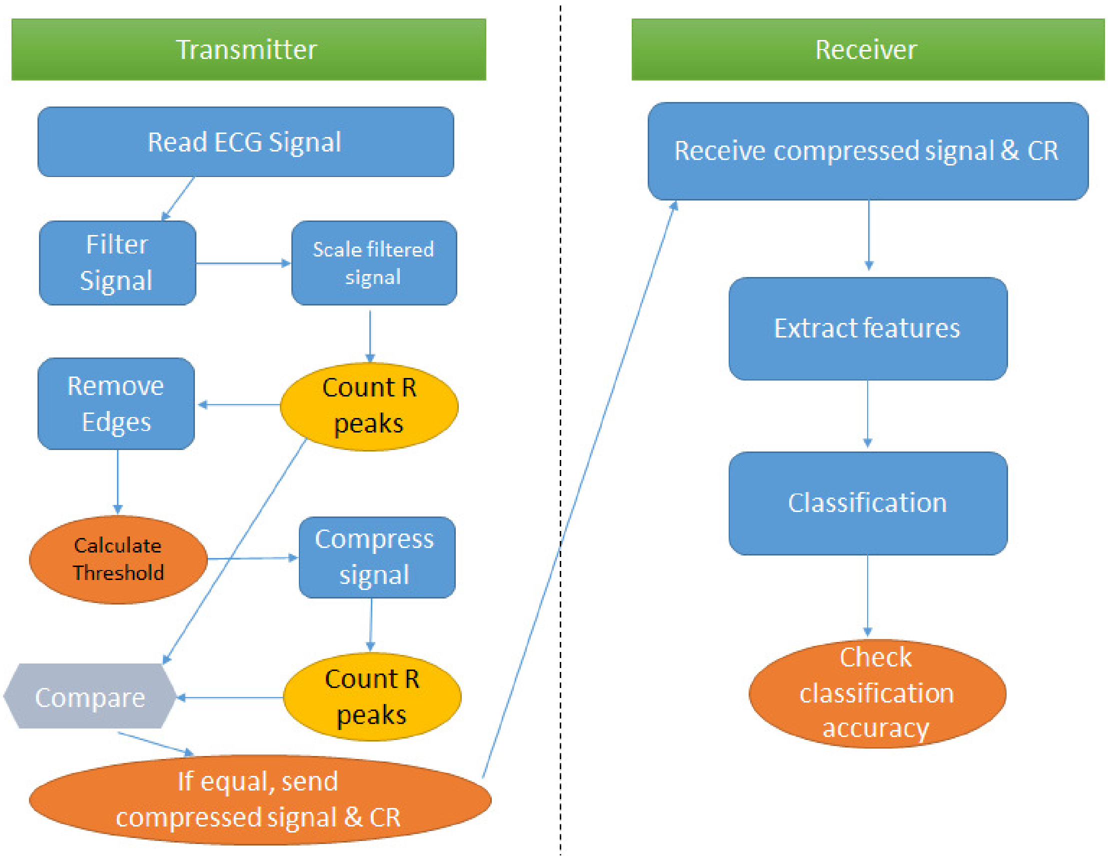


Figure 4.3: Adaptive threshold algorithm flowchart

A flowchart of the algorithm can be found in Figure 4.3. First, the raw ECG signal is entered. Then, some preprocessing is made using Savitzky–Golay filter [105]. This filter is used for scaling the signal, smoothing and differentiation. It is applied to increase the signal-to-noise ratio without distorting the signal. After that, R peaks are counted and saved. The signal edges need to be removed in this step because it contains uncompleted waves. Then, the threshold is calculated based on the novel AT algorithm. After that, the compressing step should start. The difference between left and right neighbour of each sample is calculated and compared with the threshold value. If it is higher the sample is stored, otherwise, the sample is rejected. Then the compressed signal is formed based on the stored samples after comparing. After compression, CR is calculated based on eq(4.1) that finds the ratio between the number of samples before and after compression. The number of R peaks is calculated based on the new number of samples after compression. The number of R peaks of original and compressed signals are compared. If they are equals, the transmitter will send the compressed signal with the CR to the receiver. The receiver receives the compressed signal and calculates the features based on the CR and then classify it to check the classification accuracy.

$$CR = \frac{\text{Number of samples before compression}}{\text{Number of samples after compression}} \tag{4.1}$$

Several features can be extracted in receiver side using the waves and peaks of the compressed ECG signal. QRS Complex, RR interval, Heart Rate, QT interval and Corrected QT interval (QTc) [87]. The calculation of the features must be scaled based on the CR to get similar features in transmitter and receiver.

- QRS Complex: the time interval between Q and S waves in milliseconds.
- RR interval: the time interval between two adjacent R waves in milliseconds.
- Heart Rate: calculated by dividing 60 over the RR interval in beat per minute.
- QT interval: the time interval between the start of Q wave and the end of T wave in milliseconds.
- Corrected QT interval (QTc): the QT interval normalized by the square root of RR interval in milliseconds.

The classification is made using machine learning and deep learning to increase the accuracy of the diagnosis and to reduce human exertions. For machine learning, SVM is one of the most used linear supervised machine learning algorithm for best classifying the data using a segregate hyperplane. SVM is implemented in this algorithm to find the classification accuracy of the compressed ECG signal and to draw a hyperplane between normal and abnormal compressed

ECG signals. On the other hand, deep learning depends on number of layers of Artificial Neural Network (ANN). An MLP neural network is a class of a feedforward artificial neural network that contains multiple layers of perceptrons. MLP used in this algorithm as a classifier for best classification accuracy of compressed ECG signals. MLP can differentiate compressed data that are not separated linearly.

For such applications, computational complexity should be low. Computational complexity means the number of resources required to run the code in time and memory. How much time does it take to run the code? Stands for time complexity and can be calculated using *Big O* notation [106], [107] and [108]. For our algorithm *Big O* can be calculated as shown in Figure 4.4. The first three steps for opining and filtering required only $\mathcal{O}(1)$. Then, step 4 till 13, for data compression algorithm required only $\mathcal{O}(n)$. So, the steps for opining, filtering and compression required only $\mathcal{O}(n)$. With adding feature extraction totally it required $\mathcal{O}(n^2)$. Thus, based on the calculations, the time complexity with adding data compression steps or without are the same which is $\mathcal{O}(n^2)$. Moreover, the steps for data compression required only $\mathcal{O}(n)$.

4.2 Performance Analysis

With what probability or condition, the accuracy of using compressed data is equal or at least similar to the accuracy of using raw data.

Assume:

- x is the original signal
- y is the compressed signal formed from x
- $NoSx$ is the total number of samples in signal x
- $NoSy$ is the total number of samples in signal y
- *Rpeakx* is the total number of Rpeaks in signal x

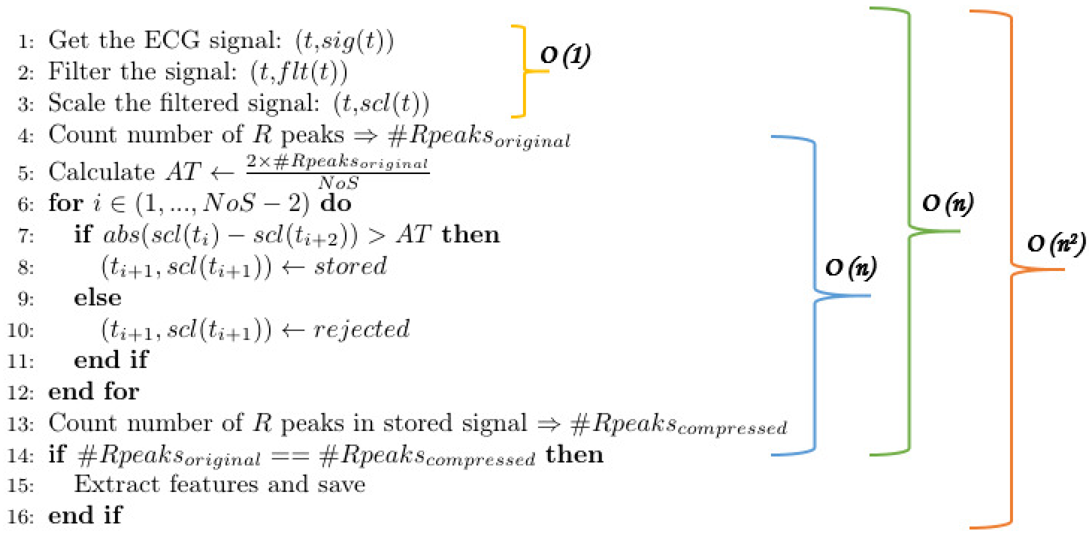


Figure 4.4: Adaptive threshold algorithm computational complexity

- $Rpeaky$ is the total number of Rpeaks in signal y
- $A(x)$ is the classification accuracy of the signal x
- $A(y)$ is the classification accuracy of the signal y

Proof. $A(x) \sim A(y)$

Proof the accuracy of the signal before compression is similar to the accuracy of the signal after compression.

1. After compression, y size is smaller than $x \Rightarrow NoSy < NoSx \Rightarrow$ lets say $M < N$.
2. To proof that accuracy are similar $A(x) \sim A(y)$, we have to proof that the features are similar $\Rightarrow Features(x) \sim Features(y)$.
3. After applying the threshold equation in eq(4.2) to compress $x \Rightarrow y$ is formed.

$$AT = \frac{2 * \#Rpeakx}{NoSx} \tag{4.2}$$

- Let's start with $Rpeaks \Rightarrow Rpeakx{==}Rpeaky$, So how many samples should be reduced to keep the number of $Rpeaks$ similar. Lets say $NoSx = N$, $NoSy = M$ and $Rpeakx = Rpeaky = R \Rightarrow$ lets proof $M{<}N$

$Rpeaky = Rpeakx$
$R = \frac{AT*NoSx}{2}$
$AT = \frac{2R}{N}$

$NoSy < NoSx$
$M = N$ - s
$=\frac{2R}{AT} - s$

$\Rightarrow M < N$
$\Rightarrow$ So M should be reduced by s where s is the number of deducted samples from N to give the same number of $Rpeaks$ in x and y.

When the number of $Rpeaks$ are the same in x and y signals this means the number of $Qpeaks$ and $Speaks$ are the same because they are adjacent with each $Rpeak$ as shown in Figure 4.5. Now the number of $Rpeaks$, $Qpeaks$ and $Speaks$ are similar lets proof the other features:

- QRS complex
This feature will not be affected because Q and S peaks are the same in x and y signals as well as $Rpeaks$. Therefore, it can be calculated correctly.

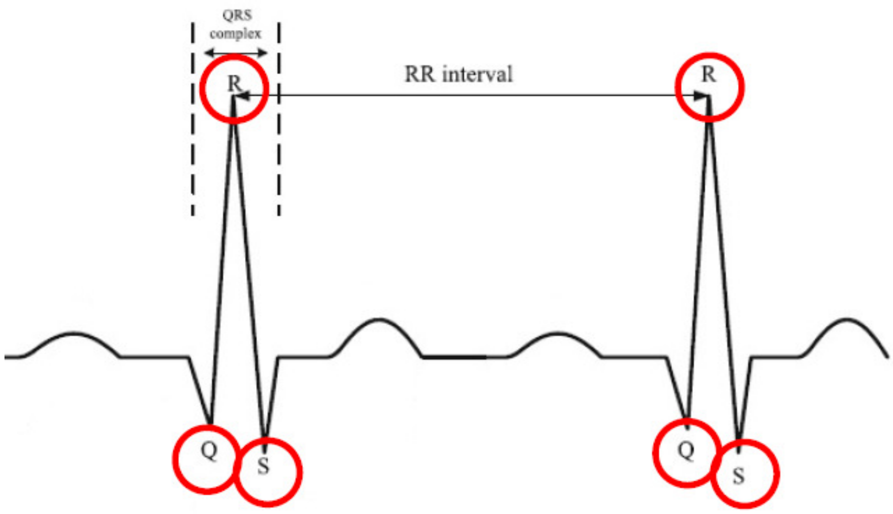


Figure 4.5: The relation between R, Q and S peaks in normal ECG signal

- RR interval

  Once the $Rpeaks$ are the same in x and y signals this means the time interval between two adjacent R waves can be calculated and scaled based on CR and saved as RR interval.

- Heart rate

  Heart rate is the same in x and y signals because it depends on RR interval which is proved above that it is similar in x and y signals, and can be calculated based on eq(4.3).

$$HR(bpm) = \frac{60}{RRinterval} \tag{4.3}$$

- QT interval

  Once there are similar number of $Rpeaks$ in x and y signals, and RR interval can be found between two adjacent $Rpeaks$ in x and y signals then QT interval can be found in x and y signals and they are similar as shown in Figure 4.6.

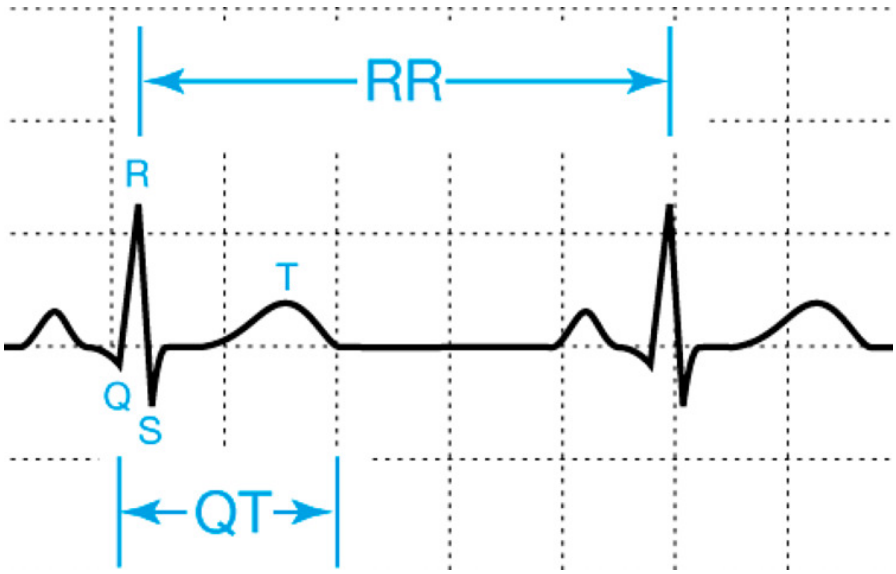


Figure 4.6: The relation between RR interval and QT interval

- QTc interval

  It depends on QT and RR interval which already proved above that they are similar in x and y signals, and can be calculated based on eq(4.4).

$$QTc = \frac{QT}{\sqrt{RRinterval}} \tag{4.4}$$

From the above analysis $y \mathrel{!=} x$ shown $NoSy < NoSx$: $Features(x) \sim Features(y) \Rightarrow A(x) \sim A(y)$

□

4.3 Simulation Analysis

Here, the simulation set-up is presented to study the performance of the proposed algorithm. In addition, various experiments with various heart conditions are conducted.

4.3.1 Simulation Setup

The algorithm was applied on 48 ECG signals from MIT-BIH Arrhythmia database to prove it and the results were explained in the followed sections.

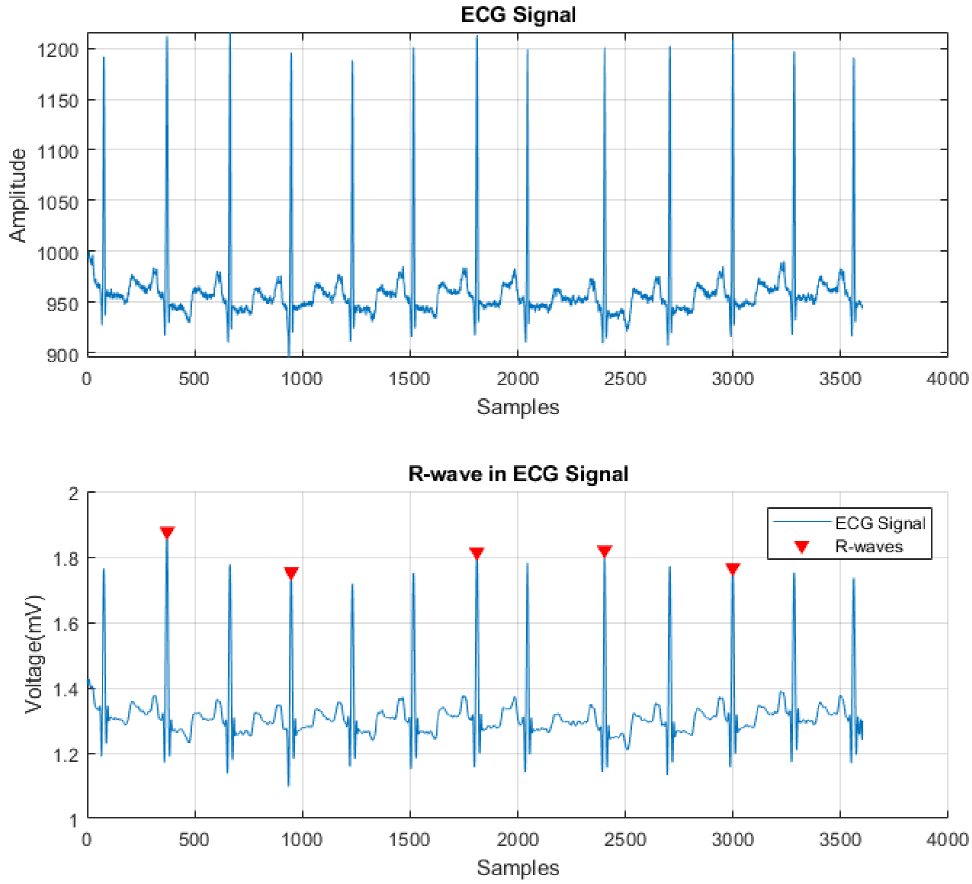


Figure 4.7: Raw ECG signal and marked R peaks

4.3.2 Experiment Results

The raw signal of the first patient can be found in Figure 4.7 plotted in samples per amplitude. The highest number of samples reached 3600. The highest amplitude reached 1210. The five main waves repeated in the whole signal but the starting of each peak can not be recognized due to the noise. After filtering and scaling, the signal was ready for compression. R peaks, the highest peak in each 500 samples, were marked as signal sparsity with red triangles and saved as shown in Figure 4.7.

The NoS for this signal was 3600 samples. AT was calculated by dividing the number of R peaks over the NoS. The signal is ready now for compression. Start with the second sample and then find the absolute difference between first and third sample. If the difference is higher than the

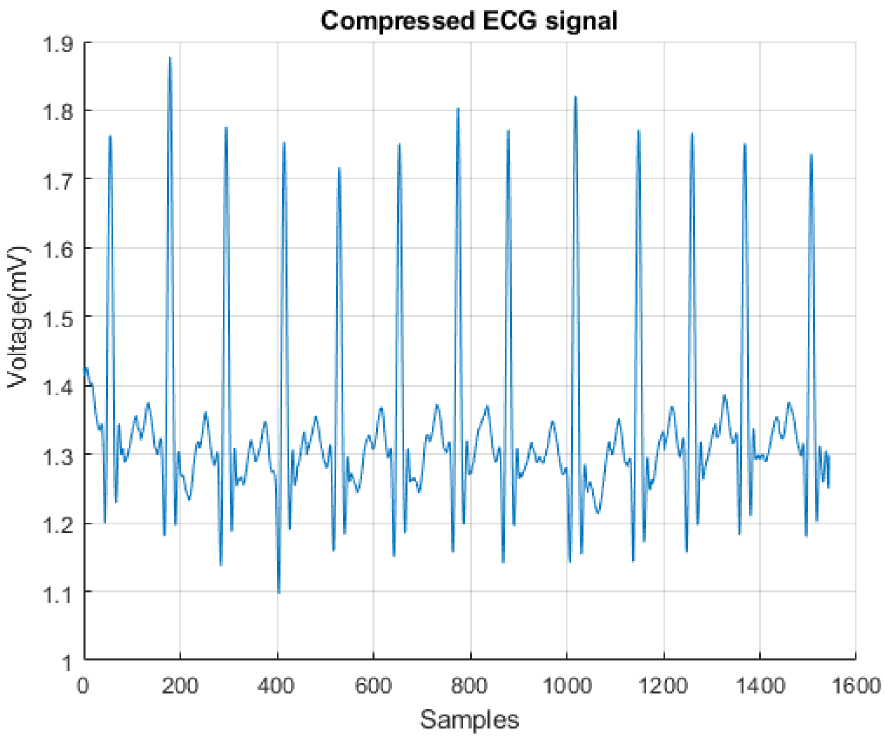


Figure 4.8: Compressed ECG signal using adaptive amplitude threshold compression algorithm

calculated AT then the second sample is saved otherwise it should be rejected. By following the same steps until the last sample, the saved samples are forming the compressed signal as shown in Figure 4.8. In this figure, the waves are not affected they just shrank and the NoS after compression is 1543 samples. Therefore, the CR can be calculated based on eq(4.1) and the result is 2.33. This means around 57.14% of the signal size is eliminated to keep space without destroying the signal itself and with keeping the most important metrics from it. The CR of 2.33 is much acceptable as a ratio for compression for healthcare sector without affecting accuracy of the diagnosis.

To validate the threshold value is correct and the compressed signal is similar to the original, the number of R peaks are calculated from the compressed signal using the same technique for the

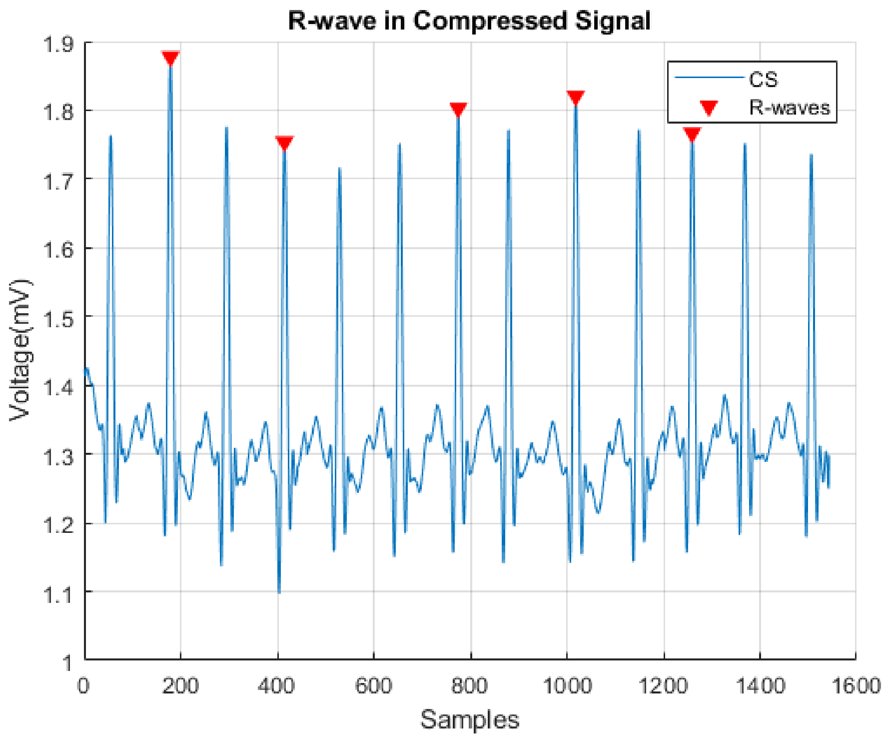


Figure 4.9: Marked R peaks in ECG signal after signal compression

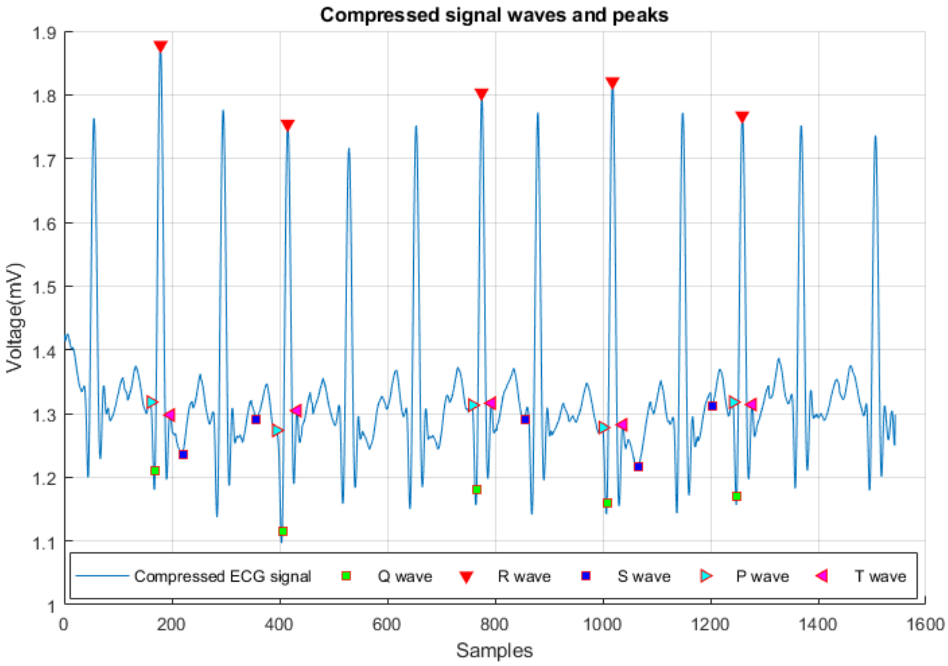


Figure 4.10: Marked Q, R, S, P and T peaks in ECG signal after signal compression

original signal by finding highest amplitude in each 500 samples with taking into consideration the CR in calculation. Figure 4.9 shows the number of R peaks marked with red triangle. Then a message is displayed with the quality of the threshold value to continue the algorithm. If they equals, the transmitter should send the compressed signal and CR to the receiver. The number of R peaks for that patient after compression is similar to the original signal.

4.3.3 Effects of data compression on the feature extraction of ECG signals

The compressed signal is ready now for the feature extraction step using the same technique for feature extraction on original signal with taking into consideration the CR value in calculation. The five waves and peaks of the compressed signal for the first patient are marked as shown in Figure 4.10. The x-axis shows the number of samples and y-axis represents the voltage. Each peak of a wave is marked with coloured triangle or square as expressed. Green square for the starting of Q wave, Red triangle for the starting of R wave, Blue square for the starting of S wave, Turquoise triangle for the starting of P wave, and Pink triangle for the starting of T wave. The detection of the peaks worked smoothly and each peak marked correctly that's end in correct feature values. Then, the five features are calculated and the feature values are:

- QRS is 37.00 ms
- Heart rate is 106.27 bpm
- RR interval is 564.61 ms
- QT interval is 225.61 ms

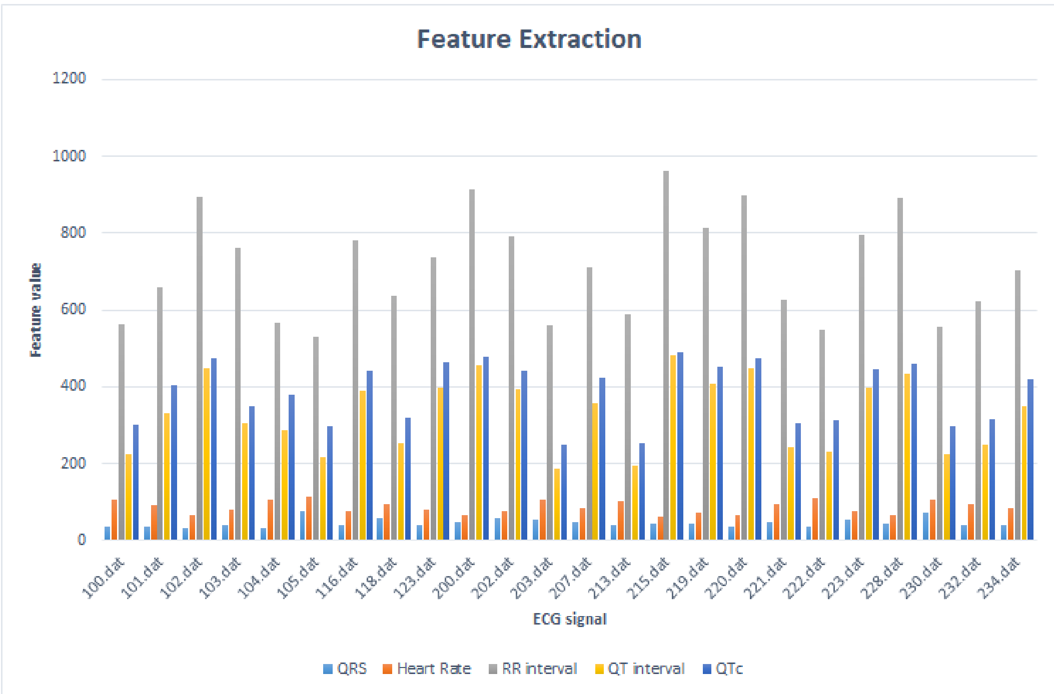


Figure 4.11: Features values of compressed ECG signals of all patients: QRS in Blue bar, Heart rate in Orange, RR interval in Grey, QT interval in Yellow and QTc in dark Blue

By doing the same steps and storing all the extracted future values of all patients, Figure 4.11 summarizes the results. The x-axis represents the compressed ECG signal for all patients and y-axis shows the feature values. Each feature has different colour: Blue for QRS, Orange for Heart rate, Gray for RR interval, Yellow for QT interval and dark Blue for QTc. By colouring each feature type, it gives detailed explanation for each feature value of the whole patients. All these features are smoothly extracted without any anomaly values. They are adjacent to each other based on the colours with ranged heights.

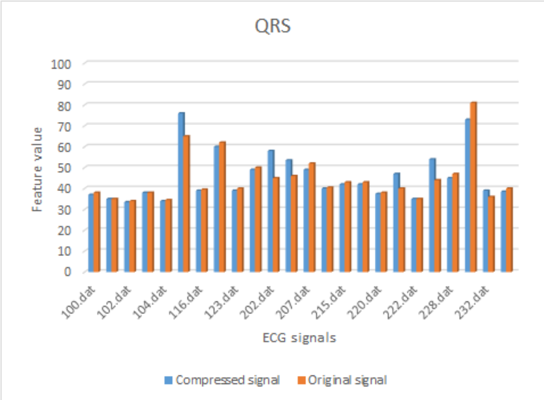
To verify the algorithm, the extracted features of the ECG signals before and after compression are compared. Figure 4.12 shows the differences and similarities for all patients based on each feature value in each sub figure. The x-axis shows the ECG signals for all patients and y-axis represents the feature values. There are five sub figures titled based on feature values: QRS, heart rate, RR interval, QT interval and QTc interval. The Blue bars stand for compressed signal feature value for each patient and Orange bars express the uncompressed signal feature value for each patient. The five sub figures show the differences and similarities for each feature values among all the ECG signals (original and compressed).There was an increase in QRS, HR, QT and QTc with 3%, 1%, 2% and 3% respectively. However, there was a decrease in RR with 1% only. Therefore, the difference are very small which achieve high compression and save energy. Hence, this algorithm is efficient in extracting the features from the compressed domain without the need to reconstruct them.

4.3.4 Effects of data compression on the classification of ECG signal

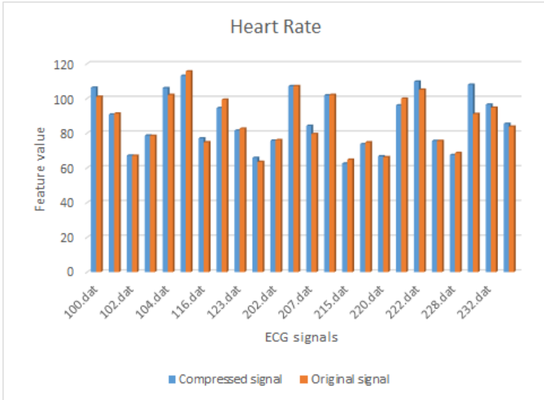
The saved features of the compressed ECG signals were passed to machine learning and deep learning for classification from the compressed domain.

Machine Learning

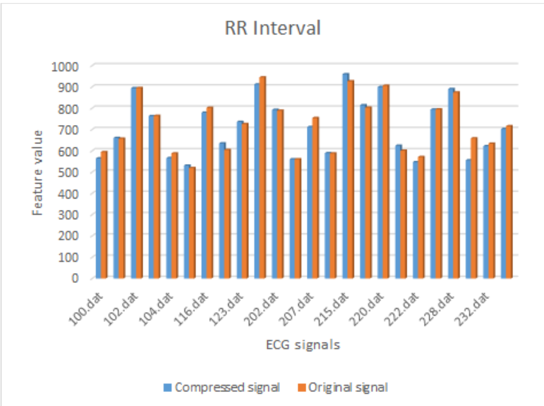
A full SVM machine learning classification method was implemented in Matlab. The data from the feature extraction step was divided into two sets: 80% of data for training and 20% of data



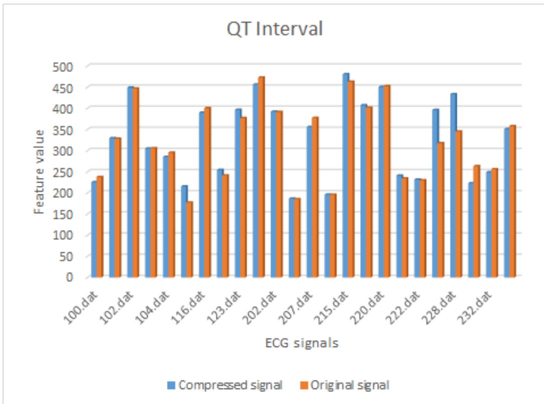
(a) QRS



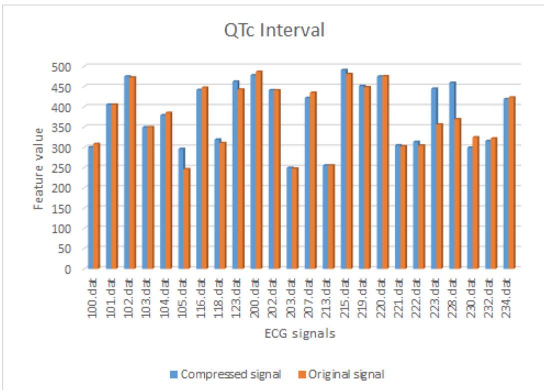
(b) Heart rate



(c) RR interval



(d) QT interval



(e) QTc interval

Figure 4.12: Extracted feature values compared between: compressed ECG signals in Blue bars and original ECG signals in Orange bars

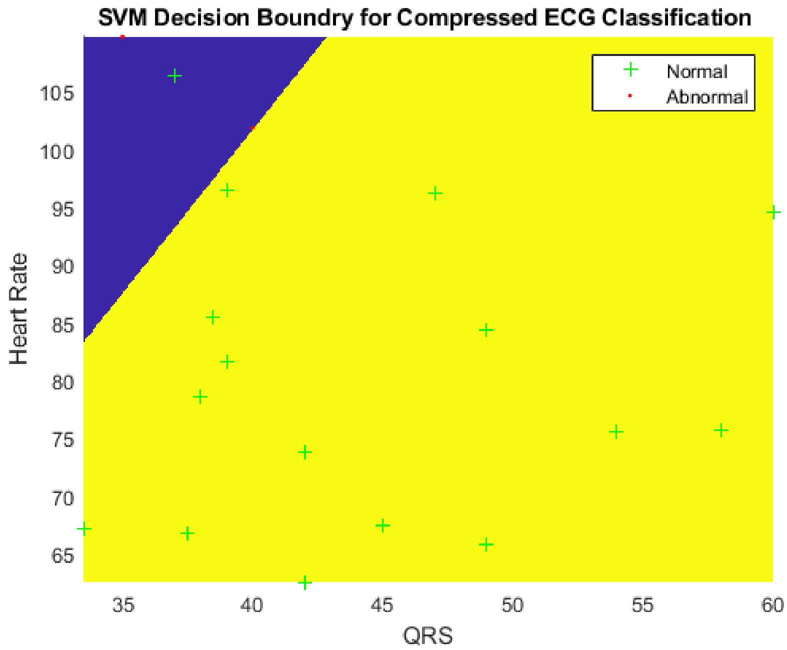


Figure 4.13: SVM classification of compressed ECG signals in two classes: normal class in Yellow and abnormal class in Blue

for testing. Two features were selected heart rate and QRS. The method is able to differentiate between normal and abnormal compressed ECG signals by drawing a linear decision boundary as shown in Figure 4.13. The Green plus shows the normal values and Red dots represents the abnormal. The Blue area for abnormality and Yellow area for normal values. The hyperplane divided the figure into two areas for normal and abnormal for any future data.

In comparison with SVM result of the original signals based on the feature extraction of the ECG signal without compression, the decision boundary can be found in Figure 4.14. Here, the hyperplane differentiate between normal and abnormal areas with slightly different values. The classification accuracy for compressed signal is 89.47% which is 2% lower in comparison with the classification accuracy of the original ECG signal which is 91.67%. This means the classification accuracy decreased a little bit due to the data compression but save cost and there is no need to make any reconstruction. As a result, classifying from the compressed domain will give accurate

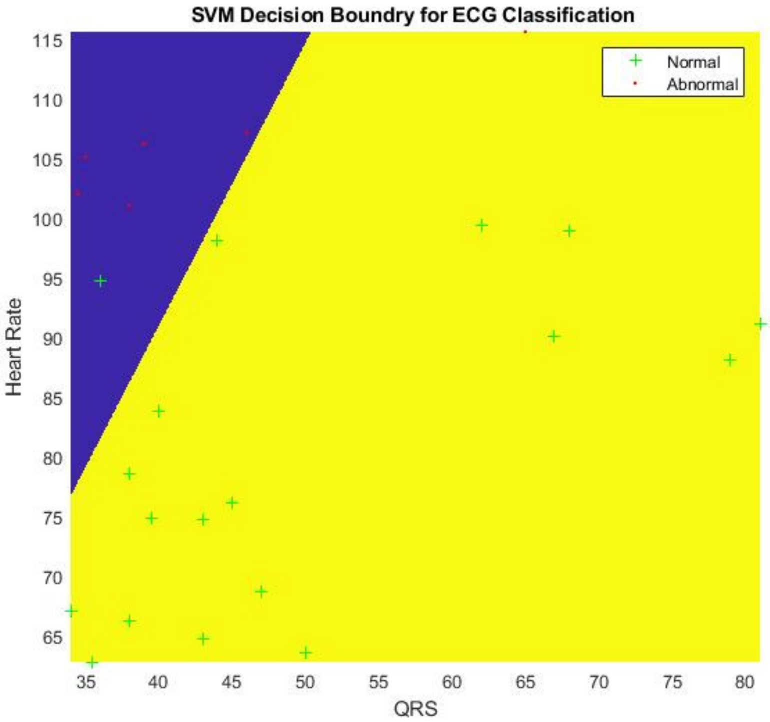


Figure 4.14: SVM classification of original ECG signals in two classes: normal class in Yellow and abnormal class in Blue

results and will save the time and space.

Deep Learning

The saved features of the compressed ECG signals was passed to the implemented MLP deep learning classification method. For training, 80% of total data was used while, the remaining 20% of data for testing. Two features were selected as input; heart rate and QRS. The number of hidden layers in the neural network were two each one of them contains 10 neurons. The learning rate selected to be 0.15 and the maximum number of epoch was 500. Accuracy of MLP classification on original and compressed signals were compared as shown in Figure 4.15 and Figure 4.16. The x-axis for both figures represent the number of epochs and y-axis show the

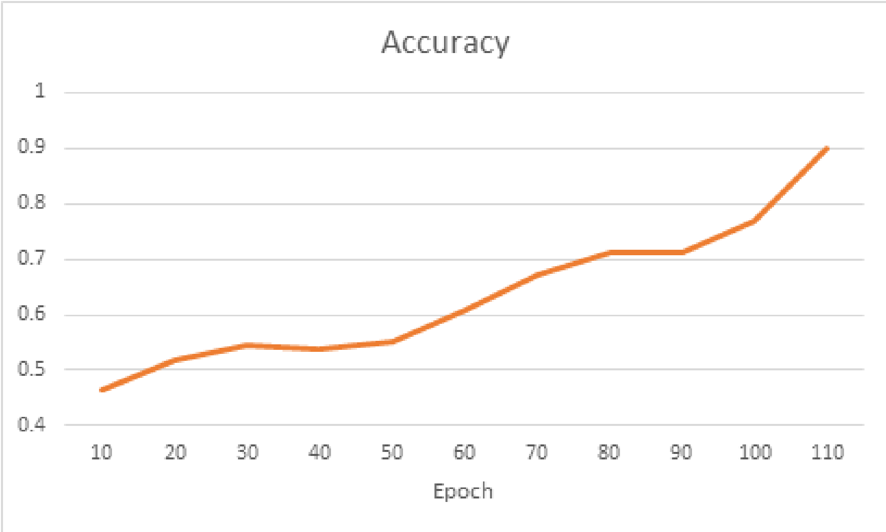


Figure 4.15: Accuracy of MLP classification on compressed ECG signals

accuracy reached. In Figure 4.15, the classification accuracy of the compressed ECG signals shown in Orange line. The accuracy after 10 epochs was 45% and then jumps to 90% after 110 epochs which is the final accuracy reached. In the other hand, the classification accuracy of the original ECG signals represented in Figure 4.16. The accuracy after 10 epochs was 51% and then jumps to 91% after 90 epochs which is the final accuracy reached. Thus, both figures have different accuracy lines but at the end the final accuracy of the compressed signal is 90% after 110 epochs while it was 91% in the original after 90 epochs. Thus, the classification results was affected only by a minimization of 1% using compression and there is no need for any reconstruction on signals after compression. In this way, the space is saved and the time is reduced.

4.4 Summary

In this chapter, Adaptive amplitude threshold compression algorithm was proposed for homecare cardiac management system. The algorithm was tested on a number of ECG signals and performed very well. The feature values of compressed and original signal were similar with only

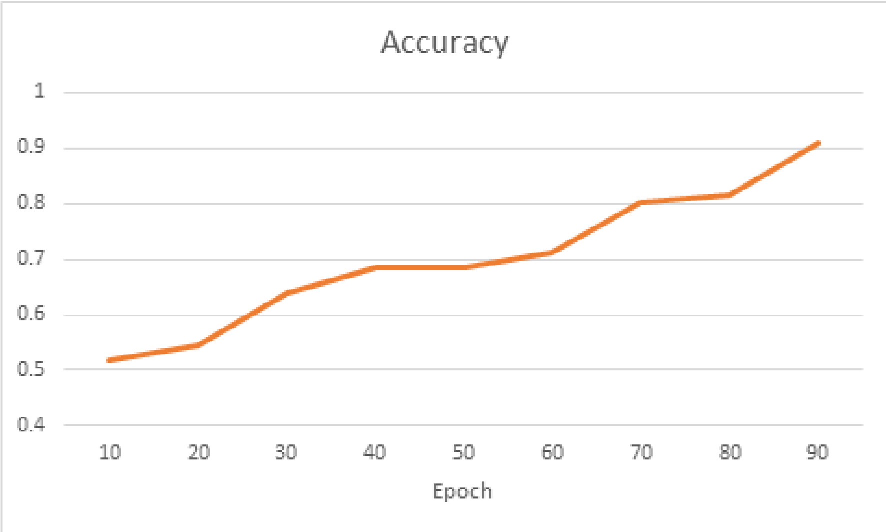


Figure 4.16: Accuracy of MLP classification on original ECG signals

1%, 2% or 3% of changes that did not affect the machine learning and deep learning classification accuracy results and did not require any kind of reconstruction. Thus, this algorithm outperform others in time and space provision and in preserving the signal. In general, designing ECG compression method for real time ECG monitoring will always be the trade-off between memory requirement, power consumption and fast monitoring and response.

The main conclusions are:

- The proposed model benefited from fast transmission time more than the proposed model in Chapter 3. In Chapter 3 proposed model, large number of ECG signals need to be transmitted that requires long transmission time. To satisfy fast response of homecare system, the proposed model in Chapter 4 using data compression is able to transmit more ECG signals in fast transmission time without affecting the content of the medical data.
- The proposed model feature values are similar to the feature values of the model in Chapter 3 with very little differences that not affect classification results.

- The throughput was improved by the proposed model by an average percentage greater than or equal to 43% when the data compression is used.
- The required storage space was reduced by an average percentage greater than or equal to 57% when the data compression is used.

Chapter 5

Compressive Sensing based Cardiac Homecare System

As the Cardiac homecare systems need to be fast and in real time response, the transmission time for the data between sender and receiver should be very fast. To have fast transmission time, the amount of data should be reduced. Compressive sensing is one of the ways to reduce the data size for transmission, and receiver can return the original file using reconstruction. To improve the decision accuracy and in the same time achieves fast response, this chapter obtains Objective 3 in Chapter 1 by developing the proposed model in Chapter 3 to have Cardiac Homecare System based compressive sensing which solves Gap 2 and Gap 3 in Chapter 2. In addition, Gap 3 is addressed where the enhanced model can achieve fast response for real time homecare systems.

This chapter proposes the compressive sensing based Cardiac Homecare system model that gives the channel between sender and receiver the ability to carry small amount of data while having high accuracy and true decisions. Also, various experiments are conducted with different percentage of accuracy, errors and false alarm to measure the performance of the proposed model.

5.1 Proposed Algorithm

Compressive sensing is a signal processing technique capable to minimize the required number of samples for successful signal reconstruction by exploring the properties of sparsity. Compressive sensing requires that the signal (to be compressed) has to be sparse in one domain. The sparsity of the signal defined by the number of significant amplitude in signal. Compressive sensing produces several advantages, such as smaller data size, less memory storage usage, less power consumption and higher data transmission rate. Because of all these characteristics, compressive sensing has been used in a wide range of applications. Our Cardiac Homecare System requires such technique to benefit from these advantages.

ECG signal is checked to be sparse in frequency domain, e.g., with sparsity X. Therefore, K random measurements are taken in time domain where $K > X$. This novel algorithm

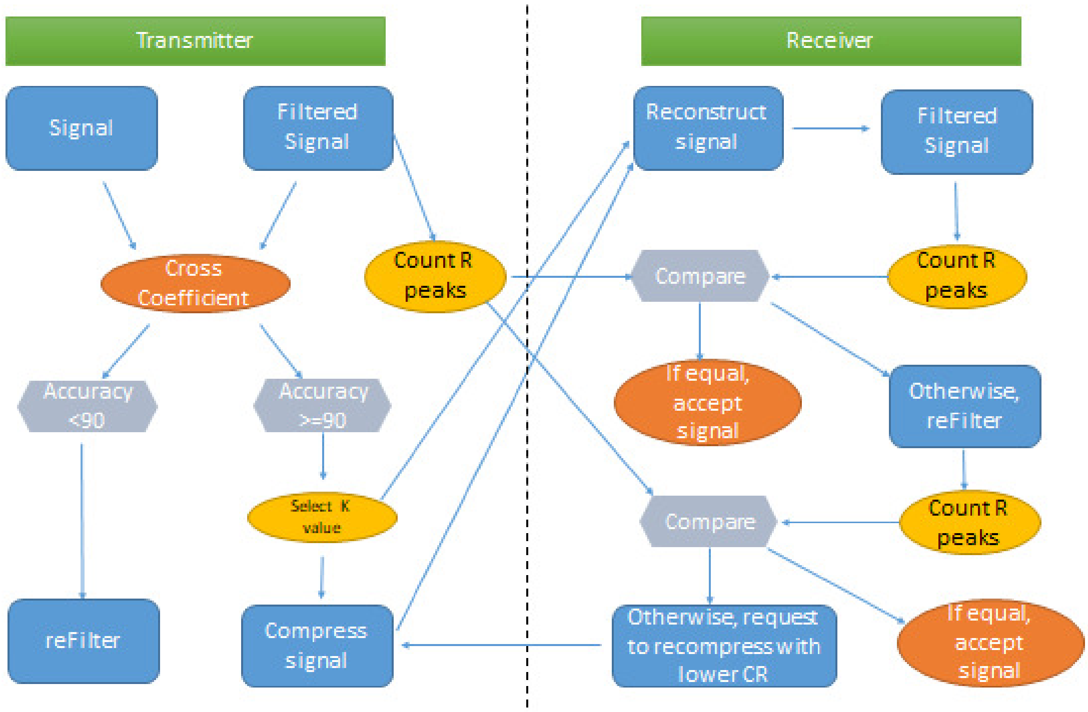


Figure 5.1: Cardiac homecare compressive sensing algorithm flowchart

demonstrates the compressive sensing using a sparse ECG signal. The algorithm works as shown in Figure 5.1. The transmitter takes the raw ECG signal and filter it using Savitzky–Golay filter to clear it from noise. Number of R peaks are counted from the filtered signal and saved. After that, the original and filtered signal are compared using cross coefficient that measures the similarity between them. If the comparison result is less than 90% that means the signal after filtering is altered and re-filtering is needed. Otherwise, the original and filtered signal looks similar and K value (the dictionary) selected for compressing the signal.

To compress the signal, Discrete Fourier transform (DFT) is applied by creating a DFT matrix to compress the signal then take DFT of the signal. After that, random rows that are related to the data are selected from DFT matrix. Then, few columns are picked up from the matrix based on the random rows to create a measurement matrix. Then, finally compress the signal using that matrix. Now the compressed signal is ready to be used.

The compressed signal along with the shared K value and R peaks are transmitted to the receiver. The receiver takes the compressed signal and reconstruct it using K value. Then, the reconstructed signal is filtered using Savitzky–Golay filter. After that, R peaks are counted from the filtered signal and saved. Then, a comparison is made between the number of R peaks in the filtered original ECG signal (that was transmitted with the compressed signal) and filtered reconstructed ECG signal. If they are equal, the receiver should accept the reconstructed signal and make feature extraction and classification from it. Otherwise, the reconstructed signal needs to re-filter again. After re-filtering R peaks are counted again and compared with number of R peaks in original signal. If they are equal the receiver should accept the signal and make the feature extraction and classification from it. Otherwise, the receiver should request from the transmitter to re-compress with lower compression ratio and select different K value.

The transmitter will return back to selecting K value step and maximize it a little bet to minimize the compression ratio. And then compress the signal and send it back to the receiver. The receiver will take the compressed signal and make the reconstruction step with the new K value. After reconstructing, the full signal is filtered. After filtering, R peaks are counted and saved. The counted R peaks along with the received one from the transmitter are compared. If they are equal, the signal is accepted with the new K value. Otherwise, re-filtering is required. R peaks are counted again and compared with the received one form the transmitter to accept the signal when they are equal.

5.2 Simulation Analysis

This section describes the simulation set-up for evaluating the performance of the algorithm. The effect of changing parameters on the accuracy, number of errors and false alarm rate are also analysed. In addition, the optimal value for K is selected.

5.2.1 Simulation Setup

For simulation parameters, the ECG data was downloaded from PhysioBank.com. Thirty ECG signals were taken from MIT-BIH Arrhythmia database [102]. The signals were taken between the years 1975 and 1979. They were related to patients in and out the hospital. The signals in this database were made of half an hour recording from Holter device in labs [103, 104]. The raw signals were digitized in the hospital at 360 samples per second per channel. The platform used for this simulation model was built using MATLAB simulation environment version R2019a. The device used is a desktop personal computer with Intel Core i7 processor.

5.2.2 Experiment Results

The raw signal of one of the patient are shown in samples per amplitude in Figure 5.2. The main five waves of ECG signal are shown during 3600 samples. However, some noise considered that required the use of filtering. Savitzky–Golay filter is used to remove the noise and to get clear peaks and waves as shown in Figure 5.3. Moreover, the signal is plotted in frequency domain as well.

Cross coefficient is calculated to compare between original signal and filtered signal. For this patient cross coefficient is 92% which means it is acceptable to compress based on the algorithm.

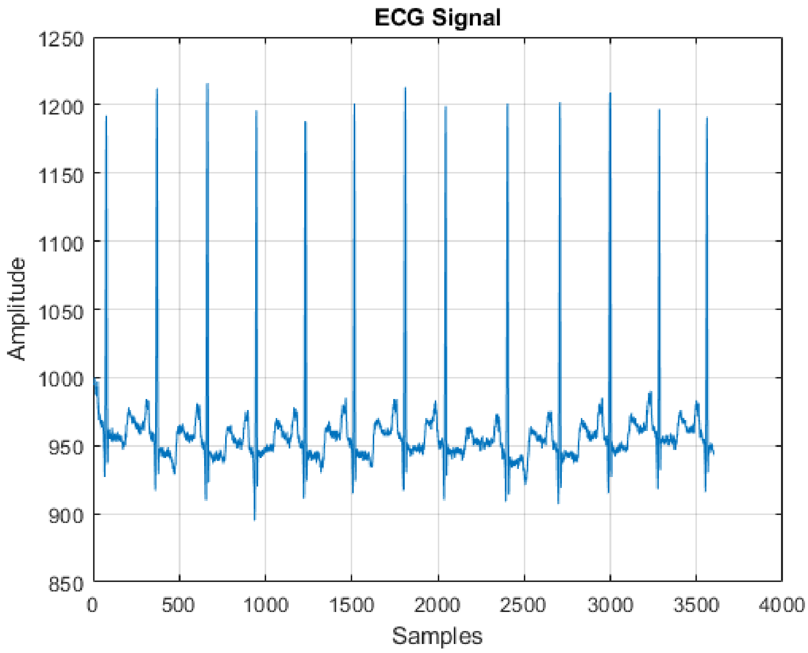


Figure 5.2: Raw ECG signal

K, the length after compressing, selected to be 900 which gives a CR of 4. Now, everything is ready for compressing in transmitter side. R peaks are counted from the filtered signal and saved. For compressing DFT is used by creating DFT matrix that used to compress the signal then taking DFT of the signal. Then select random rows of DFT matrix that is related to the data. After that, pickup few column from the matrix based on the random rows to create a measurement matrix. Then compress the signal using that matrix. Now the compressed signal is ready to be sent. The compressed signal, K value and R peaks are sent to the receiver. The receiver will run the recovery algorithm of the signal using K value and the compressed signal as shown in Figure 5.4. The waves of the recovered signal contain some noise that need to be filtered.

To accept the recovered signal some steps need to be checked. First, using Savitzky–Golay filter to filter the recovered signal to remove any noise. Then, R peaks are counted from the filtered

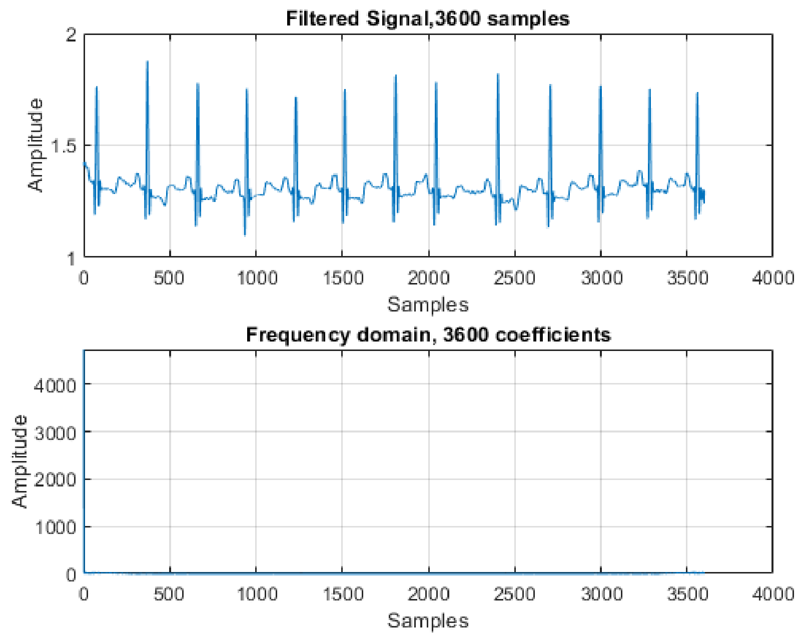


Figure 5.3: Filtered ECG signal using Savitzky–Golay filter and frequency domain

signal and saved. R peaks are compared between the original signal and the recovered signal as shown in Figure 5.5.

If they are equal, the recovered signal should be acceptable. In this patient they are equals. If they are not equals, re-filtering is needed and then R peaks are compared. If they still not equal, the receiver should request from the transmitter to recompress again using different K value that produce lower CR. In our example, the recovered signal is ready for feature extraction and classification. The five main waves Q, R, S, P and T are marked as shown in Figure 5.6. Then disease classification is made based on the features value. If any feature goes above or beyond the medical normal range mentioned in Chapter 3 a message appears with a warning regarding the patient cardiac health. For this patient Ventricular Tachyarrhythmia heart disease is configured. Using those waves, the five main features QRS, Heart rate, RR interval, QT interval and QTc interval are extracted as below:

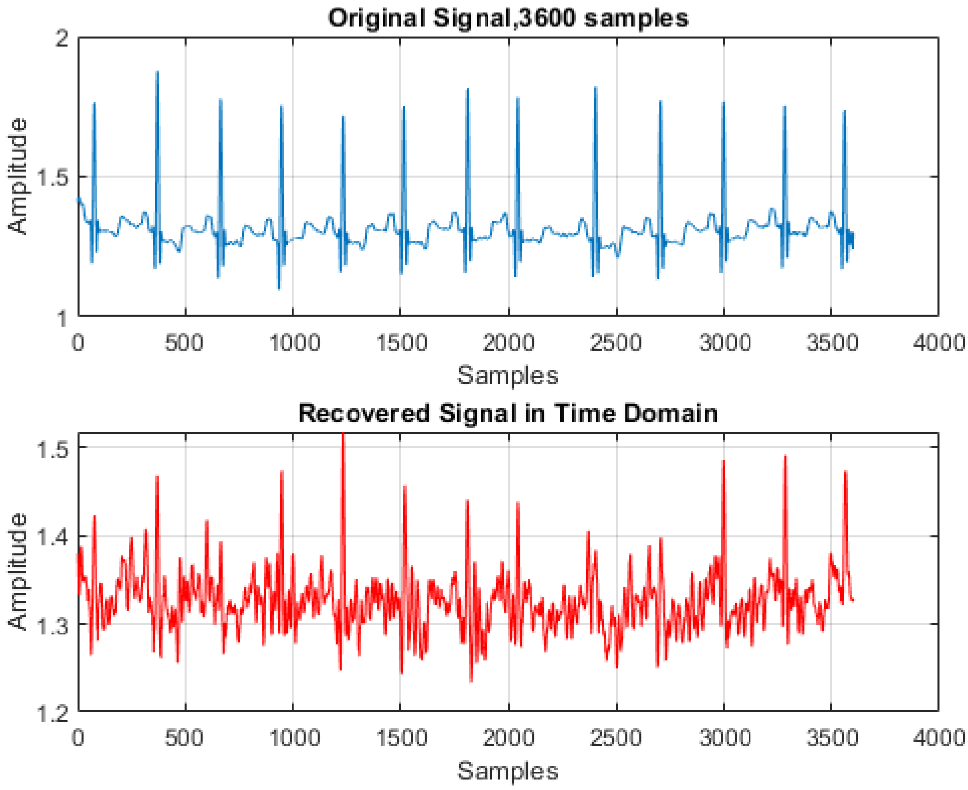


Figure 5.4: Original and recovered ECG signal after applying compressive sensing algorithm

- QRS = 43.00 ms
- Heart rate = 83.39 bpm
- RR interval = 719.50 ms
- QT interval = 288.90 ms
- QTc interval = 340.59 ms

The algorithm was checked on 30 patients. The recovery signal for all of them was acceptable except three patient. Which means, the algorithm was able to compress/recover the signals

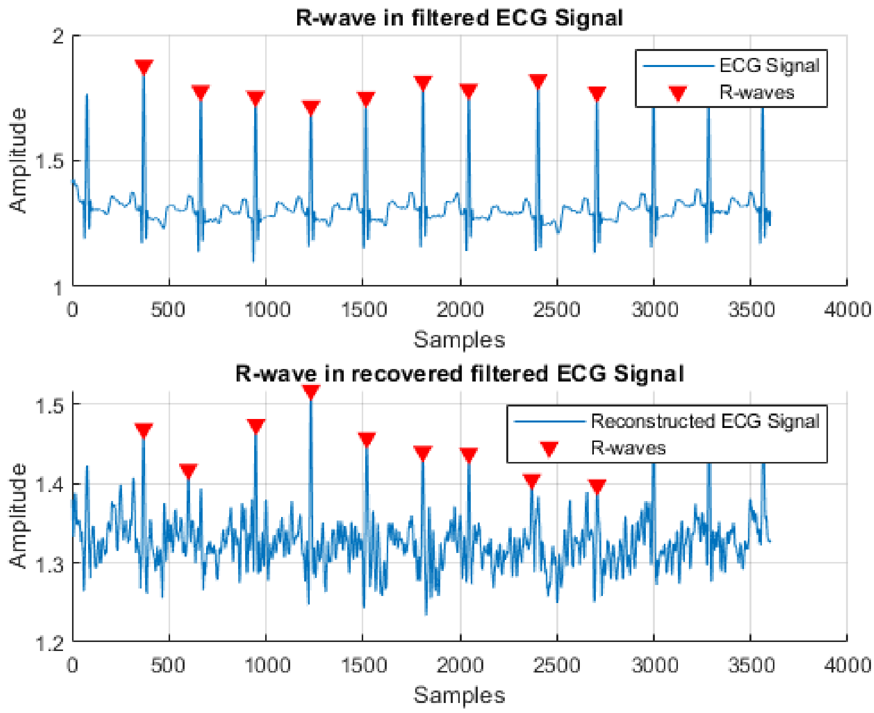


Figure 5.5: R peaks in filtered original ECG signal and recovered ECG signal

and extract features/ classify from the first round for 90% of the data. Which is a very good percentage to save time and space. The extracted features and the disease classification for those patients can be found in Table 5.1.

Second round of the algorithm

The patients on record 108, 200 and 203 need to make round two through the algorithm. Savitzky–Golay filter need to be applied again to clear the noise. Record 203 is applied for second filter. The recovered signal after second filter is shown in Figure 5.7. The waves are much clearer than before.

To accept the filtered recovered signal, R peaks should be marked and compared to the saved R peaks from the transmitter. Thus, the R peaks comparison between the filtered original signal

Table 5.1: Extracted Features

Patient record	QRS	Heart Rate	RR interval	QT interval	QTc interval	Disease Classification	Accept recovery 1'st round
100	43	68.1044	881	432.5	460.7848	Ventricular tachyarrhythmia	Accept
102	40	68.8863	871	411.75	441.1889	Ventricular tachyarrhythmia	Accept
103	36	65.4308	917	453.5	473.5792	Ventricular tachyarrhythmia	Accept
104	38	70.34	853	438.5	474.7829	Ventricular tachyarrhythmia	Accept
105	33	112.4649	533.5	227.8	311.8793	First degree of atrioventricular block & abnormal heart rate	Accept
106	37	98.8468	607	332.25	426.4525	Normal	Accept
107	82	100.0834	599.5	239.6	309.4512	First degree of atrioventricular block	Accept
108	–	–	–	–	–	–	Reject
109	34	107.7199	557	233.5	312.8667	First degree of atrioventricular block & abnormal heart rate	Accept
111	39.5	64.4468	931	456	472.596	Ventricular tachyarrhythmia	Accept
114	31.5	73.9827	811	408.75	453.8866	Ventricular tachyarrhythmia	Accept
116	42	110.9057	541	180.83	245.8554	First degree of atrioventricular block & abnormal heart rate	Accept
118	51	100.6711	596	237.1	307.1202	First degree of atrioventricular block	Accept
123	33.5	66.7408	899	443.5	467.75	Ventricular tachyarrhythmia	Accept
200	–	–	–	–	–	–	Reject
202	37.5	75.2823	797	416.25	466.2567	Ventricular tachyarrhythmia	Accept
203	–	–	–	–	–	–	Reject
207	48	78.8436	761	384.25	440.4753	Ventricular tachyarrhythmia	Accept
208	37	91.3242	657	222.1667	274.0919	Normal	Accept
212	35	103.9861	577	236.2	310.951	First degree of atrioventricular block	Accept
213	41	102.3018	586.5	238.7	311.6868	First degree of atrioventricular block	Accept
215	39.5	81.1908	739	370.5	430.9888	First degree of atrioventricular block	Accept
219	41	112.1495	535	173.3333	236.9765	First degree of atrioventricular block & abnormal heart rate	Accept
220	40	99.5851	602.5	240.9	310.3547	Normal	Accept
221	35.5	72.4638	828	422.75	464.5885	Ventricular tachyarrhythmia	Accept
222	37	69.2841	866	425.25	456.9676	Ventricular tachyarrhythmia	Accept
223	39	114.0684	526	174.6667	240.8336	First degree of atrioventricular block & abnormal heart rate	Accept
228	34.5	105.6338	568	188.3333	249.8924	First degree of atrioventricular block & abnormal heart rate	Accept
230	40	114.8325	522.5	212.6	294.117	First degree of atrioventricular block & abnormal heart rate	Accept
232	42	80.9171	741.5	283.8	329.5769	Normal	Accept
234	40	62.7615	956	476.25	487.0864	Ventricular tachyarrhythmia	Accept

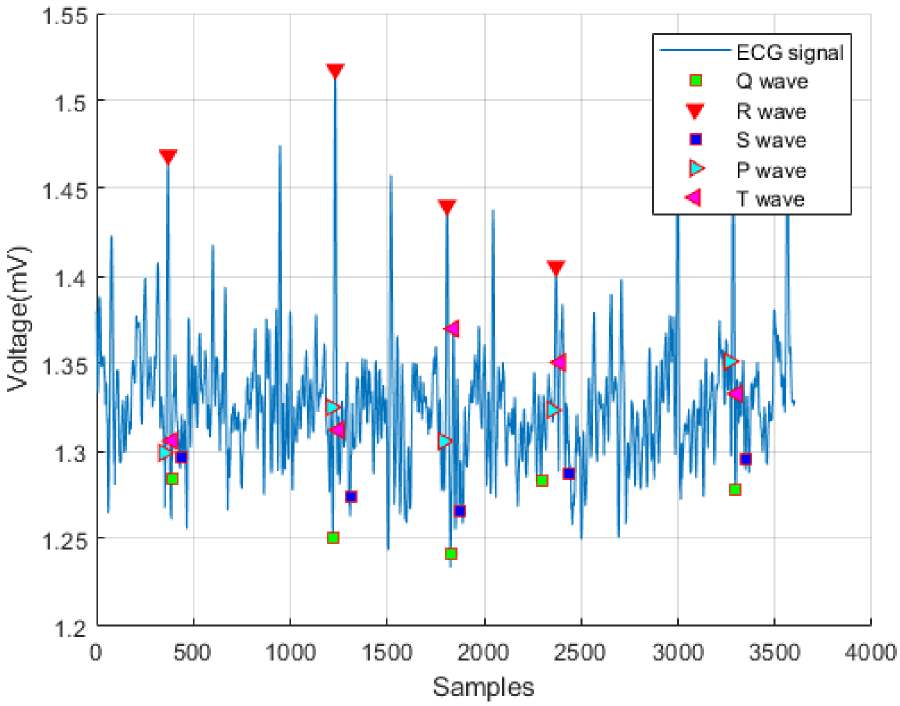


Figure 5.6: Feature extraction of reconstructed ECG signal

and recovered signal is shown in Figure 5.8. After counting the number of R peaks between filtered original and recovered they are similar and a message appeared that this recovered signal is acceptable for feature extraction and classification.

This recovered signal is acceptable for the feature extraction. The waves are clearly marked as shown in Figure 5.9. The extracted features are as below:

- QRS = 59.00 ms
- Heart rate = 98.36 bpm
- RR interval = 610.00 ms

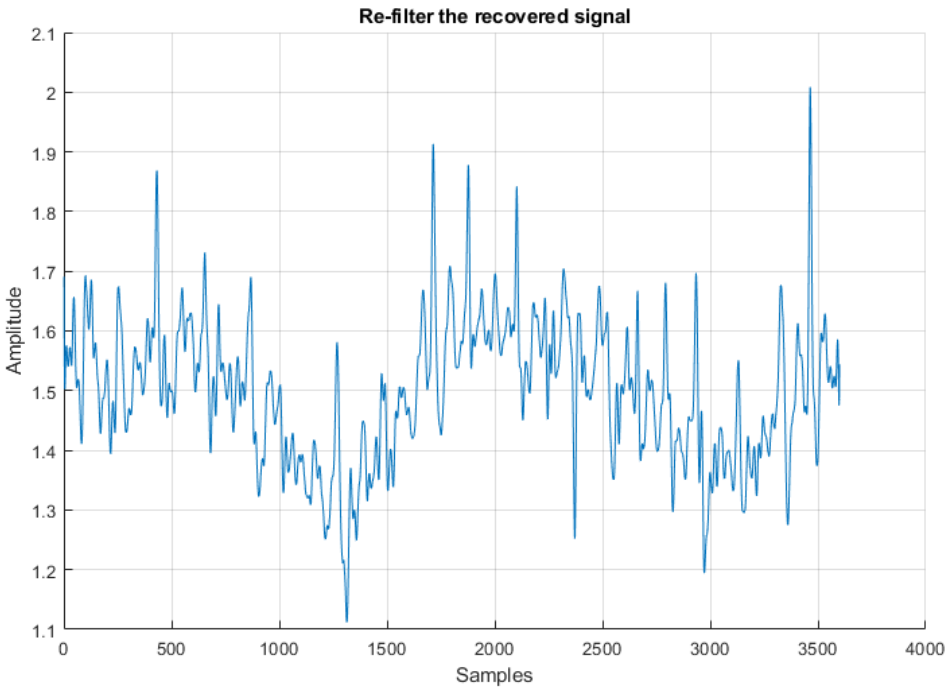


Figure 5.7: Applying Savitzky–Golay filter for the second time on reconstructed ECG signal

- QT interval = 238.90 ms
- QTc interval = 305.88 ms

This patient classify as normal without any heart disease.

Third round of the algorithm

For Record 108 and 200 based on the algorithm the receiver should send a request to the transmitter to change K value for lower CR. The K value should be increased and the CR should be decreased for the third round. The transmitter select 1000 for K value which means CR is 3.6 which is still good that minimize the data to be transmitted without destroying the important features. The results for record 108 for R peaks comparison is acceptable after changing K value.

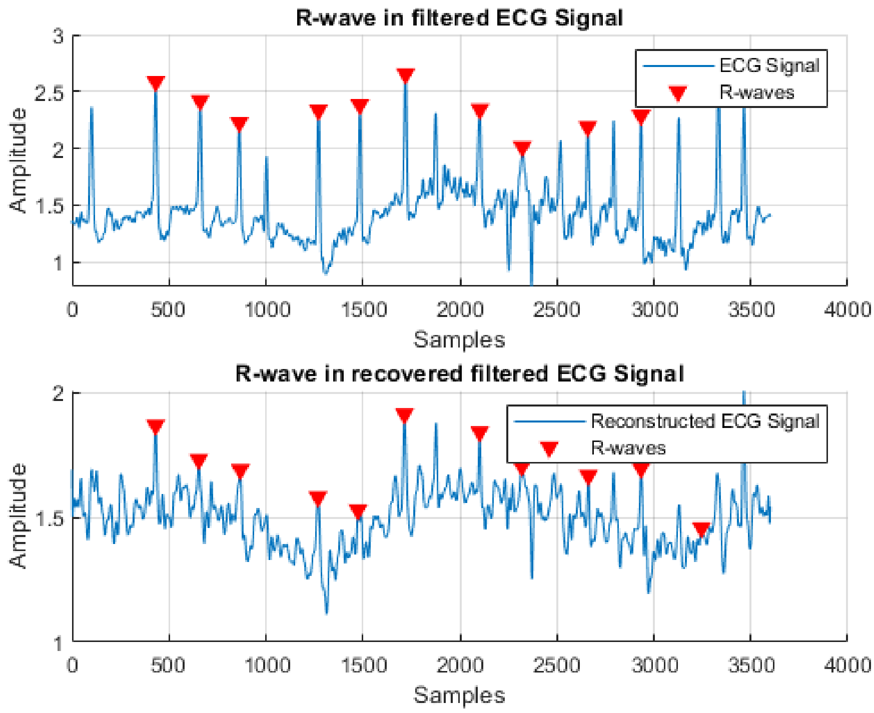


Figure 5.8: The comparison of R peaks between original and recovered ECG signals

The original signal and recovered signal can be found in Figure 5.10. They look quite similar to each other. However, this is not enough to grantee they are identical and nothing important destroyed.

To accept this recovered signal R peaks in original and recovered are compared as shown in Figure 5.11. The number of R peaks are similar in filtered original signal and recovered signal for record 108. They have the same number and all the red triangles looks identical in location and number between filtered original ECG signal and recovered one for that patient. A message displayed that this recovered signal is acceptable for features extraction and classification and this signal acceptable for the third round of the algorithm.

For feature extraction the value for each feature are expressed below:

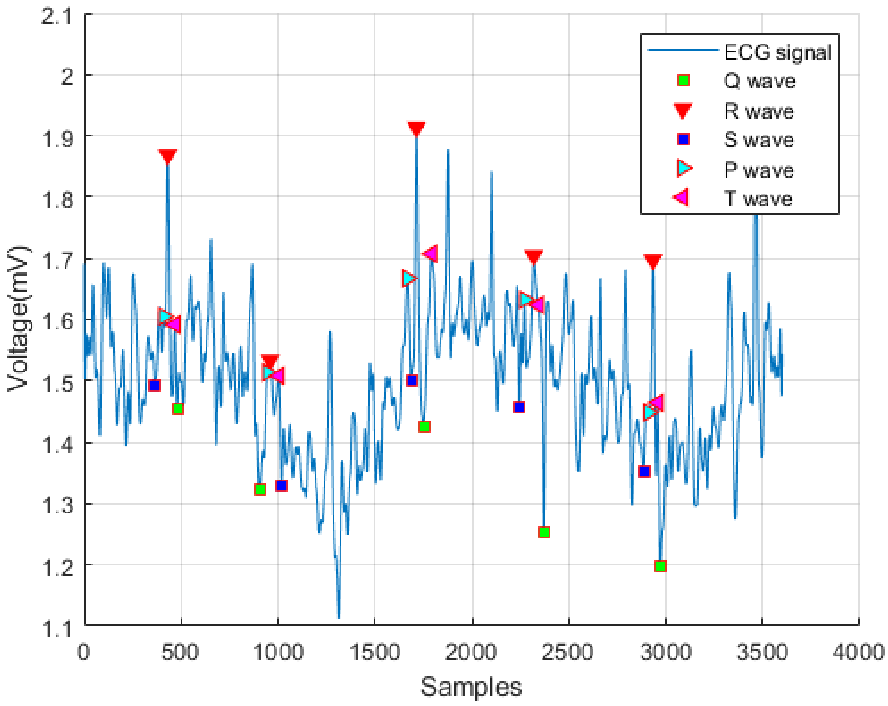


Figure 5.9: Waves and peaks in reconstructed ECG signal after applying Savitzky–Golay filter for the second time

- QRS = 61.00 ms
- Heart rate = 99.09 bpm
- RR interval = 605.50 ms
- QT interval = 244.30 ms
- QTc interval = 313.95 ms

The peaks and waves are marked in Figure 5.12 after third round of the algorithm by changing the K value. This patient classify as normal with no heart disease.

Figure 5.10: Original and recovered signals after third round of the algorithm

Study the impact of K value on classification accuracy

There is a relation between K value and the disease classification accuracy. We have to select the best value for K that do not much affect the signal waves and peaks. Moreover, selecting the best value for K leads to compressing well to reduce the bandwidth while transmitting. When choosing very low K lets say 10, the compressed size is too low and CR is very high 360 but the recovered signal is too noisy and can not be used for classification as shown in Figure 5.13. The Blue wave represents the filtered original signal and the Red wave represents the recovered signal in time domain. When using K value of 10 the recovered signal looks very noisy and it looks far away from the original signal with a lot of noise. Moreover, the standard shape for ECG is destroyed which means this K value is not suitable for compressing and the receiver will not be able to extract the features from it.

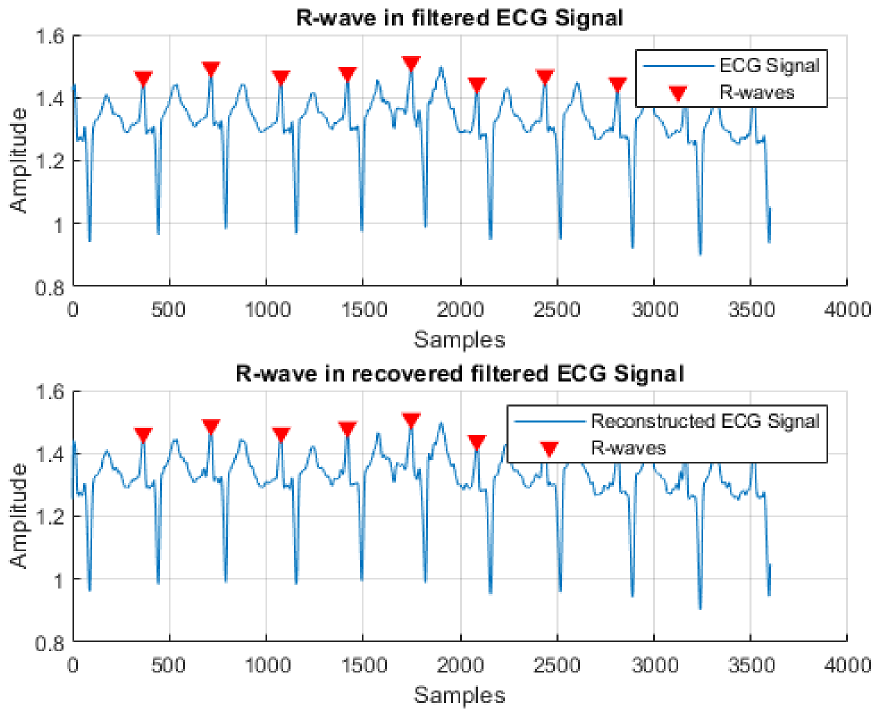


Figure 5.11: R peaks in original and recovered signals after third round of the algorithm

On the other hand, when selecting high K value let's say 3000. The compressed size is still big which means it looks quite similar to the original one in terms of size. In this manner, the benefit of using compressive sensing is not used when the data size is not reduced a lot and the transmission time to send this data looks the same to the original. Thus, having compressive sensing in that way used much time for computation without gain benefit from the technique. On the other hand, the accuracy is very good and the recovered signal looks like the original as shown in Figure 5.14 but there are no benefits from using compressive sensing with this K value.

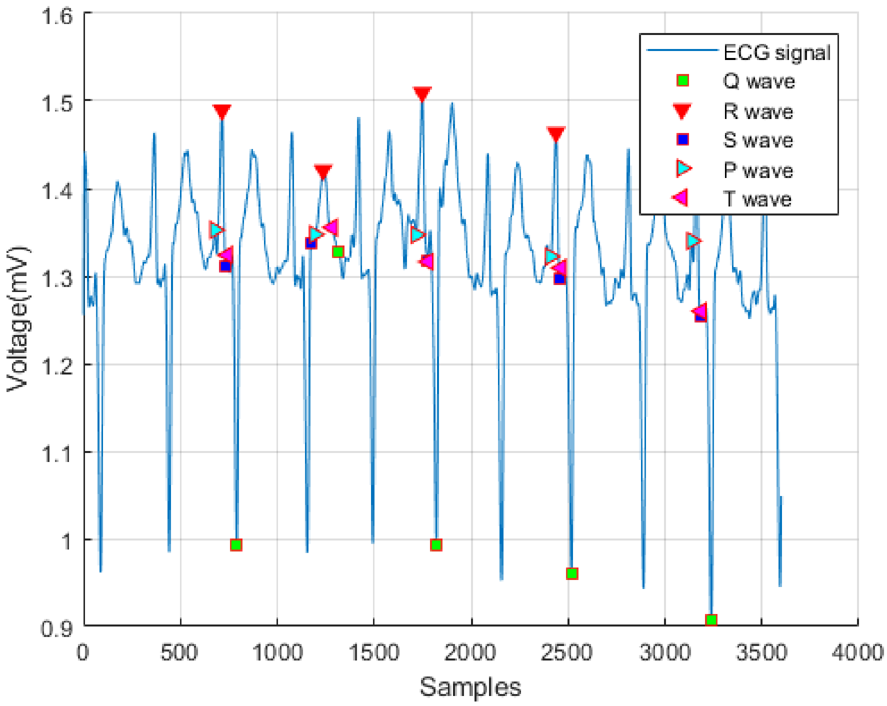


Figure 5.12: Waves and peaks in recovered signal after third round of the algorithm by changing K value

Study the impact of K value on MSE

The simulation experiments are run with updated parameters. Here the effect of various values of K on MSE is studied. So, the algorithm run several times using several values of K ranged from 360 to 3600. In each run, a plotted MSE is shown with the final value saved. After completing all the K values, all the MSE values are combined in one figure to check the effect of changing K value on MSE performance metric. By inspecting Figure 5.15, the following remarks can be made:

- MSE goes down when the value of K increases to reach approximately 0.0046.
- The K value has an impact on MSE only because K is a part of the calculation of

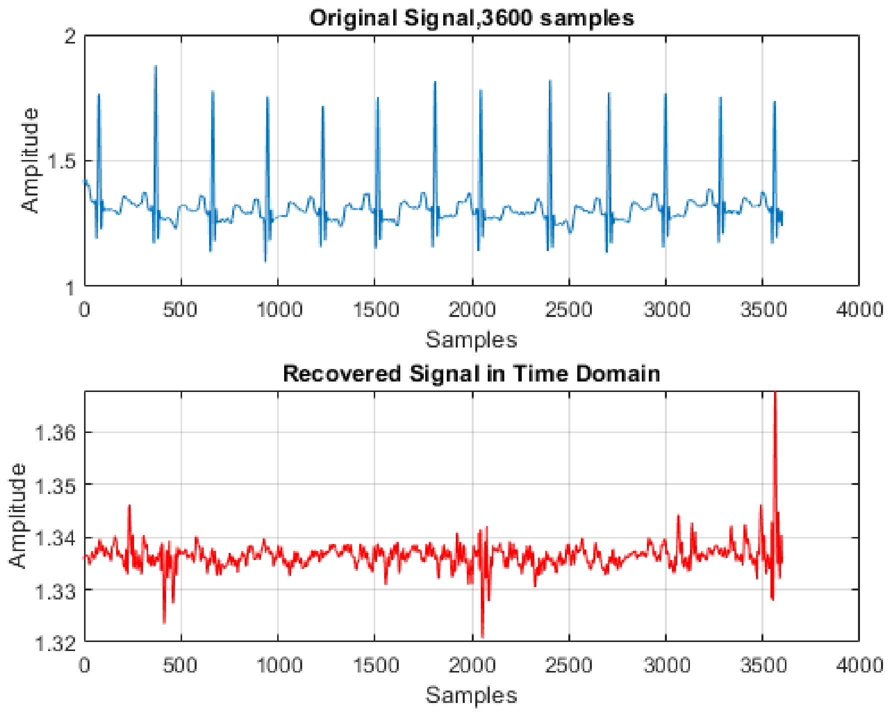


Figure 5.13: ECG signal accuracy when $K = 10$

compressive sensing. Therefore, giving high K value to indicate less errors will produce huge compressive sensing file size. In the other hand, having low K value to indicate less compressive sensing file size will results in high MSE. As a result, the model starts making false decisions regarding the normal cases.

- 900 is chosen as an optimal value for K which is the same as initial value.

Study the impact of K value on FAR

The simulation experiments are run with updated initial parameters. Here, the effect of various values of K on the false alarm rate is studied. FAR, is the number of false alarms per the total number of warnings. The K values are ranged from 360 to 3600. In each time the number of

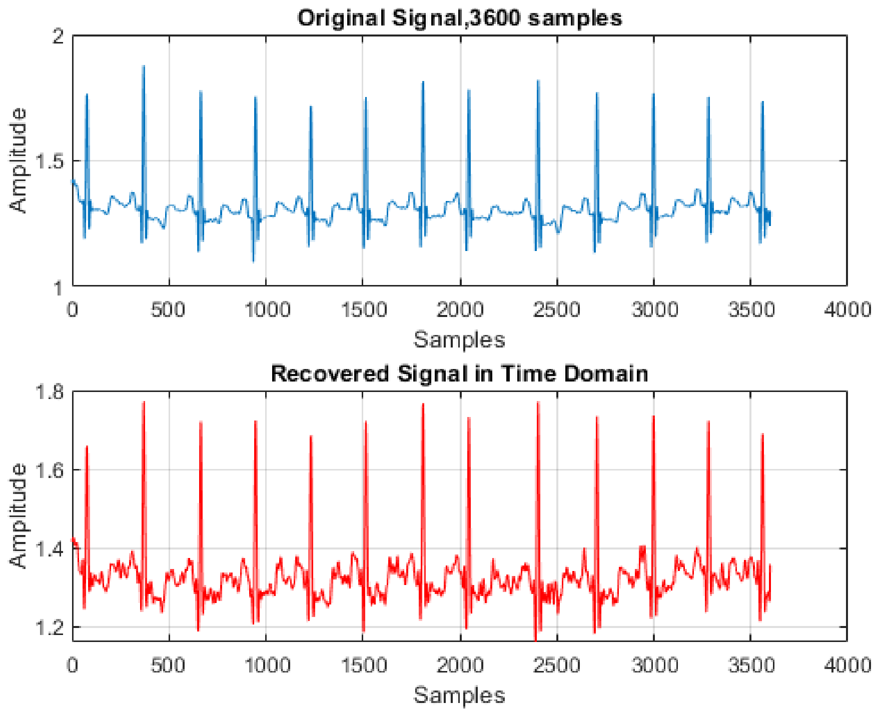


Figure 5.14: ECG signal accuracy when $K = 3000$

false alarm are counted and saved. Then all the saved false alarms for different values of K are grouped in one figure to study the impact. By inspecting Figure 5.16, the following remarks can be made:

- FAR goes down when the value of K increases to reach approximately 3%.
- The K value has an impact on FAR only because K is a part of the calculation of compressive sensing. Therefore, giving high K value results in less FAR rate but the compressive sensing file is huge. In the other hand, having low K value to indicate less compressive sensing file size will results in high FAR. As a result, the model starts making false decisions regarding the normal cases.
- 900 is chosen as an optimal value for K which is the same as initial value.

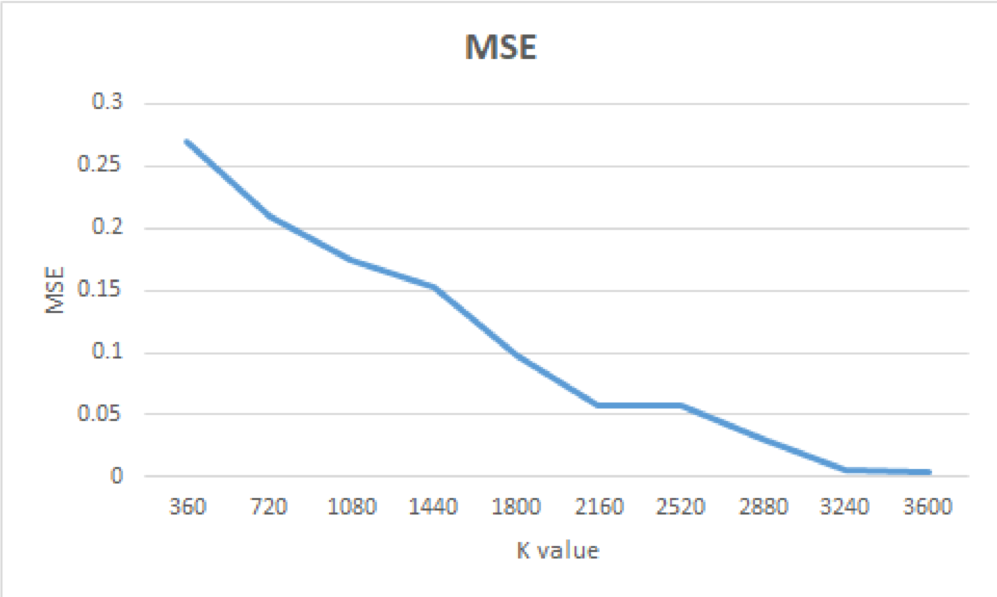


Figure 5.15: Effect of changing K value on MSE

5.3 Summary

In this chapter, a compressive sensing novel algorithm for Cardiac Homecare System was proposed. Various patient cases were considered to study the performance of the proposed algorithm. Moreover, multiple performance metrics were considered which are accuracy, errors and false alarm.

Results showed that the proposed algorithm was able to achieve 90% of the patient data from the first round with a high rate of CR which is 4. The conducted algorithm was able to extract features and classify each patient with decision on his/her heart condition. Only 10% of patient data was considered for second and third round. Three percent of data moved to second round. After filtering, the signals were accepted and the decision were considered. The other 7% of data moved to the third round. K value was maximized to minimize the CR to 3.6 which is still acceptable. The feature values and heart condition were provided for each patient.

The value of K was studied based on the classification accuracy, MSE and FAR. The main

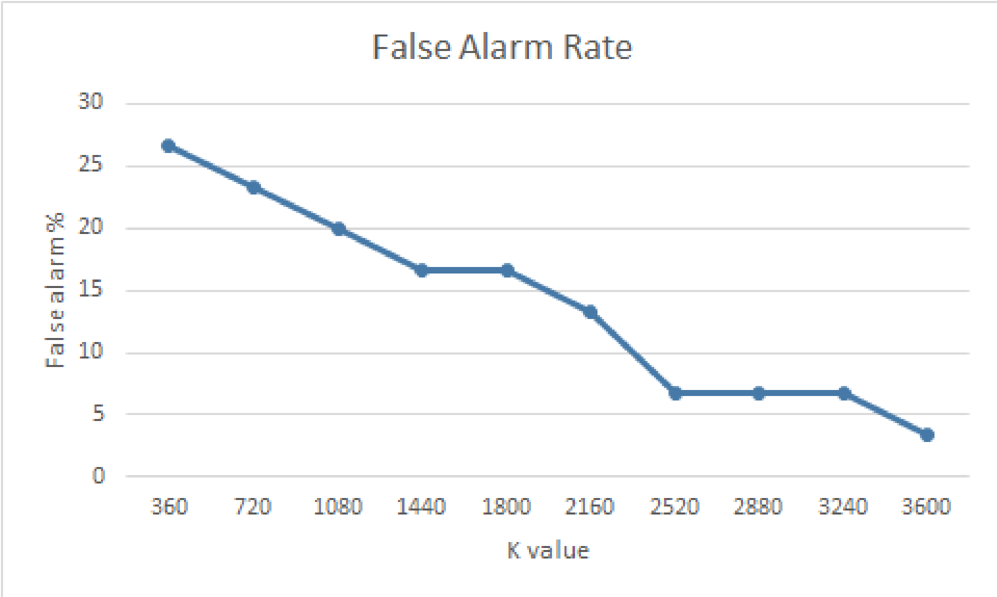


Figure 5.16: Effect of changing K value on FAR

conclusions are:

- Choosing best K value has an impact on the classification accuracy. Low K value produced bad results however, high K value produced better accuracy but with heavy compressed size and the transmission of data is slow.
- Choosing best K value has an impact on MSE value. Low K value produced high number of errors while, high K value produced lower number of errors but with huge compressive sensing file size.
- Choosing best K value has an impact on FAR. Low K value indicated high rate of false alarm and wrong decisions. However, high K value resulted in low false alarm rate but produced huge compressive sensing data size.
- Based on the experiments, 900 is chosen as an optimal value for K.

Chapter 6

Concluding Remarks

In this thesis, an in-depth analysis of IoT homecare management systems classified into three main parts healthcare systems, home automation systems and hybrid systems. Highlighting on the network, hardware and software used by those systems. Moreover, detailed background on data compression and compressive sensing is investigated. Focusing on open challenges and opportunities for homecare and defining gaps with scientific solutions to some of them. Building on the comprehensive review (in Chapter 2), a new model is introduced for enhancing the accuracy for Cardiac homecare systems. The model was able to extract the features from ECG signals and make classification and diagnosis based on three different ways to improve the accuracy; threshold values, machine learning and deep learning. Online database along with hospital database for real patients were conducted. Based on the results, the proposed model improved the accuracy of cardiac homecare system using deep learning with huge number of patients. To assess the performance, I have compared the proposed model using machine learning and deep learning with two existing models. The results showed that the proposed models outperform the existing models in terms of accuracy. The proposed model using machine learning with SVM reaches accuracy 91.67% which is higher than the existing work which is

83%. The other proposed model using deep learning with MLP improves the accuracy with 87% better than the existing work which is 69%. Moreover, Huge number of data leads to higher classification accuracy. The SVM accuracy using hospital database is much accurate than online database with accuracy reached 94%. Furthermore, MLP algorithm using hospital database produced much better results with less number of errors MSE equals 0.006 which is closed to zero in comparison to online database. Which means high level of accuracy.

Moreover, a new adaptive amplitude threshold compression algorithm designed for minimizing the data size and reducing the cost (in Chapter 4). The algorithm is worked by classifying and diagnosing the ECG signal while its compressed. It has a novelty in calculating the adaptive amplitude threshold that used for compressing. A theoretical analysis of the proposed model was conducted to validate the simulation. Results proved that the throughput is maximised and the storage space is minimized without affecting the data. The throughput after using the algorithm was improved by 43% with data compression. And the storage space was minimized by 57% when using data compression.

In addition, the proposed model (in Chapter 4) was improved by using compressive sensing. A compressive sensing based cardiac homecare system model was introduced (in Chapter 5). This model was able to extract the features and classify the signal after reconstruction to carry small amount of data through the channel between sender and receiver. Accuracy, number of errors and false alarm results proved that the model performed well in reducing the data size while transmission without affecting the classification results after reconstruction.

6.1 Limitations

The main aim of this thesis was to design models that achieve Cardiac monitoring in homecare. However, there are certain limitations while exploring the aim of this thesis. It is expected that these points will help with further research:

- Due to the COVID-19 pandemic and lockdown, the proposed model (in Chapter 3) suggested to be applied on real patients by visiting them and taking the ECG signals from them using body sensors in real time.
- The main focus of this thesis is on the Cardiac condition only in homecaring because of lack of time and resources during the pandemic.
- Because of the limited scope of thesis on ECG signals regardless of the health parameters, the proposed models only considered abnormality of ECG signals.

6.2 Future Work

In this final subsection, further interesting research topics related to the work proposed in this thesis are discussed. In future work, the proposed models could be implemented on hardware basis. Then the models can be tested inside the hospital with real patients. After that, the whole models could be established using hardware in home to achieve homecaring. Moreover, more Vital Signs can be monitored while patient at home such as body temperature, blood pressure, and respiration rate to improve the decision making regarding Cardiac condition. Furthermore, the addition of smart home sensors could improve the model such as live Cameras with motion detection and voice feature in case of any unconsciousness or heart attack happened to the patient while he or she is alone at home to provide quick assistant and save lives.

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