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A holistic health monitoring framework supported by a novel diagnostic algorithm

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A Holistic Health Monitoring Framework Supported by a Novel Diagnostic Algorithm

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List of Publications

1- Conference Papers

a. Alhemairy M., Serhani A., Atif Y., and Amin. S. (2013) Classification of Pervasive Healthcare Systems. Published in the International Conference on "Developments in eSystems Engineering" (DeSE '13). IEEE proceeding. 16th - 18th December 2013, Abu Dhabi, UAE.

b. Alhemairy M., Serhani A., Amin. S., Alahmad M. and Hijji. M. (2016) Integrated and Scalable Architecture for Providing Cost-Effective Remote Health Monitoring. Published in the International Conference on "Developments in eSystems Engineering" (DeSE '16). IEEE proceeding. August 31 – September 2, 2016. Liverpool and Leeds, England.

2- Journal Papers

a. Alahmad M., Alhemairy M., and Amin. S. (2016) A New Algorithm for Online Diseases Diagnosis. Submitted to Nature Scientific Reports (Under review).

3- Edited Book:

a. Alhemairy M., Serhani A., Amin. S., and Alahmad M. (2016) A Comprehensive Framework for Elderly Healthcare Monitoring in Smart Environment. (Invited as Chapter-in-Book and accepted to be published in "Technology and Smart Futures". Springer International Publishing AD, Cham).

4- Patent Applications:

a. Alhemairy M., Alahmad M., and Amin S. (2016) A novel algorithm for fast disease detection based on vital signs. USA Patent Applications no. US 62/377,223, filed on August 19, 2016 and Patent Application no. US 15/383,341, filed on December 19, 2016.

b. Alhemairy M., Serhani A., Amin. S., and Alahmad M. (2016) A Novel Integrated and Scalable Architecture for Remote Health Monitoring. USA Patent Applications US 15/395,121, filed on December 30, 2016.

Abstract

In the present era, technology has greatly influenced the field of medicine and healthcare. Recent innovations in wireless transmission and biosensor technology have driven the concept of potential convergences between healthcare and telecommunications. The emergent use of telemedicine technologies for remote monitoring of patients with chronic disease has enabled clinicians to manage patients remotely and in a pro-active manner with a large number of healthcare organizations and hospitals trying to implement various remote monitoring healthcare applications. Currently there are many applications available for research purposes as well as for commercial use from industry.

Many of the industrial or commercial applications, implemented by healthcare organizations, may include wireless sensors, biometric wristwatches, wireless ECG systems, mobile cardiac telemetry systems, blood pressure and glucose meters, etc. Such industrial applications aid the medical doctors in monitoring the daily activities and healthcare status of the patients considerably by utilizing the biosensors and networking technologies. Healthcare solutions and platforms vary by their purpose and features and there are no efficient classifications combining the common or distinct features among these solutions.

This thesis aims to improve the state of the art by introducing a comprehensive framework that has covered most of the required features for monitoring patients (remotely) clustered in a modular structure, which makes it flexible and scalable by adding or removing further modules or features without affecting the other modules or interrupting the platform's core operations. This modular framework employs specific functions for each module to eliminate the redundancy of the tasks or the potential overlap between them and therefore reduces cost, time and effort. Having a framework such as that proposed here will allow researchers and developers to focus more on the knowledge intrinsic to the patient-relevant data being collected and analysed as opposed to technical developments and specific programming details.

It also provides a guideline on what are the key features in the most common healthcare solutions and the drawbacks of each category. It also characterizes the existing healthcare monitoring solutions into two major categories, which include research prototypes and industrial applications. These features incorporating *non-intrusive, security-enabled, mobile-aware, integration support and context-aware* features.

Similarly, it is envisioned there is a new concept of collecting medical knowledge from external databases, such as social networks, and utilise such information to support diagnosing decisions through expert systems as well as learning techniques.

Overall, this thesis presents a systematic procedure to be used for diagnosing various kinds of diseases through developing an algorithm that incorporates mathematical expressions to determine a variable called an "Indicator" that searches a look-up table of predefined medical conditions to predict the most likely disease the patient may be suffering. By designing this algorithm and implementing a software simulator, it was also found that the proposed diagnosing algorithm is much faster and more efficient over conventional search methods in calculating the Indicator and diagnosing the medical condition, being on average between 10% and 48% faster than sequential search methods and when considering more than 40 medical conditions (diseases), reached a 92.5% level of accuracy assuming there was no intersection with vital sign values or the Indicator's range.

Keywords:

eHealth, pervasive healthcare, mobile applications, smart technology.

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Dedication

For my parents who motivated me to commence my postgraduate study and inspired me at the inauguration of my programme.

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Acronyms

ADL	Activities of Daily Living
BP	Blood Pressure
BST	Binary Search Tree
ECGs	Electrocardiograms
EPWs	Ear Pulse Waves
ERD	Entity Relationship Diagram
FNA	Fine Needle Aspiration
GPS	Global Positioning System
HR	Heart Rate
ICT	Information and Communication Technologies
ISDNs	Integrated Services Digital Networks
MDDS	Medical Diagnostic Decision Support
mHealth	Mobile Health
PDAs	Personal Digital Assistants
PHC	Pervasive Health-Care
PHT	Pervasive Healthcare Technology
POTS	Plain Old Telephone Service
RR	Respiratory Rates
SMS	Short Text Message
SPO2	Peripheral Capillary Oxygen Saturation
SWS	Smart Wearable System
TEMP	Body Temperature
WF	Weighting factor
XML	Extensible Markup Language

Chapter 1

Introduction

Chapter 1: Introduction

1.1 Context and Background

In this section, pervasive healthcare and current developments in remote healthcare-monitoring technologies are introduced, and the main enabling technologies, such as wireless communication, continuous monitoring, and self-diagnosing algorithms for diseases based on vital sign reading by sensors are covered.

As a consequence of recent developments in **medical research and technology**, the healthcare quality has been noticeably increased (Varshney, 2009). The integration between ICT technologies and medical technology has boost up the progress of Pervasive Healthcare [PHC]. Pervasive healthcare refers to providing healthcare to anyone at any time. The growing attention paid to pervasive healthcare has also been a phenomenon of technology dispersion and increasingly accepted technology imposition.

Healthcare is an important issue that affects all nations. It is a real challenge for both the developed and developing countries economically and socially. From an economic perspective, worldwide expenditure on health is projected to increase from US$7.83 trillion in 2013 to $18.28 trillion by 2040 (Dieleman, 2016). In the United States of America (USA), national health spending grew 5.3% to $3.0 trillion in 2014 (National Health Expenditures, 2015). Japan, with the third-largest healthcare expenditure after the USA and China, reported an estimated $480 billion or 9.8 percent of gross domestic product (GDP) spending on healthcare in 2013 and they expect that to grow up to 10% of GDP by 2018 (Wada, 2015). In UK, the government has allocated more than £143 billion for the healthcare national program for 2017. This is equal to 24% of the total public spending - which is equal to £600 billion- and it's anticipated to be raised to £146 billion for the following year 2018 (Office for Budget Responsibility, 2016). Moreover, the care-home market size in UK alone has been valued £14.3 billion in 2015, which form about 32% of the total healthcare market in UK - approximately £45.3 billion in 2015 - (Laing and Buisson, 2016). One of the main causes of increased healthcare expenses is the rising number of the aging population.

The **ageing population** and the massive increase in chronic diseases have encouraged the need for reliable remote healthcare systems. Age-related illness appears set to dominate future healthcare trends. One of the objectives of this research is to discuss research challenges in remote healthcare to pave the way for a pervasive, user-centred model in the context of home-based ageing populations in terms of a preventive healthcare approach.

The **worldwide population** of those over 65 is predicted to reach 761 million by 2025, more than double what it was in 1990 (Ross, 2004). For example, in the United Arab Emirates (UAE), the ageing population will account for over 15% of the population by 2020 (Fernandez-Millan et al., 2015). According to the World Health Organization's (WHO) 2016 report, life expectancy increased by 5 years between 2000 and 2015, the fastest rise since the 1960s. The problem is that as the population ages, the burden of chronic disease presents itself more clearly. It was reported that roughly 80% of general practitioner (GP) visits are associated with chronic diseases (Banos et al., 2014). Patients suffering from chronic diseases or their exacerbations utilise over 60% of hospital bed days and 67% of such patients are admitted as medical emergencies (Banos et al., 2014).

What makes the issue significant is the fact that between 70 –78% of healthcare budgets are expended on the controlling of chronic disease or related complications (Celler and Sparks, 2015). Furthermore, within industrialized nations, health expenditure costs for patients with two or more chronic conditions are six times greater than those with only one (Banos et al., 2014). What is expected for healthcare is even more dire with regards to developing countries, where the scarcity of personnel and resources (Banos et al., 2014) pose a serious challenge.

Developed countries are attempting to tackle the **increased healthcare expenditure** challenge by finding novel cost-effective healthcare solutions (Banos et al., 2014). Both industrialized nations and developing countries are trying to reduce healthcare expenses by shifting the current healthcare focus from the traditional/original medical treatment to the prediction, prevention and/or early detection and warning of diseases (Baig et al., 2014). The new focus of healthcare has led by the emerging of information and communications technologies (ICT). The integration of healthcare and information technologies has already revolutionized the healthcare field and delivered innovative, efficient and affordable solutions (Banos et al., 2014). The utilisation of ICT in conjunction with medical and engineering knowledge has empowered healthcare researchers by enhancing patient monitoring at home, in hospitals or outdoors using 2G, 3G, WiFi or online through the world wide web (Baig et al., 2014). Strides made in ICT made it possible for elderly patients to lead independent lives, for example, because of innovative monitoring solutions at home (Abo-Zahhad, Ahmed and Elnahas, 2014).

Over the past number of years, quite a few concepts have arisen as part of the new healthcare paradigm. **Medicine 2.0**, **Health 2.0/3.0, ePatient and eDoctor**, among other more established terms such as eHealth, telehealth or telemedicine, are commonly used monikers for these concepts (Banos et al., 2014). Telehealth is the use of automated ICT to provide remote medical healthcare, patient and professional health-related education, public health surveillance and health administration (Celler and Sparks, 2015). The intention of telemedicine is to deliver expert-based healthcare to isolated sites suffering from under-staffed and scarce resources by means of modern wireless ICT (Abo-Zahhad, Ahmed and Elnahas, 2014). One of the main advantages of telemedicine is cost savings - information is less costly to transfer than people (Abo-Zahhad, Ahmed and Elnahas, 2014). Many of the gains associated with telemedicine emerge from the asynchronous home telemonitoring of vital signs, which promotes patient self-management (Celler and Sparks, 2015).

One of the most successful demonstrations of the anticipated benefits of telemedicine is the Whole System Demonstrator (WSD) program of the UK Department of Health. Recent program has described the following reductions (Steventon et al., 2012):

1) Accident and emergency visits by 15%;

2) Emergency admissions by 20%;

3) Elective admissions and bed days by 14%;

4) Tariff costs by 8%; and

5) Mortality rates by 45%.

These promising findings, along with the other anticipated advantages of utilising telemedicine, have fuelled much research interest in this area.

Overall, this presents a novel eHealth expert system that is cable of diagnosing diseases promptly, accurately and remotely. Such technology can diminish hospital re-admission rates and help patients to become mobile more quickly after medication in hospitals or following surgeries. By the continuous monitoring and online detection of diseases and medical conditions, physicians would be able to decide when to discharge patients. By discharging the patients faster, this will decrease the complications in the physical and psychological status of them in addition to hospitalization length, and ultimately reduce healthcare costs.

Pervasive healthcare is a reaction to the requirement for personalized and non-hospital trouble. Pervasive healthcare removes a patient's physical presence in hospitals and provides each individual a chance to contribute personally to their own healthcare (Pai and Huang, 2011). It has the ability to be connected with an unrestricted data link as well as real-time synchronous interactions within a practical space. A data link is critical in high-risk conditions where a misplaced episodic symptom can result in a severe outcome. Using pervasive technology, healthcare, often faulted for its being impersonal, can supply the personal touch advocated by customary medicine (Olguin, Gloor and Pentland, 2009).

Remote healthcare technology is currently under development and is becoming more technically refined and robust in terms of privacy. With the advances in technology, attention on remote healthcare technology has considerably increased in the currently technologically savvy society (Pai and Huang, 2011). Having the prospective of healthcare without time and space limits, remote healthcare technology can afford the requirement of patient self-supervision, especially for long-term care arrangements. However, the vital necessity for intense observations in sensitive, high-risk conditions with need for precise results remains a significant concern.

1.2 Motivation

With sustaining networks and **wireless communication** becoming conventional, common health diagnosis has moved medication from hospital-orientated to patient-oriented through the aid of continuous monitoring based on wearable body sensors. The patient suffering from chronic diseases today can spend less time hospitalized and enjoy more of a social life at home using various monitoring technologies. The more sophisticated the healthcare monitoring systems is, the more reliable it will be. Wearable biosensors can capture critical information on body conditions and abnormal situations. Using more efficient and improved sensors will result in more accurate data that can be derived and detect the medical condition more accurately.

However, **continuous monitoring** generates a huge amount of data (big data) that needs to be handled, stored and analysed. Therefore, it is very important to extract useful information in the appropriate medical format within a very short time so that medical staff and the patients can take the appropriate actions with the aid of powerful expert systems for diagnosing a medical condition and supplying the appropriate advice as quickly as possible (Sheikhtaheri, Sadoughi and Hashemi Dehaghi, 2014). One recent United States Patent demonstrated the existence of a reliable expert system for medical diagnosis is a great challenge presently. The disease symptoms and diagnoses are quite similar and complicated, and a **regular expert system** will **search sequentially** among hundreds of thousands of rules and conditions to locate the best relative match between the symptoms and corresponding medical condition (Alhemairy, Alahmad and Amin, 2016). This of course causes delays in processing and consumes a large amount of computational resources as well as energy consumption.

This conundrum has opened the door to developing a more comprehensive platform capable of detecting and identifying various diseases based on abnormal ranges of the wearable sensors in real-time. Initially, the platform was designed for a PC application and later a lightweight version was developed for tablet PCs and on patient's and physician's mobile phones.

The medical condition search engine (or "**algorithm**") that has been conceived for this research is novel. It overcomes the limitations of other current systems (Kaplan, 2001). The online expert system is a unique mathematical expression using the values of weighting factor, index value and measured sensor values for a medical condition detection system that includes discerning a medical condition or disease from a list of defined medical conditions based on the calculation of a variable called an indicator.

1.3 Problem Statement and Key Contributions

As stated previously, the field of eHealth (telemedicine) is enjoying huge research interest in recent times. There are several classification models for healthcare monitoring solutions and in this thesis, existing healthcare monitoring systems have been surveyed and provided new classification methodology based on the research or Industrial nature of these solutions. Various systems were developed and new innovative technologies were utilized. Nevertheless, the existing eHealth systems suffer from various weaknesses and need ample improvement (Mozaffarian et al., 2015). Furthermore, many health-related aspects are not covered by existing eHealth systems.

For example, cardiac disease, which accounts for 11.13% of total deaths worldwide and that is expected to grow to more than 23.6 million annually by 2030, has received modest attention in the eHealth context, and the same applies to cardiac disease remote monitoring (Mozaffarian et al., 2015). Moreover, online diagnostic tools, which are extremely helpful by promoting patient independence and can hugely reduce healthcare expenditure by decreasing the number of GP visits, suffer from many problems. First, little research has addressed these tools and shed any insight into the algorithms they use for disease diagnosis. Second, most available online diagnostic systems such as (Isabel Healthcare, 2017) and (Familydoctor, 2017) for example; require patient awareness and knowledge of the medical conditions and symptoms they are afflicted with. These systems eventually require the patient to interact with the expert system such as (Yourdiagnosis, 2017), which is difficult especially for the elderly or illiterate. Therefore, an intelligent diagnostic system would identify the diseases and symptoms depending on vital sign readings, the predefined normal and abnormal values and the correlation between the vital signs and the most known diseases. Those issues and more problems related to online diagnostic systems are discussed in detail in Chapters 6 and 7.

Ultimately, this dissertation addresses the following problem - how to create a comprehensive healthcare-monitoring framework that provides an integrated smart technology infrastructure that monitors the vital signs of the patient at home around the clock. It must provide the elderly with instantaneous feedback based on their current medical conditions as well as communicate with their physicians for advice or calling in emergencies during contingency situations. It must then also focus on making use of a unique disease-diagnosing algorithm that has novel features relative to the prior-art for interpreting vital sign values with their corresponding medical conditions. It also needs to demonstrate enhanced accuracy in detection of diseases. Therefore, within this thesis, a new comprehensive classification of healthcare-monitoring systems has been introduced based on an extensive search of existing solutions from academia and industry. In general, the proposed framework, classification and algorithm all attempt to enhance the continuous health monitoring of the elderly and remote patients at home to help them to carry out their daily routines individually and in a non-invasive, comfortable environment.

1.3.1 Aim and Objectives

The fundamental aim of this research is to develop a comprehensive health-monitoring framework that is scalable, fully integrated and efficient. The framework must have a smart expert system that is capable of detecting and diagnosing medical conditions accurately and efficiently without physician attendance. It needs to allow non-intrusive monitoring of vital signs using a set of wearable sensors connected wirelessly to a mobile device via a web-based platform, determine reading abnormalities and potentially warn the patient and their physician at all hours. In order to accomplish this, the following research questions were formulated hereafter in Section 1.3.2.

1.3.2 Research Questions

The research questions for this study and their answers are presented in the corresponding thesis sections. However, answers to these research questions can be found in a summary in **Chapter 8:** "**Conclusion and Future Work**".

Question 1: How can existing healthcare solutions be classified and compared? What comparison criteria should be used?

1.1 Which comparison criteria will discriminate between health-monitoring solutions?

1.2 How to provide comprehensive categorization and comparison between different healthcare solutions?

Question 2: Does the existing healthcare-monitoring frameworks offer efficient and comprehensive solutions?

2.1 What are the main features of the new proposed framework in this study beyond the current state of the art?

2.2 Do the existing healthcare classification models capture all possible key features, such as being non-intrusive, security-enabled, mobility-aware, support integration and context-aware?

2.3 To what extent should a healthcare solution possess smart features? What are the key barriers that challenge their implementation?

Question 3: What are the main features of the new proposed algorithm for health diagnostics in this study that are beyond the current state of the art?

3.1 Can expert healthcare systems based on vital sign data collected from sensors provide high efficiency such that they are beyond the current state of the art?

Given the goals and research questions established, this work will need to fulfil the following objectives:

- **Survey existing healthcare monitoring solutions and provide new classifications that encompass both academic and industrial solutions.**
- **Propose a healthcare-monitoring framework based on an integrated and scalable architecture.**
- **Develop an algorithm that can detect abnormalities in human vital signs using systematic procedures for self-diagnosis of diseases.**
- **Implement and test a prototype system for vital sign monitoring that employs the developed algorithm within an efficient mobile application for an online disease diagnosis tool on a real-time basis.**

1.4 Research Contributions

This dissertation contributes to the following areas associated with empowering the field of the pervasive healthcare-monitoring and medical expert systems in order to foster better quality of human life.

1.4.1 Classifying Pervasive Healthcare Solutions

This research surveys existing pervasive healthcare systems and characterizes them as academia- or industrial-based, and then develops a set of criteria to compare these solutions. There is discussion of certain drawbacks of existing solutions, and future directions are proposed that are predicted to shape those pervasive healthcare systems to come.

1.4.2 Integrated and Scalable Architecture

A healthcare monitoring system framework is put forth based on an integrated and scalable architecture that permits flexibility and enables interoperability between the myriads of healthcare monitoring devices and products.

The proposed framework features an integrated smart technologies infrastructure that are able to monitor vital signs of patients at home around the clock. It offers a set of services that includes providing patients and specifically the elderly with instantaneous feedback based on their current medical conditions as well as communicating with their physician for advice or emergencies in contingency situations. The proposed framework consists of sensors and actuators that continuously monitor the health of patients and assists them in carrying out their daily routines individually while they are at home.

1.4.3 New Algorithm for Online Disease Detection Based on Vital Signs

Then an algorithm has been developed for an online disease diagnosis expert system, representing a systematic procedure for self-diagnosis. The system incorporates several medical conditions, and each is associated with specific symptoms and signs that are mapped directly to several types of sensors and their unique readings. The proposed disease diagnosis approach begins with reading the user's real-time vital signs via a wearable sensor system, and then incorporates new mathematical expressions applied to search for a predefined diseases look-up table for the corresponding disease. All in all, this aids in the assessment of physical health by providing diagnosis of possible diseases, and checking treatment progress. The evaluation process showed the superiority of the developed algorithm in comparison with traditional techniques, and the algorithm itself was novel and efficient in terms of functionality, response time and resource utilization.

Overall, the key contributions of this work can be summarized into three main parts:

1. A classification model that provides a comprehensive categorization and comparison of systems from both academia and industry.
2. A comprehensive framework for health monitoring and diagnosis that exhibits novel features and is capable for scalability and integration.
3. An algorithm that can be utilized for efficient disease diagnosis with mobile- or web-based tools.

1.5 Research Questions to Contributions Mapping

No.	Research Question	Contribution(s)	Related publication
1	**How can existing healthcare solutions be classified and compared? What comparison criteria should be used?**	Propose a new classification and comparison criteria based on surveying existing healthcare solutions.	1. Classification of Pervasive Healthcare Systems (DeSE'13 Conf.)
2	**Does the existing healthcare-monitoring frameworks offer efficient and comprehensive solutions?**	Proposed a comprehensive framework for healthcare monitoring with new features that is fully integrated and scalable.	1. Integrated and Scalable Architecture for Providing Cost-Effective Remote Health Monitoring. (DeSE'16 Conf.) 2. A Novel Integrated and Scalable Architecture for Remote Health Monitoring. (US Patent Application). 3. A Comprehensive Framework for Elderly Healthcare Monitoring in Smart Environment. (published Chapter-in-Book)
3	**What are the main features of the new proposed algorithm for health diagnostics in this study that are beyond the current state of the art?**	Propose, implement and test a system that utilize a novel online disease detection algorithm based on body vital signs.	1. A New Algorithm for Online Diseases Diagnosis. (Submitted to journal). 2. A Novel Algorithm for fast disease detection based on vital signs. (US Patent Application).

1.6 Thesis Organization

The first chapter introduces the work of the thesis, the research questions, the methodology and the knowledge contributions. The rest of this thesis is organized as follows.

Chapter 2 features the literature review related to disease detection and remote health-monitoring systems. In particular, the algorithms related to wearable medical sensors and online medical expert systems are covered. Chapter 3 describes the methodology underlying this research thesis. Chapter 3 describes the methodology used in this research. Chapter 4 outlines the classification of existing healthcare solutions and comparison criteria. Moving along, Chapter 5 proposes a new framework for healthcare solutions, while Chapter 6 introduces the new proposed algorithm for health diagnostics features and explains what comprises its core modules. Subsequently, Chapter 7 describes the implementation and evaluation of the proposed online disease detection's algorithm and the main components of the online eHealth system. Finally, Chapter 8 presents an overall summary of the work reported herein and draws conclusions that are relevant to future research improvements and investigations.

Chapter 2

Literature Review

Chapter 2: Literature Review

2.1 Chapter Overview

This chapter features a survey of the current literature on eHealth technologies, pervasive healthcare and health automation systems. Following recognition of the medical diagnostic decision support (MDDS), the prior art of algorithms for MDDSs from patient’s vital signs is then covered. The chapter concludes by discussing and comparing the most relevant publications and patent literature.

2.2 Introduction

Advancements in communication technology have facilitated the progress made in eHealth technology and has driven the growing interest in distance heath monitoring. Many factors have led to the increased interest in the field of telemedicine, among which are the drastically reduced healthcare costs, the persistently expanding global elderly population and the continuously improving communication, information and wearable sensors technologies. These factors have all created a demand for eHealth systems and devices, a demand that was easily matched with a huge number of prototypes and applications from both research and industrial developments teams around the world. Telemedicine (also referred to as "telehealth" or "e-health" or “eHealth” or “Health 2.0” or “Medicine 2.0” or “mHealth”) can be defined as the synergy between ICTs and medical systems and devices in order to deliver real-time information about a patient’s health status. This information can be sent directly to the patient to empower them in taking the appropriate course of action regarding their health or it can be conveyed to the patient’s healthcare provider represented by the hospital’s physician and nurses or even the patient’s guardian.

Many research studies have outlined the use of **telemedicine to monitor patient’s vital signs**, such as heart rate, blood pressure, temperature and arterial oxygen saturation. The continuous monitoring of these vital signs is critical in many cases. Before the existence of telemedicine, there was only the possibility of hospitalized bedtime, the main driver of increasing healthcare costs (Steventon et al., 2012). Although the measurement for blood pressure signs by patient at home has some challenges in terms of the accuracy and reliability and has received vast calibration test by the industry and clinicians to improve the accuracy; however, this subject is outside this research scope. During the experimental work; the blood pressure – for instance- was captured using the same device every time to avoid the differences between various vendors. Moreover, the average of 3 consequent readings was used to ensure the accuracy with 60 seconds intervals between each readings. Monitoring the heart’s mechanical and electrical dynamics and its immediate periphery are fundamental to fully characterizing heart functioning and variations (Celler and Sparks, 2015). For many years, the biophysical properties of the heart’s components have been measured by the conventional use of electrocardiograms (ECGs), blood pressure and heartbeat rate determination to obtain values of the different heart parameters. The ECG procedure employs multiple probes placed on defined locations on a bare chest, and these probes generate electrical current as a result of the electrical activity stemming from each heartbeat at the chest surface (Abo-Zahhad, 2014). Recently, Alahmad (2016) proposed a new technique to extract ECG signals through using a piezoelectric sensor to pick up vibrations from heartbeats and convert them into electrical output signals. Afterwards, piezoelectric and signal processing methods were utilised to take out the corresponding ECG signal from the piezoelectric sensor's output voltage signal (Alahmad, 2016).

2.3 Search Methods and Strategy

In this section, the method used to identify research and development in the field of eHealth technologies is described. In addition, the work in the field of pervasive healthcare has been classified and the differences in the various terminologies has been explored. To this end, a systematic literature study was conducted to locate articles related to eHealth systems and technologies and the identified subjects examined in concurrence with the aforementioned topic.

For the literature review on the general concept, I made use of the software, Publish or Perish, v.4.26 (Harzing, 2010) to acquire and index academic citations. The program employs Google Scholar and Microsoft Academic Search to obtain the raw citations and then analyses them and outputs many metrics. Among the metrics that are utilised in the search were two key indicators - the total number of citations per paper and the average number of citations per paper per year. Then, the following electronic databases were searched to acquire the actual papers: IEEE Xplore, ACM Digital library, Google Scholar, and Coventry University online library. Using Publish or Perish, the years between 2010 and 2016 were searched with these search terms: *mHealth, m-Health, eHealth, e-Health and telemedicine*.

With regards to the literature on the proposed algorithm for an online disease diagnostic tool, it has been thoroughly evaluated the relevant literature for the proposed system and algorithm to discern the most relevant literature known and published up to the date of writing this thesis in order to assess the originality of the research and the novelty of the contribution. The search was carried out on Google, Google Scholar, Science-Direct, IEEE, CiteSeerX and Google Patents to obtain a list of cited references based on the matched keyword criteria. The first top 50 references in each searched database were reviewed and screened to establish their relevancy to the proposed system. This comprehensive search focused on two main contributions of this thesis: 1) **Framework for Remote Healthcare-Monitoring Systems**"; and 2) "**Algorithm for Medical Condition Detection from Vital Signs, an Online Disease Detection and Diagnosis Expert System**". This was performed from two perspectives - the publication-literature (non-patent references) viewpoint and that of the patent-literature (patent references). Further details on the search outcomes will be discussed in details in Sections 2.6 and 2.7

2.4 Basic Taxonomy

The field of telemedicine has acquired a tremendous amount of attention in recent years. This attention can be quantified with the massive number of publications in terms of both original research papers and reviews. Here, it has been sought to examine the major research contributions to the field. It was initially needed to understand the difference between the various terminologies that are used interchangeably in the field of eHealth. Those terminologies include but are not limited to: Medicine 2.0, Health 2.0/3.0, ePatient, eDoctor, eHealth, mhealth, telehealth, telemedicine, pervasive healthcare and ubiquitous healthcare (Banos et al., 2014). To understand those terminologies, it was needed to know how computer systems have evolved over time and the dimension of this evolution - eHealth is generally the integration between computer systems and health services. Thus, the evolution of eHealth technologies will follow the evolution of computer systems theoretically. Lyytinen and Yoo (2002) superbly described the progress made in computing systems over the years and the dimensions of pervasive computing, as can be seen in Figure 2.1. They argued that traditional computers were large, static and lacked intelligence. In the first dimension, computers became smaller and more portable such that the users were able to take them anywhere they chose (mobile). With the second dimension, computers evolved into more invisible and intelligent machines. They came to sense our existence without notice and adjusted themselves according to our environment and needs (pervasive).

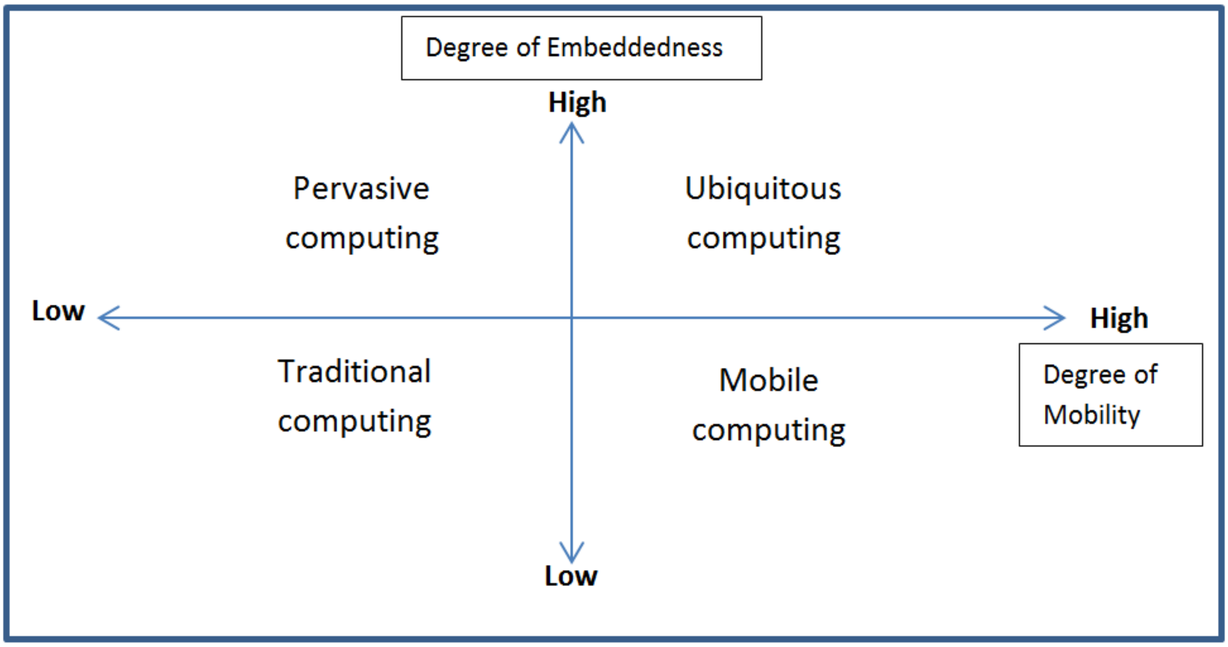


Figure 2.1: Progress made in computing systems over years (Lyytinen & Yoo, 2002)

Respectively, electronic healthcare systems have also evolved significantly. Initially, the use of the computer in healthcare was rather superficial - automating manual processes or keeping electronic records of data, and they only existed within hospital walls. At present, healthcare systems are even becoming more mobile, such that a patient's medical information can be transmitted from the ambulance before they arrive at the hospital. These sorts of systems are everywhere - they are embodied in our mobile phones (ex. Samsung heart rate and SpO2monitor) and accessible through our laptops (ex. online diagnostic services). In addition, those devices grew to be more intelligent and ambient, from strictly life-saving machines to devices that can analyse, manage and even predict medical events based on given data and algorithms (ex. medical expert system).

Therefore, one of the best ways to categorize research efforts in the field of eHealth is to classify them following the computer system evolution dimensions described by Lyytinen and Yoo (2002). To place things into context, Figure 2.2 portrays the general classification scheme for computerized healthcare systems from this work's perspective. The same characterization will be used throughout this literature review. Note, that the computerized health system terminologies are used interchangeably.

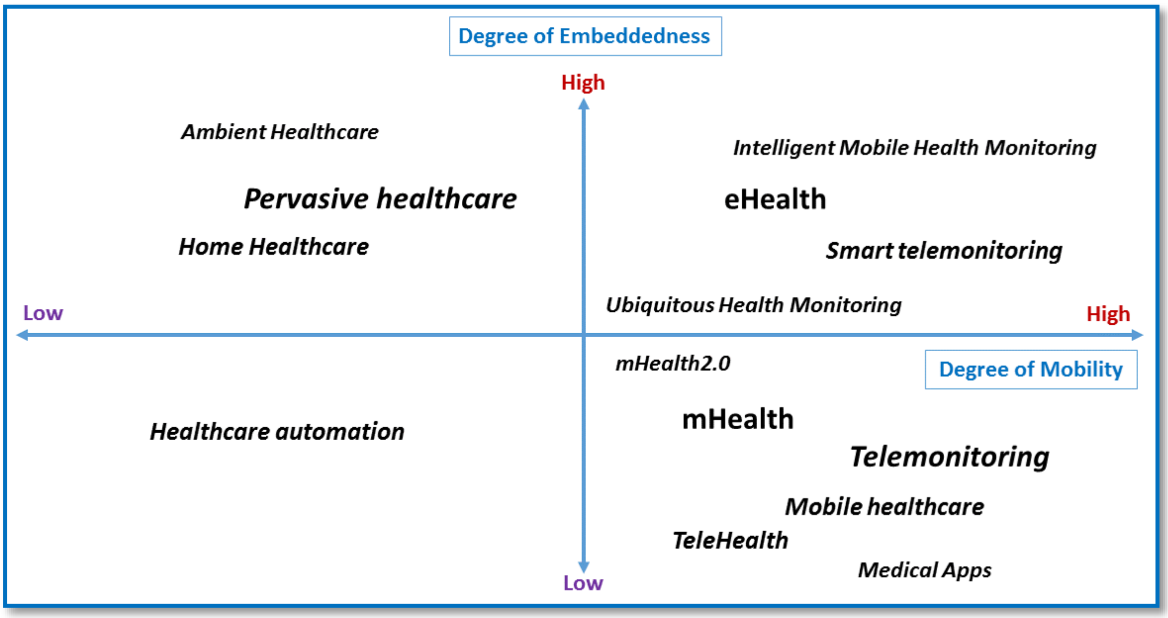


Figure 2.2: Classification of Healthcare systems (Alhemairy et al., US Patent, 2016)

In Figure 2.2, the size of the text represents the frequency of use of each classified term, whereas the most frequent terms will be utilised to describe each dimension. The frequency of each term has been taken from the number of published articles that involve that term within its context for the last three years (from 2014 to 2017) and based on that the size of the term was determined in Figure 2.2. For example, the terms: "eHealth", "mHealth" and "TeleHealth" were found in about 15,000 – 16,000 articles, and thus they are represented in the same font size. While the terms: "Ubiquitous Health Monitoring" and "Medical Apps" were mentioned in about 700 – 1,500 articles only, and thus they were represented in smaller fonts and so on.

Therefore, this review of the literature will be structured into the following four categories:

1. **Healthcare automation systems;**
2. **mHealth systems;**
3. **Pervasive healthcare systems; and**
4. **eHealth systems.**

In the subsequent sections, each of the four categories will be briefly covered:

2.4.1 Healthcare Automation Systems

Computer usage in healthcare organizations began early in the 1970s, with the spread of minicomputers later an important factor in their widespread deployment for hospital systems (Kohn et al., 2000). Apparently, their preliminary use was limited to automating administrative processes, such as hospital billing, financial applications and physician billing (Kohn et al., 2000). The discussion about healthcare automation and computerization is beyond the scope of this review and our study, so it will not be discussed further. However, it requires mentioning here for the sake of completeness and competence of the literature review study.

2.4.2 mHealth Systems

mHealth (or "mobile health") can be defined as the clinical and public health practices sustained by mobile units, such as mobile phones, patient monitoring devices, PDAs and other wireless devices (Hollis et al., 2015). It implies the utilisation of mobile's core functionality, such as voice and short messaging service (SMS), in addition to its communicative capabilities, such as General Packet Radio Service (GPRS), 3G and 4G mobile telecommunications (3G and 4G systems), Global Positioning System (GPS) and Bluetooth technology (Hollis et al., 2015).

mHealth's main goal is to enhance human health and welfare by continuously monitoring their physical status, promptly diagnosing medical illnesses and supplying just-in-time interpolations in the user's normal mobile environment (Kumar et al., 2013). Similar to how mobile phones are a natural evolution of the telephone, mHealth, as Tachakra et al. (2003) have explained, is the natural evolution of telemedicine, making use of the current progress in mobile networks for the benefit of medical applications (Tachakra et al., 2003).

Mobile technology existed long before its recognition of its critical role in healthcare. The origin of modern mHealth technology can be traced back to 1905 when Willem Einthoven transmitted an ECG from the hospital to his laboratory through standard telephone lines (Thuemmler et al., 2009). Tele-consultation came into practice in 1920 when a Norwegian hospital was connected with ships at sea via Bergen Radio. In April 1924, the Radio News in the USA presented the emergence of the same tele-consultation concept in a news article (Krein et al., 2007). Thereafter, significant events occurred with the creation of the International Radio Medical Centre in Italy in 1935 and the Centre for Maritime Health Care in France in 1945 to provide medical support to ship crews and remote islands. In the late 1940s, Cooley and Cohen experimented with X-ray transmission over telephone wires and the term “telegnosis” was coined in 1950 (Thuemmler et al., 2009).

In the latter part of the 1950s, Jutras transmitted video recordings and radiograms through a coaxial cable, resulting in the term “tele-fluoroscopy”. Tele-medical-education started in the late 1950s and early 1960s as medical instructional programs on the television (Sneha and Varshney, 2007; Varshney, 2009). The first televised medical conference took place in 1965 featuring an open heart surgery being performed by several hospitals in Houston, TX, and Geneva that were linked through an international communication satellite. In 1959, Wittson used a two-way closed circuit television as a teaching and diagnostic tool focused on neuro-anatomy at the Nebraska Psychiatric Institute. The service was intended for group therapy through television supervision and monitoring (Munnelly and Clarke 2007). The result was improved patient consultation and rehabilitation and reduced hospitalization.

Among the pioneers of mobile healthcare technology is the National Aeronautics and Space Administration (NASA), historically one of the most supportive organizations in this field. Concerned with the wellness of astronauts during space missions, NASA scientists developed technological devices for the measurement and transmission of physiological and medical data between space and earth stations in the 1960s (Lankton and Wilson, 2007). In 1970 such efforts had been applied into medical apparatus for the rural area such as the native reservations in Arizona state to link the local hospitals via mobile units (Garson, 2008). A complete healthcare technology service appeared in 1968 between the Airport Health Station in Logan and the Harvard Medical School (Munnelly and Clarke 2007). Another project encompassed connecting ten remote units together via television network between the New Hampshire Medical and central hub at Dartmouth, to support the medical education and the medical services (Pai and Huang, 2011).

Modern mobile technology has also undergone evolutionary phases, where first generation of wireless mobile communications supported voice communication only (Tachakra et al., 2003). However, the second generation featured more advanced voice services, fax & SMS. Table 2.1 summarizes the advancement of wireless communication technologies. The unveiling of 5G is expected to be in 2020 (Dan and Dan, 2014).

Table 2.1: Advancement of wireless communication technologies (1980 - 2020)

	1 G	2G	2G+	3G	4G	5G
Year	1980s ‡	1990s ‡		2000 ‡	2010 ‡	2020 ‡
Data Rate	2.4 kbps ‡	Up to 9.6 Kbps**	Up to 115 Kbps**	Up to 2 Mbps**	Up to 1 Gbps*	More than 1 Gbps*
Applications	Voice Only**	SMS, Internet**	E-mail, File Transfer, HTTP-based Web Services**	Internet and Multimedia**	Dynamic Information Access, Wearable Devices*	Dynamic Information Access, Wearable Devices with Artificial Intelligence Capabilities*
Roaming	Restricted, Not Global**	Restricted, Not Global**	Restricted, Not Global**	Global**	Global*	Global*

*(Dan and Dan, 2014); **(Tachakra et al., 2003), ‡(Li et al., 2009)

Evidently, mHealth technologies and applications have evolved substantially. In 1997, a group of researchers at the University of Maryland at Baltimore and HCI Technologies developed a mHealth system that was capable of transmitting real-time patient vital signs data, audio and video images of aid activities from inside an ambulance to the intensive care unit directly. The system employed wireless digital cellular communications and internal hospital network (Intranet) technology. The goal of the project was to provide key information to the medical staff preceding the patient's arrival in emergency situations (Gagliano and Xiao, 1997). Further, the European Commission funded a two-years mobile health project, "MOMEDA" (Tachakra et al., 2003), which stand for: Mobile Medical Data. The objective was to design software that would allow pocket-sized mobile phones to receive computer tomography images, magnetic images and patient information wirelessly from the hospital workstation using a GSM network. The pocket-size terminals would be used by neurosurgeons or radiologists to make initial diagnoses and offer consultation when needed. Also, the system permitted patients to receive customized information regarding their medical condition, granting them an active role in the treatment process (Tachakra et al., 2003). The MOMEDA system was sponsored by European Commission to allow access to information about specific disease information from the patients their planned medical procedures and lifestyle on hospitalization and after discharge. The patients data (such as vital signs & medical images) are also provided to the physician for consulting on emergency cases while a patient is in an ambulance for instance. This has in turn reduced treatment time, improved medical diagnosis, and reduced the costs by developing an integrated portable medical platform in emergency situation (Reddy, K. et al., 2014).

2.4.3 Pervasive Healthcare Systems

Lyytinen and Yoo described pervasive computing as the reciprocal interaction between an intelligent computing device and an intelligent environment (Lyytinen and Yoo, 2002). The intelligence of the computing device stems from its ability to adapt itself to the environment entered. Thus, the computing device becomes context aware. On the other hand, the intelligence of the environment emanates from its ability to detect other computing devices accessing it and adjust accordingly. Lyytinen and Yoo contended that for the environment to be intelligent, it must be embedded with sensors, pads, badges, etc. (Lyytinen and Yoo, 2002). Similarly, a pervasive healthcare system is an intelligent system that is capable of sensing the medical condition and is completely aware of the therapeutic needs, thereby adapts itself as appropriate without human intervention.

Many pervasive healthcare technology devices have been tested via experimental trials in hospitals as well as in patients' homes. Infrared technology, motion sensors (infra-red detection or acoustical detection), video cameras, and so on, that use wireless, internet, integrated services digital networks (ISDNs) and telephone lines have been installed in healthcare facilities (Thuemmler et al., 2009). For example, a non-invasive system for measuring breathing rate was created by Cho and Cho (2015). The system comprises three parts: a piezoelectric sensor, device for breath extraction that performs basic signal processing (i.e., amplification and filtering), and a viewer to display the acquired signal after being filtered and processed. The working principle behind the system is founded upon the subject first lying on a bed mattress. On top of the mattress, there is a cloth-covered sensor pad, which surrounds an off-the-shelf piezoelectric sensor. In theory, the breathing patterns of the subject will cause the piezoelectric sensor to generate a voltage signal reflecting pressure changes induced by breathing. This voltage signal will then be sent to a microcontroller fixed on a biosignal processing board (Cho and Cho, 2015). To test the proposed system performance, an experiment with three subjects was implemented. An algorithm was designed to count breathing cycles, and it employed a threshold breathing signal level. The experiments showed that this threshold is variable and should be changed based on the subject to yield optimal results. The proposed system error rate was found to be less than 5%.

Bifulco et al. (2014) proposed a system that used a polyvinylidene fluoride (PVDF) piezo film sensor to monitor the mechanical activity of the heart, heart sounds and the respiration rate (Bifulco et al., 2014). The sensor was positioned on the subject's sternum and fixed in place by a chest strap. The subject's ECG signal was simultaneously logged and served as a benchmark for cardiac activity. It was observed that the raw signal acquired from the sensor included information related to respiration, heart sounds and the mechanical activity of the heart, and the acquired signal was decomposed to obtain the necessary data by filtering. A frequency band of 0.05-1 Hz was used to acquire the respiratory signal while one of 1-50 Hz was utilised to acquire the seismocardiography signal. Although the study reported the use of 3, consecutive heartbeats to validate the results, they did not describe the number of subjects that were participated in the experiment, their ages nor gender. Further, the study did not report any quantitative results.

Shu et al. (2015) detailed the design and construction of a device that is appropriate for longstanding heart rate observation (Shu et al., 2015). The aim of the device was to free the user from exterior difficulties that are usually associated with heart monitoring, such as ECG. The hypotheses tested in the study can be stated as follows - if a flexible pressure sensor was modified to improve its sensitivity, then it could recognize the discrete pressure variations caused by arterial pulse. As a consequence, this sensor can be used to measure heart rate from the wrist. The system developed had two components - a flexible pressure sensor and signal processing circuit. The sensor's pressure sensing layer was fabricated with two sheets of surface-modified piezoresistive polymer nanocomposite films positioned to face each other internally. Externally, the polymer films were wrapped by another two sheets of patterned flexible copper clad laminate (FCCL) film. This external layer had two roles, namely to protect the sensing layer and act as the device's electrode. Another layer was added to insulate the device from exterior moisture and corruption, this layer made of PI bond-ply (π bonds). It also ensured that the four layers of material were firmly bonded. The devices' capabilities were evaluated with an automated setup that consisted of a computer connected to a micro-positioner, force gauge and electric measurement apparatus, with Labview software coordinating the testing. It was assessed for 100 cycles, and the findings indicated the device responded linearly to exterior pressure with a sensitivity of approximately 13.4 kilopascal (kPa). Further, the average error rate of the device was less than 3% when compared with a commercial electronic sphygmomanometer, a major feat.

Park et al. (2015) addressed whether in-ear pulse waves (EPWs) could be harnessed to monitor heart rate (Park, 2015). To this end, they designed a scissor-shaped device with a piezoelectric film sensor and a signal processing circuit, with high wearability and the ability to acquire steady readings in mind. The piezoelectric film sensor sheet was customized through being metallicized with silver ink to enable its use in this particular application. Theoretically, the piezoelectric sensor sheet would converts the in ear pulse waves (EPWs) into an electrical voltage signal. The voltage signal would be transmitted to the signal processing circuit, boosting the EPW and restraining noise. The signal processing circuit, based on an embedded algorithm and knowledge-based rules, would thereby detect real-time peaks of the EPW voltage signal, the number of peaks denoting the subject's heart rate. To establish the accuracy of the device, a clinical trial was performed implementing a reference ECG for the sake of comparison with the EPWs. The qualitative results suggested that the EPW periods between consecutive peaks corresponded perfectly to the ECG periods between consecutive peaks. Quantitatively, the study reported a sensitivity of 97.25%, with a positive predictive value of 97.17%, and mean absolute difference of just 0.62, and accordingly, the study was demonstrated a highly accurate heart rate monitoring device utilising in-ear pressure variance.

Clearly, pervasive healthcare technology is primarily concerned with sensors and how they are developed, embedded and controlled to make the interaction with a computer system as natural and easy as possible. Pervasive healthcare also involves developing new algorithms that will add intelligence to the computer system, rendering the pervasive healthcare system autonomous, context aware and reliable (Varshney, 2007).

2.4.4 eHealth Systems

Ubiquitous healthcare systems are those that are both intelligent and mobile. eHealth systems signify the integration between mobile computing healthcare systems and pervasive healthcare computing functionality. While mHealth is focused on increasing patients' mobility, medical data rates, health information accessibility and capacity, pervasive healthcare technology concentrates on developing new biomedical sensing models and technologies. In addition to implementing innovative medical computer algorithms, eHealth is concerned with what is the most optimal architecture to accommodate both realms and integrate the best of both worlds to conceive the ultimate benefit.

Over the last 10 years, there has been much research and commercial activity in the eHealth arena. For instance, PhysioDroid is a health and fitness eHealth system (Banos et al., 2014). The system monitors both physiological signals and user behaviour by employing a wearable monitoring sensor, a mobile terminal and a remote storage server. The wearable monitoring sensor registers a user’s vital sign data and transfers it to the mobile unit through a Bluetooth connection. The mobile device runs an app that was implemented specifically for the purpose of the study with two purposes – to gather physiological data sent by the sensor and save it locally and transmit the data to a remote storage server using WiFi or 3G technology. The app also offers a pleasant user interface that makes continuously monitoring vital signs easy and will set off an alarm if necessary. The app will also allow the user to make emergency calls. Interestingly, clinical specialists also can use the app to view their patient's real-time physiological status. Therefore, the app has two user interfaces that provides two different levels of information, one for the patient and one for the physician. Although PhysioDroid is a complete eHealth system, it lacks further intelligence. Likely, the developers will need to incorporate sophisticated data mining and decision support techniques.

No-Touch is a diabetes monitoring eHealth system for children (Årsand et al., 2012) that conveys a child’s blood glucose data to their parent’s mobile phone automatically. A blood glucose measurement is performed, followed by the data being sent through Bluetooth to the child's mobile phone that is programmed to send the reading automatically via short message service (SMS) to the parents' mobile phones. The system helps parents track their childrens' blood glucose levels and act accordingly. eCAALYX (Enhanced Complete Ambient Assisted Living Experiment, 2009-2012) is another eHealth project (the first one addressed earlier in this review was the MOMEDA Project (Tachakra et al., 2003) funded by European Commission (Boulos et al., 2011). The goal of the proposed study was to establish an elderly eHealth system for those suffering from a number of chronic diseases. During the prototype planning, implementation, testing and medical trials of the system, all stakeholders were involved, including but not limited to patients, physicians, guardians and management. The proposed eHealth system consisted of an Android smartphone app, a wearable smart garment with wireless health sensors and a remote server. The health sensors sent the physiological data using Bluetooth technology to the patient's mobile phone, which at this point had several roles. First, it acted as a transmission medium between the wearable health sensors and the remote server via internet technology. The second role was tracking the patient's current geographic location using the mobile GPS. Third, the mobile phone is equipped with an intelligent mechanism that would allow it to detect abnormalities, such as tachycardia, early signs of respiratory infections, etc. Finally, the mobile phone is armed with a simple, intuitive and accessible user interface, readily permitting patients to view their recent physiological data, take new readings from the sensors and connect with their guardian or physician.

2.5 MDDS

As this study in the next chapter surveys new algorithms for online disease diagnostic systems, it is important to take into account Medical Diagnostic Decision Support systems seeing they have been the centre of much research in recent years. It must be noted that the same taxonomy that was used throughout this review is applicable to MDSS systems, as well, which can be classified into two board categories - commercial systems and research-based systems. Most commercial systems are part of pervasive healthcare systems while research-based systems fall under the category of hospital automation systems. Commercial systems have been found to have moderate capabilities and the majority provide the same set of services with only minor differences. Table 2.2 presents a comparison between the most common commercial MDDS systems.

Table 2.2: A comparison between the most frequently used MDDS systems

	Types				Disadvantages				Advantages				
	Typing of symptoms	**Selection of symptom category**	**Answer questions**	**Analyses images**	**Knowledge of medical terms**	**Large number of diagnoses**	**Requires complex details**	**Must have an account**	**Highlights common diseases**	**Features fatal diseases**	**Symptoms suggestions**	**Disease and symptom Description**	**Provides single diagnosis**
(Isabel Healthcare)[1]	x				x	x			x	x	x	x	
(WebMD Symptom Checker)[2]		x			x	x	x				x		
(Healthline Symptom Checker)[3]	x				x	x					x	x	
(Familydoctor)[4]		x			x		x					x	
(Yourdiagnosis)[5]			x	x		x						x	
(Healthline Top Symptoms)[6]	x	x			x			x				x	
(Mayo Clinic: Symptom Checker)[7]		x			x		x						
(Everyday Health)[8]	x	x	x				x						x
Proposed System (Alhemairy et al., 2016)[9]									x	x		x	x

[1](Symptomchecker.isabelhealthcare.com, 2017), [2](WebMD, 2017),[3](Healthline.com, 2017),[4](familydoctor.org, 2017),[5](Yourdiagnosis.com, 2017),[6](AARP, 2017),[7](Mayo Clinic, 2017),[8](Everydayhealth.com, 2017), [9](Alhemairy et al., 2016).

As can be gauged from Table 2.2, there are four main techniques used to infer a diagnosis. Namely, typing the symptoms, selecting symptoms from a given list, answering questions and analysing images provided by the user. The most frequently used technique is "**Symptoms typing**". Its popularity lies in the fact that it serves as an easy method for the diagnostic tool developer to extract the features associated with a specific disease. Unfortunately, there are two disadvantages associated with it - the user could be prone to spelling mistakes and they must know the medical term for the symptoms being suffered. To overcome these drawbacks, most of the systems that employ it provide suggestions for symptoms as the user commences typing, nevertheless, patients still find those types of system hard to use. “**Selecting a category**” for the symptoms is also a well-liked input technique for diagnostic systems. With this method, though the user may not have issues with spelling, they still need to identify the medical term for their symptoms. Additionally, the user may become fatigued before they reach a diagnosis for their condition because every category selection elicits a new subcategory. The two previous methods provide the user with a huge list of possible diagnoses, but the “**Answering questions**” technique mostly provides the user with a single possible diagnosis, albeit with major disadvantages. For one, the user could become frustrated by the lengthy set of questions. The user might also not know the answer for most of the medical questions being asked. Third, this technique takes a huge amount of time compared with those mentioned earlier, and taken together, these shortcomings may discourage the user from using the system on a regular basis. That said, the “**Image analysis**” technique is quite unique – it requires minimal intervention from the user, making it rather ideal. Unfortunately, it only works with a disease that can be diagnosed with a medical image, such as skin disease, cancer, digestive tract and kidney failure. With respect to commercial systems reviewed, one capable of discerning skin disease through user-provided images was found.

Research-based diagnostic systems are more advanced and employ various techniques for input and processing. These systems can be classified based on their scope and the methodology to perform classification, and so they were allocated to three categories: general scope MDDS systems, specialized scope MDDS systems and specific scope MDDS systems. Table 2.3 provides examples of MDDS research-based systems for each category.

Table 2.3: MDDS research-based systems according to category

General scope MDDS	Specialized scope MDDS	Specific scope MDDS
DXplain (Barnett et al., 1987) takes clinical results (signs, symptoms, laboratory records) to yield a ranked list of diagnoses	**MYCIN** (Shortliffe et al., 1975) guides physicians regarding antimicrobial therapy	Diagnosing Kidney Disease (Raja et al.,2008)
DDX (Riches et al., 2016) Diagnosis Checklist Tool aids clinicians in broadening their differential diagnosis and recognizing a disease	**CADIAG-2** (Kumar, 2015) for rheumatic diseases and pancreatic diseases	Detecting Brain Tumours (Benamrane et al., 2005)

The bulk of general scope MDDS systems are pervasive healthcare systems because they allow users to diagnose their medical conditions within the home, school or any location that has an internet connection, which is the opposite of the traditional scenario where only doctors diagnose patients within a hospital's walls. General scope systems like DXplain, QMR (Kaplan, 2001), DiagnosisPro (Aronson, 1997) and DDX (Riches et al., 2016) usually cover a wide range of diseases. For instance, the DDX database consists of 3500 different diagnostic labels and DXplain database includes 2400 diseases. Specialized scope MDDS and specific scope MDDS systems fall under hospital automation healthcare systems. These systems are not meant to be used by the public anywhere (not pervasive), and instead are for use by a specialist within medical institutions. Their main purpose is to improve diagnostic accuracy performed by specialists. Specialized scope MDDS systems usually cover a specific branch of medicine. For instance, MYCIN is one focused on drug recommendation and, more specifically, antimicrobial therapy. CADIAG2 is tailored to rheumatic and pancreatic diseases. Specific scope MDDS systems are typically specialized in a single disease or disorder. For instance, Raja et al. (2008) described a MDDS system for detecting kidney diseases while

Benamrane et al. (2005) referred to one that detected brain tumours with great precision.

Most of the time, inputs to research-based specific scope MDDS are either medical images or numerical values that describe the disease under consideration. Raj et al. (2008) produced a system to diagnose kidney disease (Raja et al., 2008) that takes ultrasound kidney images as the input. The system was implemented using artificial neural networks and fuzzy logic. Their combination made the system reach an accuracy of 92.3%. Another system that took medical images as an input was that of Benamrane et al. (Benamrane et al., 2005). Theirs used MRI images of the human brain to detect brain tumours. They also employed both artificial neural networks and fuzzy logic. The classification accuracy based on some of MRI images reached between 99.4% and 100%. Numerical data to diagnose disease has also proven valuable, such as the work of Andre et al. (as cited in Pe and Sipper, 1999), where a Wisconsin breast cancer database was the basis of assessing the performance of their system. The system employed fuzzy logic and a genetic algorithm to perform the classification. The data set was comprised of nine numerical values that referred to the visual characteristics of the tumour cell, such as clump thickness and uniformity of cell size. The system featured a very superb classification accuracy of 97%. Nazmy et al. (as cited in Ubeyli, 2009) used 6 classes of ECG signals to establish heart disease, creating a system that employed artificial neural networks and fuzzy logic. This hybrid system achieved a classification accuracy of 97%. Most research-based diagnostic systems tend to use artificial intelligence for taxonomy. There are many methodologies used by MDDS, and these have included algorithms, databanks with analytical functions, mathematical models, pattern recognition techniques, decision analytical systems and rule-based systems (expert systems). Yet, modern methods include but are not limited to fuzzy logic, artificial neural networks and genetic algorithm. Table 2.4 lists samples of MDDS research-based systems based on the input data.

Table 2.4: MDDS research-based systems according to input data

Reference	Methodology	Input	Purpose	Accuracy
Raja et al. (2008)	neuro-fuzzy hybrid	ultrasound kidney images	diagnosing kidney disease	92.30%
Benamrane et al. (2005)	neuro-fuzzy hybrid	MRI images of human brain	detecting brain tumours	99.4 % with certain images
Andre et al. (1999)	fuzzy with genetic algorithm	Nine visually assessed characteristics of an FNA sample (integer values)	Diagnosis of breast cancer in Wisconsin (USA)	97%
Nazmy et al. (2009)	neuro-fuzzy	ECG signals	Diagnose heart diseases	97%

Next, it will be focused more on the literature for algorithms in healthcare and medical systems and what the relatively common concepts between the cited references and the proposed algorithm are as well as the differences in mechanism and unique features.

2.6 Further Novelty of Framework for Providing Remote Health Monitoring

A literature review search was performed to establish the most relevant publications and potential patents to a framework for providing remote healthcare-monitoring systems. The results showed that the general concept of remote health monitoring is known, however, nine patent references and three publication references (non-patents) were found to be particularly interesting. It is important to note that these cited literature references are based on the information available to us from the online search and to the best of our knowledge, was the extent of the published scholarly work at the moment of writing this thesis. Section 2.3 outlines the Search and Methods Strategy for determining the novelty of our proposed framework related to a remote health monitoring system employing multiple modules from the publication-literature.

It appears the general concept of a framework for providing remote health monitoring has been dealt with before. However, there are various novel modules from the literature, such as the combination of prompting manual intervention by a medical expert, generating urgent warnings in cases of emergencies and obtaining further medical rules and data from social networks for use in the knowledge database of the system. Therefore, it has formed the basis of a potential patent application. Further details and discussion on the novelty of the proposed framework for remote health monitoring is found in section 5.6.4 in chapter 5, where there is discussion of the comprehensive search results from: A) related publications (non-patents references); and B) published patent publications. Therefore, a patent application at the USA Patent and Trademark Office [USPTO] was successfully filed. The patent holds the number **US 15/395,121** and a filing date of December 30, 2016**.**

2.7 Further Novelty of Algorithms for Medical Systems Based on Vital Signs

A systematic literature review was conducted to establish the most relevant and intriguing publications and patents related to algorithms for medical condition detection from vital signs. Specifically, the search focused on the following subject matter: *"***A diagnostic algorithm utilising monitored biosensor information associated with a user's vital signs, wherein the ranges of the measurements of the vital signs could be**

applied to diagnosing a patient; the diagnosis system could be accessed via a mobile device". The results of the search, analysis of those results and comments on the cited references are set out in the sections hereafter. As mentioned earlier in Section 2.3, the search was concentrated on the relevancy to the proposed system from the publication-literature, where 11 cited references were identified and discussed while there are 15 patent-literature references cited and discussed here. Further details surrounding the novelty of the proposed algorithm for disease detection based on vital signs is located insection 6.6 in chapter 6, where the comprehensive search results were discussed from: 1) the related publications (non-patent references); and 2) the published patent references. It was anticipated that calculating an indicator value with the particular formula developed and searching for that value in a look-up table to diagnose a disease would be novel and consequently, two patent applications were filed recently at the USA Patent and Trademark Office [USPTO]. The patents hold the number **US 62/377,223**, which was filed on August 19, 2016. and patent application no. **US 15/383,341**, filed on December 19, 2016.

2.8 Summary:

This chapter browsed the development of the most known healthcare monitoring systems and compared the common features among the literature references against the proposed framework and algorithm in this study. Further assessment on the novelty of the proposed solutions with the most relevant published articles and patents, showed that the Framework and the Algorithm had novel features and potential in enhancing the remote medical monitoring and the efficiency in diagnosing some diseases.

Chapter 3

Research Methodology

Chapter 3: Research Methodology

3.1 Chapter Overview

This chapter describes the research methodology employed in the current study. There is first an explanation of the philosophy and motivation, followed by a discussion of the context behind researching this topic and the methodological model used to conduct this work. Subsequently, the phases of the research, the outcomes and the original contributions developed are fielded.

3.2 Introduction:

Using the appropriate methodology is quintessential to research as it involves the planning of the study and how it will answer the research questions. It is also considered the driver of accomplishing the study aims and objectives. Therefore, using the correct techniques will simplify finding adequate solutions for the research questions. The choice of the methodology will be influenced by practical considerations and resource availability.

Herein, the methodology was followed as depicted in Figure 3.1, inspired from Kumar's famed research process phases (Kumar, 2010). It was selected because of its intelligibility as it has also been adopted in similar research projects dedicated to developing a framework for intelligent systems and their evaluation. The following phases are the fundamental phases of this research and will be explained further later in this chapter.

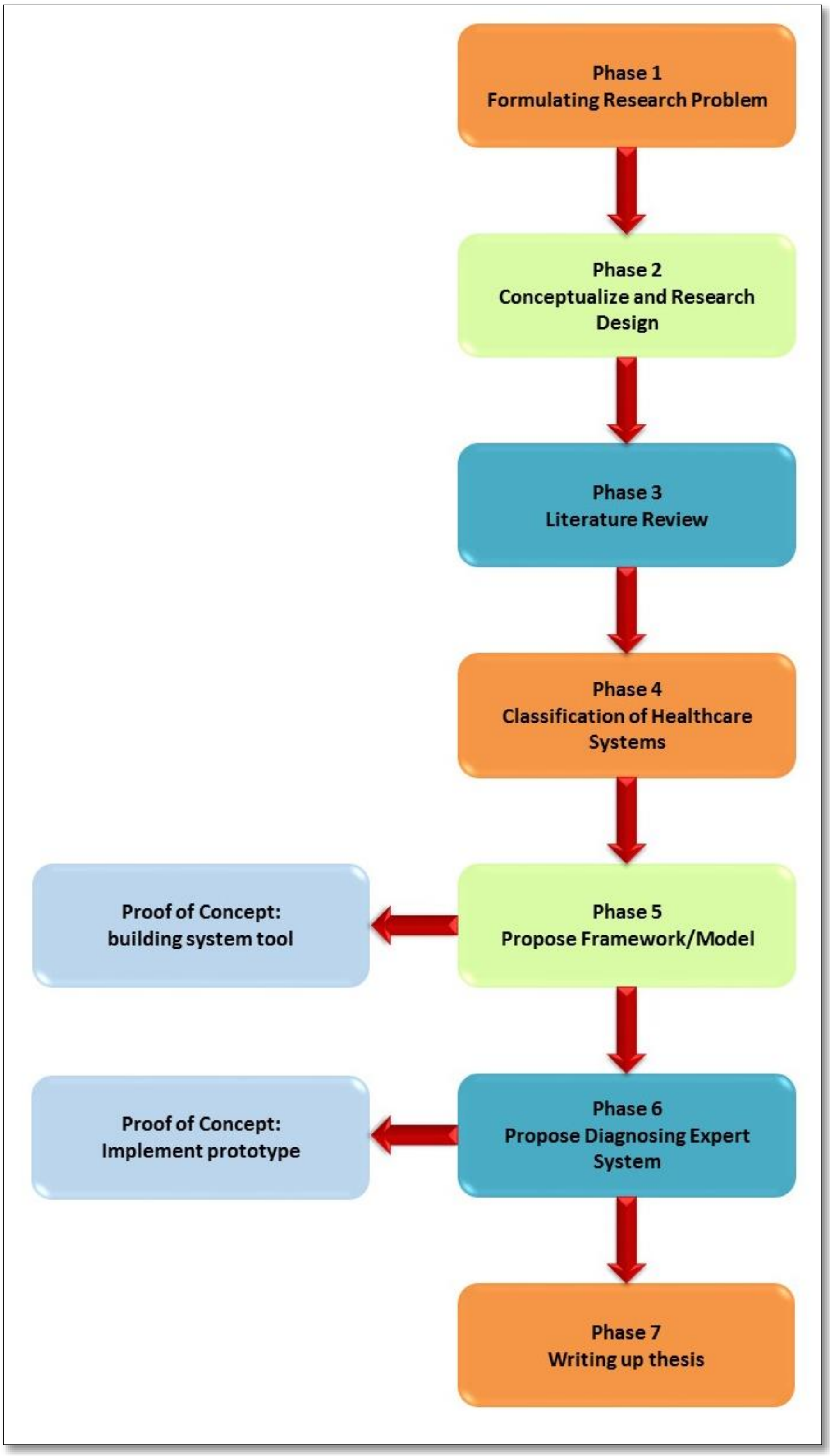


Figure 3.1: Research methodology

3.3 Phase 1: Formulating the Research Problem

3.3.1 Introduction

Elderly people living with their families is a major social phenomenon in the UAE that has arisen. However, the percentage of UAE elderly that live in care centres is very low and does not represent the increasing number of ageing individuals. For example, in Ajman city, the total population is around 300,000, while there were only eight residents of elderly care centres (Ministry of Social Affairs, 2012), six persons in 2013 and a drop to just four in 2014 (Ministry of Social Affairs, 2015). This reflects the strong ties and social bonds in UAE society, where the absolute majority of families embrace the elderly within their homes and take care of them. Additionally, the percentage of elderly residents in hospitals is also small and they are usually those with major disabilities or suffering from critical medical conditions that require sophisticated medical care attention around the clock. The hospitals are usually forced to return nearly 20% of admitted elderly patients to their families against relatives' wishes and approximately 30% are sent back with the family's consent; 25% die because of chronic diseases (Al Ali, 2013).

In line with the conceptual stage of this research, a continuous healthcare-monitoring system for the elderly at home is portrayed in Figure 3.2.

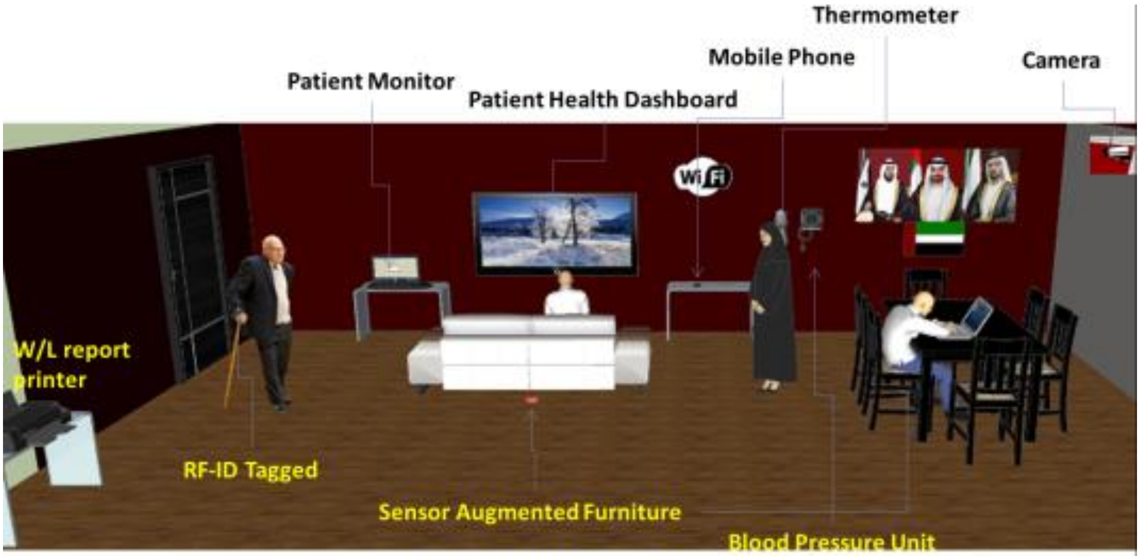


Figure 3.2: Concept of a healthcare-monitoring system for the elderly in homes

3.3.2 Importance of this Study

Traditionally, Emirati families take care of their elderly at home, part of the social fabric driven by religion to take care of parents as they grow older and require further assistance. With this, though the UAE is a country with a relatively young population, studies show that the elderly segment of the UAE is growing at a rate of 10.3% annually, considered to be very high (Al Ali, 2013; UNDP UAE, 2007), with this rise expected to reach more than 11% in 2030, and in 2050, approximately 30 - 35% of the UAE population will be elderly, just as shown in Table 3.1 (Ministry of Social Affairs, 2012). This anticipated increase is based on the massive improvements in healthcare services and lifestyle.

Table 3.1: Elderly increase at UAE from 2005-2050 (Ministry of Social Affairs, 2012)

Years	2005-2006	2012	2017	2030	2050
Percentage of Elderly Population	+8%	+4.0%	+6%	+11%	+ 30 - 35%

3.4 Phase 2: Conceptualization and Research Design

According to the aforementioned statistics, it is clear that there is a great challenge for UAE society in the form of being able to provide continuous healthcare monitoring and medical assistance, in addition to social care, to this growing group of people living within their family's homes, especially in cases where the existing homes are not conducive to the appropriate facilities or equipped with proper infrastructure to monitor healthcare status. Therefore, it is apparent there is a need to address this issue through an innovative healthcare-monitoring framework, one that is capable of utilising ICT and links medical centres and the elderly at homes with the support of expert systems to analyse various situations and provide recommendations and elicit human intervention where required, i.e., calling for an ambulance in the case of emergencies. The framework must also be comprehensive and more efficient than what is available in terms of the prior art. It should also be non-intrusive and independent on human intervention by having the ability to monitor patient vital signs at home without interrupting patient's ADL or compromising their privacy.

3.4.1 National or International scale?

It was also necessary to further investigate the existing healthcare-monitoring solutions to provide a reliable and comprehensive platform to support the elderly at home. It was crucial at this stage to review the opinions of the elderly and their awareness of medical technologies that could be integrated into their homes, clothing or mobile devices and whether they would accept the use of it. An interesting study conducted by Martina in Germany (Ziefle and Rocker, 2010) determined elderly acceptance of healthcare technologies at home accounted for 75% of that population with regards to using integrated healthcare technologies (50% said "Yes" and 25% replied "Probably Yes"), such as wearable technologies.

Similar questions to those posed in Martina's study were asked to a random sample of the elderly in UAE in 2013, where between 60-70% of the respondents consented to integrated healthcare technologies (60% said "Yes" and 20% replied "Probably Yes"). They also believed in the value of using medical devices and technologies to monitor their heath vital signs as opposed to regular clinical visits or receiving medical staff visits at homes. The age range of Martina's study was between 40 to 92 years of age, while in the UAE study, this range was between 60 and 70. The broad age range in the first study explains why UAE had a slightly higher acceptance rate than Germany. Figures 3.3 and 3.4 portray the differences between both studies.

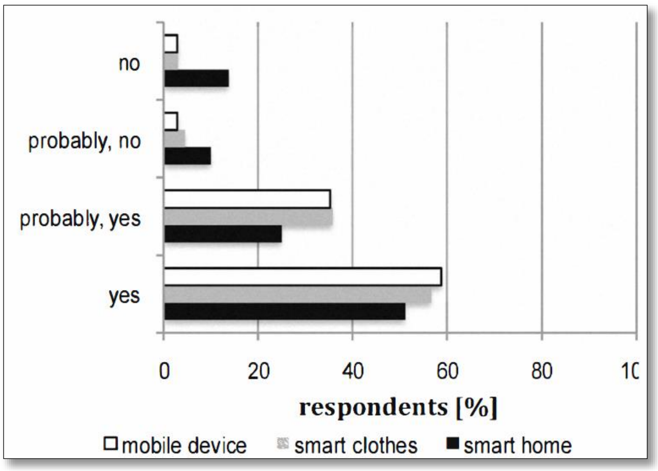


Figure 3.3: General willingness for embedded health technologies (Germany)

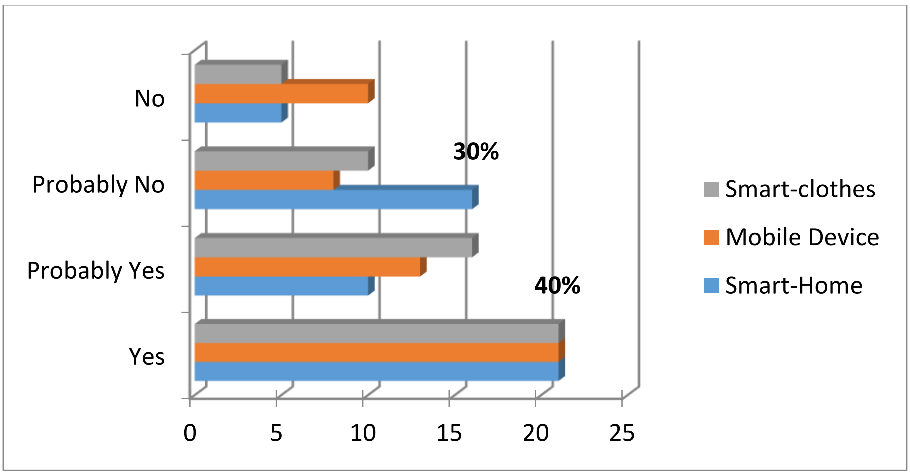


Figure 3.4: General willingness for embedded health technologies (UAE)

In considering these issues at the international level, the statistics uncovered a similar trend for the elderly in UAE. For instance, the World Population Ageing Report (2015) showed that in 2030, there would be an increase of up to 11% in the elderly population; it also anticipates that in 2099, more than 30% of the world's residents will be 60+ years old.

Taking this all together, it was decided to generalize the target of the study and the healthcare-monitoring framework, and not concentrate on a specific context or jurisdiction. Minor differences, such as cultural and privacy concerns, may be studied separately and can be tackled while implementing the framework in the real-life environment such as video monitoring at home.

3.5 Phase 3: Literature Review

In this phase, an intensive literature review was performed in three major areas:

A) Common features of healthcare solutions;
B) Frameworks for healthcare-monitoring systems; and
C) Diagnosing methodologies for the expert system.

The literature review was valuable for establishing the state of the art and highlighting the merits as well as drawbacks of the existing solutions, and accordingly identifying where it can be contributed in order to enhance the healthcare for elderly at homes.

The systematic literature review was carried out by searching for the most relevant papers on eHealth systems and technologies with search engines like Google, Google Scholar, Science-Direct, Elsevier, IEEE explore, and Google Patents.

3.6 Phase 4: Classification of Healthcare Systems

During this phase, more than 30 well-known healthcare solutions in the field of pervasive healthcare were classified and the common features were compared. It was observed that the existing healthcare-monitoring solutions fell into two major categories - research prototypes and commercial products. A comparison criteria was developed to differentiate between the existing systems and prototypes. The most important features incorporated within these systems were non-intrusiveness, security enabled, mobility aware, support integration and context-aware. The comparison list is featured in Table 4.1 in Chapter 4.

3.7 Phase 5: Proposing a Comprehensive Healthcare-Monitoring Framework

After the literature review, the key components of the healthcare-monitoring system were identified (see Figure 3.5). These components were collecting the daily activities by a set of sensors and storing the data in a database. Afterwards, the data was processed using various intelligent techniques and analysed before taking appropriate action, such as determining patient ADL to evaluate their well-being on the basis of their normal routines or detecting of abnormalities and warning the patients and/or physicians of potential emergencies.

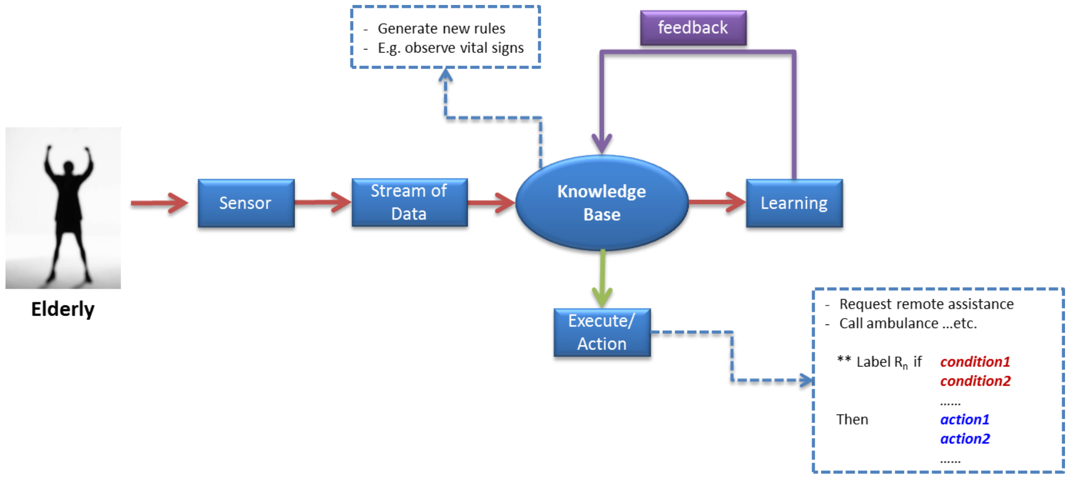


Figure 3.5: Key components of healthcare-monitoring framework

In the proposed framework, the **modular architecture was chosen** with clear and defined interfaces between different modules and standard communication protocols, enabling scalability, interoperability and smooth integration, rendering it a very comprehensive solution. The framework was enhanced by adding innovative modules that consisted of a combination of interventions by a medical expert and generating urgent warnings in cases of emergencies. Additionally, there was the prompting to use different **filtering techniques**, including **low-pass filters**, **high-pass filters** and **noise removal** to eliminate noise, errors or invalid values, which is an advantage over the other healthcare remote-monitoring systems. Moreover, the integration of the **Social Network Analytics** Module to acquire health data from social networks enriched the knowledge base of the expert system and the overall framework based on the very large amount of medical information available on social networks (i.e., Twitter, Facebook) nowadays. The comprehensive and scalable framework that is proposed in this study can be found in Figure 5.1 in Chapter 5.

However, **continuous monitoring** generates huge amount of data (big data) that needs to be handled, stored and analysed. Hence, it is crucial to extract useful information in the appropriate medical format within a very short timeframe so that the medical staff and patients can respond accordingly with help of powerful expert systems in diagnosing medical conditions. As such, the framework was supported by an innovative expert system that correlated the vital sign values with the predefined medical symptoms to provide patients with an accurate diagnosis of their health issues continuously on an around the clock basis and independently from a physician's intervention or personal attendance to the case.

3.7.1 Framework: Proof-of-Concept

In order to prove the applicability of the proposed framework, a mobile application as well as web application prototypes were developed so that its components would be experimented with. Implemented were the key constituents in the monitoring framework, including data acquisition, data processing, data analysis and data visualization. Table 5.2 in Chapter 5 offers a brief description of the technologies and devices used in the prototype implementation. For example, the data acquisition collected the data from the sensors via Bluetooth, sent them to the mobile applications via Wi-Fi and then stored it in a database. The diagnostic engine tested the vital sign values against the predefined medical rules and conditions and generated recommendations or triggered other actions, such as the Emergency/Intervention Module. Finally, the Data Visualization Module displayed charts, medical advice and warnings to the system users i.e., the patient, physician and system administrator on their mobile device. Further descriptions and how each module works are found in Section 5.4.2.

3.8 Phase 6: Proposing of the Diagnostic Expert System

Apparently, the standard procedure for continuous healthcare monitoring for patients is to attend and remain in a room at the hospital, lie on a bed, wear set of sensors and connect to many devices, of course waiting until the recording is complete and the physicians interpret the vital signs report, enquiring about symptoms and finally provide their assessment. This paradigm has been changed with the development of the pervasive healthcare, wireless sensors and internet connectivity, where medical monitoring devices are now able to follow patients remotely. The patient's vital signs are captured anytime and anywhere and sent through mobile networks (3G, WiFi) to a medical gateway. Subsequently, the hospital physician will be able to monitor the patient and analyse their health condition for any potential issues.

3.8.1 Expert System: Proof-of-Concept

In order to demonstrate the applicability of the **new proposed algorithm for health diagnostics** in real-life situations, the main functions and components were developed and various experiments were performed. Thereafter, several measurements were taken to evaluate the system's performance and accuracy of the newly proposed algorithm.

To validate the eHealth architecture and disease-detection algorithm, a test bench was developed that consisted of three elements as presented in Figure 3.6 - the wearable sensor simulator, the medical gateway and the eHealth remote server. The simulator facilitated the simulation of various medical sensor (i.e. BP, HR) output and was installed on a tablet. In the actual system, the simulator will be replaced by a set of wearable medical sensors mounted on the patient. Digital values of the vital signs are sent from the simulator to the medical gateway using Bluetooth wireless network technology. The medical gateway (an Android application running on a tablet) collects vital signs and displays them in real-time; simultaneously, these values are transferred to the eHealth server for further analysis and disease detection. The eHealth server screens vital sign values using the proposed algorithm for disease detection (explained in Chapters 6 and 7). Once a disease has been detected, the server sends a notification to the patient (displayed in real-time on the tablet) and an email alert will be sent to the doctor.

In the system setup, the sensors were simulated capturing the vital signs directly from the body in real-time and sent to a gateway, which is comprised of software running on an Android-based tablet. The gateway is connected with the sensor simulator using a Bluetooth protocol. The **eHealth** Server is hosted and accessed via the Cloud and involves the eHealth expert system connected with the **gateway** through the internet using a WiFi network. Another server hosts the database and the captured vital signs for disease detection. Figure 3.6 outlines how various components of the system are connected and communicate.

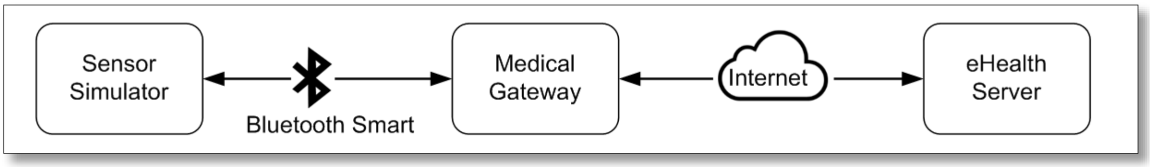


Figure 3.6: Overview of system connectivity

3.9 Phase 9: Writing up thesis

This was the last phase in the study, where all pieces of the study were gathered and sorted out in the research methodology described earlier. The thesis was divided into eight chapters reflecting the main phases of the study. It focused also on the three major contributions of knowledge to the field of remote healthcare, and have been published in peer-review conferences, chapter in a book, filing two US patents and two articles currently under review in reputed journals.

3.10 Summary:

Apparently, the number of elderly population is growing worldwide in general and in UAE in specific due to the advancement of healthcare services, and therefore there will be a need to develop more reliable supporting systems. This chapter highlighted the main concept of the study, the research methodology used as well as the flow between various chapters.

Chapter 4

Classification of Pervasive Healthcare Systems

Chapter 4: Classification of Pervasive Healthcare Systems

4.1 Chapter Overview

This chapter surveys the existing pervasive healthcare systems and classifies them as academia-based or industrial-based. It then develops a set of criteria to compare these solutions, while also discussing certain drawbacks of existing solutions and proposing future directions in pervasive healthcare. This paves the way to putting forth a novel healthcare monitoring framework in the next chapter.

4.2 Introduction

As a consequence of the current developments in ubiquitous computing, healthcare service availability and quality have noticeably increased (Satyanarayanan, 2001; Varshney, 2009). Pervasive healthcare is conceived to provide healthcare to anyone, at anytime and anywhere (Varshney, 2007). The integration of mobile technology and broadband communications and the proliferation of innovative medical devices have advanced the pervasive healthcare by providing healthcare services beyond the restrictions of place, time and quality. Pervasive healthcare has not grown out of the evolution of technology alone, but also from patient awareness and acceptance in embracing it (Katz and Rice, 2009; Saha and Mukherjee, 2003; Riva, 2005).

Recently, many pervasive healthcare electronic devices have been assessed experimentally in hospitals as well as in patients' homes. Examples of these include sensors and video cameras, which use Wi-Fi, Bluetooth, infra-red or cellular GSM/3G networks to gain access to the internet and demonstrate their remote potential. Increasing instances of these devices have been seen installed in healthcare facilities

(Varshney, 2007) as well as in patients' residences. Research on pervasive healthcare technology (PHT) started in early 2000 with the intent of improving patient self-sufficiency, independence and healthcare mobility through continuous monitoring (Varshney, 2007), making use of evolving ubiquitous computing technologies and sophisticated communication systems.

4.3 Background on Pervasive Healthcare Monitoring

Traditional non-invasive PHT often requires patient physical engagement in embracing medical devices at a certain time and place. However, recent developments in pervasive monitoring systems have focused on automated and unobstructive PHT that is not restricted by such factors. This is an extension of the previous definition of pervasive healthcare from Varshney (2007) as PHT is not only presented to anyone at anytime and anywhere, but also autonomously and unobtrusively. An earlier PHT investigation used video telephony (Thuemmler et al., 2009) to stream live and interactive video communications through plain old telephone service (POTS) for its wide availability and relatively low cost (Lankton and Wilson, 2007). Using video telephony, healthcare professionals can review therapies and provide support in real-time. More importantly, this approach minimizes limitations by permitting care providers to monitor a patients emotional and mental status, not only physiological information and vital signs (Olguin, 2009).

Other types of PHTs are enabled by portable sensors, which integrate wireless technology and clinical devices. Examples of these devices include tele-devices, such as tele-ECG and ring sensors that are generally carried by patients in order to benefit from

PHT services. Data from ECG, pulse rate, respiration rate and oxygen saturation levels are collected and forwarded to healthcare providers automatically (Tu, Zhou and Piramuthu, 2009; Varshney, 2007). This continuously monitored data can supply important clinical insights for timely and accurate diagnosis regularly and enable end-to-end monitoring between the patient at any location with his medical caregiver or physician. Figure 4.1 (Varshney, 2007) portrays an example of a healthcare monitoring framework. Advanced pervasive devices that automatically collect multiple clinical indicators have already been successfully deployed in body sensor network systems (Nachman et al., 2010).

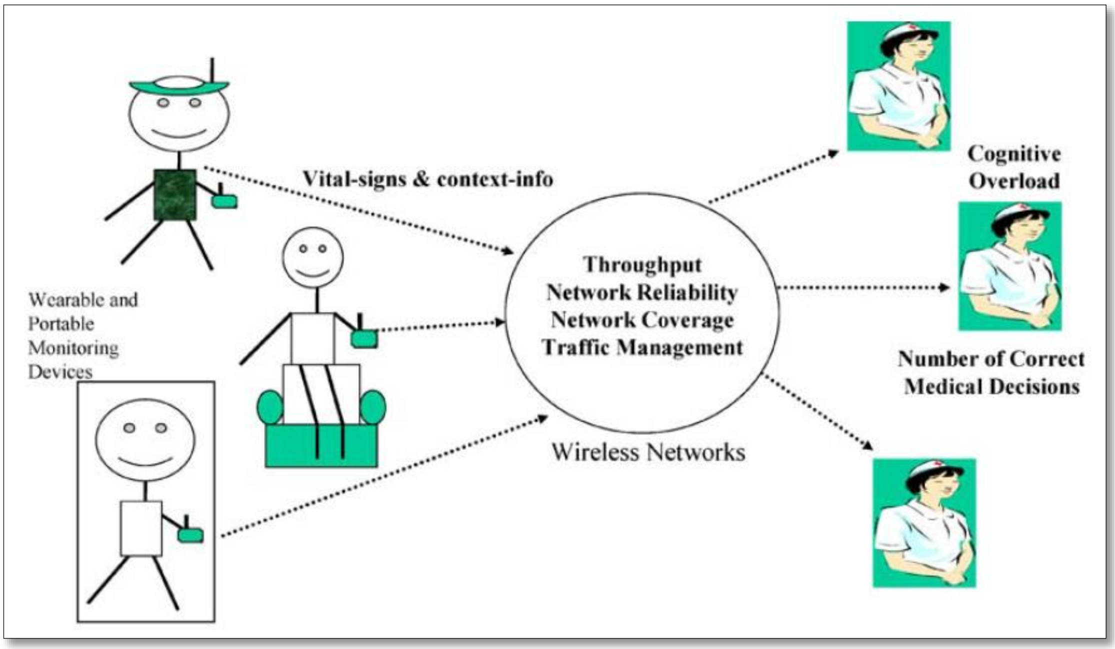


Figure 4.1: Health monitoring system (Varshney, 2007)

A PHT system equipped with multiple sensors is able to collect, process and wirelessly transmit the received data via a secured link to a computer for further analysis. PHT devices that do not require patients to wear tele-devices have also been created. For example, mattresses, toilets, kitchen appliances and clothing embedded with monitors to sense sleep patterns, body weight, body temperature and pulse rate have been evaluated (Bardram, 2005; Coronato and Pietro, 2010). Further experiments have concentrated on advanced tele-sensing systems to gather scattered vital signs from the body (Ziefle and Rocker, 2010).

These systems can gather multiple clinical parameters and are able to operate autonomously without disturbing the normal lives of patients. PHT is built upon a widely deployed wireless network and advanced computing technologies, and such solutions have primarily involved disease risk management (Anderson and Wittwer, 2004). However, growing market incentives in a wide range of healthcare fields are propelling the continued development and consumption of PHT. Besides, this practice has had profound influences on specialized healthcare catering to the elderly, disabled, underserved and critically ill population of patients (Washburn and Hornberger, 2008).

Healthcare benefits from the recent technological revolution are enormous. A group of researchers at *Partners Healthcare in Boston* has conducted several studies looking at using technology to conduct "*virtual visits*" between patients and primary care providers. In two separate studies, they showed that both patients and primary care providers felt that a virtual visit was indeed a useful alternative to the traditional in-person visit (Lankton and Wilson, 2007).

There is growing evidence that the benefits of pervasive healthcare are worth considering. One obvious advantage is that pervasive healthcare can often replace a physical visit, which is a tremendous convenience for the patient (Pai and Huang, 2011).

Of interest is that a survey involving 2,000 physicians showed that 7% of physicians reported they use online conferencing systems to communicate with patients (Munnelly and Clarke, 2007). With this, among PHT developments, tele-monitoring is the fastest growing category that is highly suited to particularly ageing patients for home-based monitoring. In 2004, various studies found that the total healthcare technology market was worth roughly $380 million USD (*Office of Technology Policy an Overview of e-Waste Policy Issues*, 2006). In 2007, it was predicted that the tele-home care market alone would grow three times into the billions by 2010 (Blobel, 2007), and this prediction has been actually validated (Pai and Huang, 2011). For instance, aaccording to a latest healthcare market study in UK; the care-home market for elderly in UK alone worth £14.3 billion in 2015. This figure consists about 32% of the total healthcare market which reached £45.3 billion on the same year (Laing and Buisson, 2016). On the global scale; the world pervasive healthcare demand is expected to cost USD 391.41 billion by 2021, growing by 10% between 2016 and 2021 (according to a recent report published on September last year). The home healthcare market cost covers the following: diagnostics and monitoring devices, healthcare devices, mobility assist tools and other medical services (Zion Market Research, 2016).

Here, two common types of PHT solutions were opted for: (1) non-commercial academic solutions (prototypes); and (2) industrial applications (commercial solutions). A comparison of these was been carried out for specific features, i.e., being security enabled and mobile aware and featuring integration support (Kenny, 2006). Another study (Orwat et al., 2008) reviewed healthcare systems with characteristics like use of mobile devices, wearable items, implanted devices and stationary devices as well as context awareness. However, in this study, an alternative set of criteria were proposed to differentiate significantly between pervasive healthcare solutions that were introduced recently (see Section 4.5).

4.4 Classification of Pervasive Healthcare Systems

Pervasive healthcare solutions differ with respect to their ability to demonstrate and apply their services as well as their support of integration with other heterogeneous systems. Further, they may also vary in the degree to which these solutions can provide highly scalable solutions.

4.4.1 Research-Based Solutions

In the current era of technology, pervasive healthcare applications make it possible to provide effective and efficient medical homecare to patients that need it. However, these applications face several challenges and issues, such as patient mobility, network connectivity and the limited resources of mobile devices and sensors to collect and transmit sensory data. Hence, several non-commercial and prototype models may prove valuable in addressing these challenges. A variety of wireless and networking technologies have already been implemented in healthcare to ensure the integrity of medical applications. Embedded devices, like bio-shirts, are considered appropriate and efficient answers for incorporating innovative technologies and facilitating healthcare delivery. They permit healthcare specialists to acquire real-time information from constantly analysed and monitored health status data. Furthermore, non-commercial applications may also allow users to seek alternative diagnosis by communicating the information regarding their healthcare conditions with a number of specialists (Magedanz et al., 2005).

4.4.2 Industrial/Commercial-Based Applications

There has been a far-reaching set of pervasive healthcare solutions from the industry sector. "Recent commercial innovations in wireless transmission and biosensor technology have advanced the concept of potential convergences between healthcare and telecommunications" (Varshney, 2009). According to recent research and literature surveys, an extremely large number of healthcare organizations and hospitals are trying to adopt and implement commercial and industrial applications of PHTs in order to enhance confidentiality and integrity of their procedures. Various industrial or commercial applications put in place by healthcare organizations may include developments such as wireless "Polymap" systems, biometric wristwatches, connected "Shimmers", wireless ECG systems, mobile cardiac outpatient telemetry (MCOT) and "2Net" platforms for wireless health devices. These all may significantly help physicians in monitoring the daily activities and health conditions of patients and depend on the utilisation and appropriate utility of pre-programmed sensors (Varshney, 2009).

4.5 Comparison Criteria

Table 4.1 lists two types of pervasive healthcare solutions addressing the main challenges of pervasive healthcare. These could include non-commercial solutions (prototypes) and industrial applications (commercial products). To grasp the efficiency of these applications, the important features are included, though these may or not be supported by the investigated applications, and specifically: non-intrusiveness, security enabled, mobility aware, support integration and context aware. A portion of these are tackled in Varshney (2009).

4.5.1 Non-Intrusive Pervasive Healthcare

Non-intrusive healthcare solutions are characterized by their ability to be utilised without disturbing the normal life and activities of a patient under observation. They may include sensors for monitoring vital signs, mobile devices to collect sensory data and the communication protocols to transmit such data. They also might involve a sort of physical disturbance of a patient's body, such as medical examination where the areas of the body are not sensibly probed and the skin is not damaged. Physicians use non-intrusive devices to diagnose illnesses from their initial stages (Magedanz et al., 2005) to avoid further severe consequences.

4.5.2 Security-Enabled Devices in Pervasive Healthcare

In the field of medicine and healthcare, it is necessary for healthcare organizations to ensure the confidentiality and integrity of patient information. Thus, security-enabled devices are paramount in negating disclosure or misuse of that information. Regarding PHTs, security-enabled devices may greatly aid healthcare organizations in protecting sensitive private information, reducing risks and vulnerabilities regarding confidential information while ensuring the availability and integrity of that information (Varshney, 2009; Magedanz et al., 2005).

4.5.3 Mobility-Aware Devices in Pervasive Healthcare

Mobile-aware devices have a major role in guaranteeing effective and smooth healthcare operations, permitting healthcare organizations to stay updated in terms of the medical conditions of patients as well as their health-related activities anywhere and anytime in local and even global contexts (Varshney, 2009; Bardram, 2005). This is possible thanks to mobile devices that are connected to back-end systems via wireless, 3G or 4G networks.

4.5.4 Integration Support Across Heterogeneous Pervasive Healthcare Systems

In heterogeneous pervasive healthcare systems, integration support is a significant feature for fostering communication and interoperation of PHTs to facilitate collaboration between healthcare professionals. This communication interoperability and professional collaboration may greatly assist patients in receiving superior diagnosis and quality treatments (Magedanz et al., 2005). Standard protocols will eventually permit full integration of heterogeneous healthcare systems so they offer a complete set of services independent of the underlying infrastructure and architecture.

4.5.5 Context-Aware Devices in Pervasive Healthcare

As mentioned before, context-aware devices may play a vital role in making certain the integrity and confidentiality of patient information (Bottazzi, Corradi and Montanari, 2006). Context awareness refers to “any information that can be used to characterize the situation of an entity” (Dey, 2001).

Healthcare organizations manage and collect contextual data, both unstructured and structured from a variety of different sources. Context awareness also refers to indicators of location and other situational patterns of mobile users and may encompass hints to medical practitioners about prevailing trends. Context-aware PHTs in hospitals can also incorporate the data of patients and medical staff, such as staff duty time, into the clinical workflow to quickly locate appropriate staff and equipment to increase patient satisfaction (Cisco, 2017). These types of PHTs may aid healthcare organizations in collectively archiving, delivering, managing and creating the data required for operational requirements of healthcare centres (Varshney, 2009; Magedanz et al., 2005; Benharref and Serhani, 2014).

4.6 Discussion and Analytics

Based on the comparative study from Table 4.1 that contrasts existing pervasive healthcare solutions from academia and industry, it has been noticed there are the following relationships and patterns that exist between commercial and non-commercial pervasive solutions:

- Most of the compared solutions (either non-commercial or commercial) were designed to be non-intrusive, i.e., among more than 30 solutions that were studied, only three systems failed to characterize non-intrusiveness, one being from academia (*Numera*) and two other solutions from the industry sector. This shows that the non-disturbance and convenience of a patient daily activity are basic rules for attempting to introduce PHT solutions.
- Mobile awareness is strongly integrated for both types of solutions. More than 90% of non-commercial and about 80% of commercial models support mobility. The few exceptions, for instance, wireless ECG or "*ShimmerConnect*", are relatively more processing power-aware than the other solutions and require continuous data transmission to a base station.

In general, the large-scale adoption of mobile-awareness features in most PHT solutions reflects the support of telecommunication technologies, such as mobile devices, Wi-Fi and 3G/4G networks to put forward novel healthcare monitoring services to patients anywhere and anytime.

- More than 70% of non-commercial prototypes are not context aware, though more than 60% of the investigated commercial solutions are. This is demonstrative of the fact that academic research concentrates on more challenging aspects, such as non-intrusiveness and mobility, rather than context awareness and security. This trend may be attributed to these solutions having been developed for demonstration, proof-of-concept or testing purposes to serve research ends. Hence, they have not been widely introduced for general community use. Meanwhile, commercial products face market competition forces and launch as fully loaded devices with qualities that are crucial to users, such as integration with other appliances and high security.
- The security-enabled feature is present in approximately 50% of both commercial and non-commercial solutions. This illustrates that the importance of preserving patients' data privacy and that security is less insignificant to PHT developers. However, this is a weakness that will hinder future absorption of PHTs and has to be addressed in any future solutions.
- More than 70% of commercial prototypes support integration while less than 50% of non-commercial products have integration capabilities. As discussed earlier, academic research varies from commercial products, focusing on

different key features, such as non-intrusiveness and mobility. However, integration is also a discriminating factor that characterizes a complete healthcare solution with a larger range of services from different systems.

- Few solutions have been demonstrated robust by implementing all five key features. Examples include DiaSend and CareMatix from the non-commercial group, while 2Net/QualComm, Equivital, MedStar, MedApps and Mindray are equipped with all five features.
- An interesting point to consider in the listed pervasive solutions; is that none had not even one or two of the five features examined in this study. This shows that the selected features in this comparison were critical features for any successful pervasive healthcare system.

The aforementioned features can enhance the efficiency of PHT solutions. However, there is an innovative trend to integrate advanced smart data-intensive processing and elaborate analytics to sustain next-generation of PHT solutions (Benharref, Serhani and Nujum, 2014).

Table 4.1: Classification of pervasive healthcare solutions (Alhemairy et al., 2013)

Technology Type	**Name**	**Manufacturer**	**Classification Criteria**				
			Non-Intrusive	**Security Enabled**	**Mobile Aware**	**Support Integration**	**Context-Aware**
Prototype-Based Solutions (Non-	LiveNet	-	Yes	No	Yes	No	Yes
	AUBADE	-	Yes	No	Yes	Yes	No
	Bio-Shirt	-	Yes	No	Yes	No	No
	CP-1THW Wireless Software for Health Monitoring System	A&D	Yes	No	No	Yes	No
	DiaSend	-	Yes	Yes	Yes	Yes	Yes
	Numera	-	No	No	Yes	No	No

	Carematix Wellness System (CWS)	CareMatrix	Yes	No	Yes	Yes	Yes
	Health Buddy System	Bosch HealthCare	Yes	Yes	Yes	Yes	No
	e-bra/ e-vest	-	Yes	Yes	Yes	No	No
	MagIC	-	Yes	Yes	Yes	No	No
	LifeShirt™	-	Yes	No	Yes	No	No
	BioHarness™ BT	Zephyr Technology Corporation	Yes	Yes	Yes	No	No
	MyGlucoHealth	Entra Health Systems	Yes	No	Yes	Yes	Yes
	Biosign	Biosign Technologies Inc.	Yes	Yes	Yes	No	No
Existing Industrial/Commercial Applications	2Net Platform	QualComm	Yes	Yes	Yes	Yes	Yes
	MCOT (Mobile CardiacOutpatient Telemetry)	CardioNet	Yes	No	Yes	Yes	Yes
	Wireless ECG System	LifeSync	Yes	No	No	Yes	No
	ShimmerConnect	Shimmer	Yes	Yes	No	No	No
	Biometric wristwatch	Hitachi	Yes	Yes	Yes	No	Yes
	Equivital™ personal devices	Equivital	Yes	Yes	Yes	Yes	Yes
	Polymap Wireless "Polytel System	A&D	Yes	Yes	Yes	No	No
	MedStar	CyberNetMedical	Yes	Yes	Yes	Yes	Yes
	HomMed Genesis™ DM Remote Patient Care Monitor	HoneyWell	Yes	No	No	Yes	Yes
	Viterion 100 TeleHealth Monitor	Viterion	No	Yes	Yes	No	Yes
	VitelNet (Mobile Health Monitoring)	VitelNet	No	No	Yes	Yes	Yes
	Medapps (Web & Cloud based solutions & Products)	Medapps	Yes	Yes	Yes	Yes	Yes
	Mindray (Patient Monitoring System)	Mindray	Yes	Yes	Yes	Yes	Yes
	Mercury Parkinson's disease Epilepsy	-	Yes	No	Yes	Yes	Yes
	CodeBlue: Wireless Sensors for Medical Care	-	Yes	No	Yes	Yes	No
	Aubade	-	Yes	No	Yes	Yes	No
	Pelex-04	Pinmed	Yes	Yes	Yes	No	No
	Sensium™ Life Platform TZ2050	Toumaz	Yes	Yes	Yes	Yes	No

4.7 Key Properties of Comprehensive Pervasive Healthcare Solution

In this section, the current properties of pervasive healthcare solutions that were identified and analysed in the previous section are expanded upon, with novel properties that could characterize next-generation PHT solutions and eventually add value. These properties are mainly related to smart behaviour and data-intensive management.

4.7.1 Smart Behaviour

Smart healthcare solutions refer to end-to-end architecture that intelligently implements unique features, like self-adaptation of services in different contexts and reacting proactively to critical situations. They behave autonomously to respond to different conditions and requirements. The following are some traits of these prospective PHT solutions:

- *Self-adaptive*: healthcare systems should adapt to different patient environments, disease types and network conditions.
- *Proactive behaviour*: the system should take the necessary actions to avoid any severe or resource-shortage conditions. Such actions might include: (1) sending only urgent information when the mobile network is loaded; and (2) switching to standby mode when a patient is in an ideal condition.
- *Autonomous behaviour*: the system should implement a set of intelligent processes that will be triggered to respond to a number of situations, analyse contextual parameters, execute a set of prescribed actions and collect new contextual information for utility future similar situations.

4.7.2 Data-Intensive Management in Pervasive Healthcare

Pervasive healthcare generates an enormous amount of data resulting from executing various types of operations, including monitoring and gathering health-related data. Health data processing, analytics and interpretation reveal patterns and trends crucial for health professionals. These processes necessitate high performance data centres, powerful servers and advanced data analytics tools. Therefore, a pervasive healthcare solution could use the evolving Cloud infrastructure, platform and services to guarantee high performance, scalable and reliable healthcare services. Advanced processing and analytics tools could be applied to intensive health data processing; for example; *NoSQL* and *Hadoop* platforms introduced by Prof. Edlich (Edlich, 2017) and Borthakur (Hadoop.apache.org, 2017) respectively.

4.7.3 Social Network Integration

In general, pervasive healthcare has greatly improved, with continuous monitoring becoming a fundamental component of future healthcare systems. This chapter has summarized and contrasted a number of leading pervasive healthcare technologies and surveyed their capabilities and shortcomings. It also identified a set of criteria used to undertake the comparative study. Most of these products were released in the first decade of this century and, therefore, the research is restricted to that time period. Many of these investigated solutions are already operational on mobile platforms. They appear easier to use and can be readily integrated into the user's lifestyle, making personal care and maintenance significantly easier than ever before (Schaechinger et al., 2003).

4.8 Summary:

Surveying the common features in the famous existing pervasive healthcare systems shoed some interesting figures, for instance; mobility aware is available in the majority of commercial and non-commercial systems. A similar figure was indicated for security-enabled feature, this shows that the importance of the mobility and the patient privacy for any successful healthcare system.

This chapter also highlighted the future trend in Pervasive Healthcare such as; self-adaptive, proactive – and autonomous behaviours. main concept of the study, the research methodology used as well as the flow between various chapters.

Chapter 5

Integrated and Scalable Framework for Remote (Health) Monitoring:

Chapter 5: Integrated and Scalable Framework for Remote (Health) Monitoring

5.1 Chapter Overview

This chapter proposes an integrated and scalable framework for remote health monitoring. The framework has an integrated and scalable architecture consisting of multiple modules. A number of those modules are novel and were integrated within a healthcare-monitoring framework for the first time. Each module performs a specific set of functions, which provides flexibility and enables interoperability between myriads of healthcare-monitoring devices. The proposed framework relies on the analytics of both evidenced data collected from sensors as well as the massive amount of data collected from social networks. A prototype of the framework was developed to evaluate the applicability and efficiency of monitoring and analytics practices.

5.2 Introduction

Worldwide demographic trends clearly point to the world population ageing based on a combination of dropping mortality rates and increased life expectancy. The global community is seeking solutions to address the pressing societal challenge of providing effective and efficient healthcare to the elderly. It is difficult to achieve satisfactory results merely by relying on scaling up conventional healthcare infrastructures - these techniques will not be sufficient to independently assist the elderly to live alone in their home if they are suffering from chronic diseases, thus require continuous health monitoring. It is imperative to exploit the developments in emergent technologies, such as bio-sensors, mobiles and networks, to provide remote health monitoring services along with the physical infrastructural facilities. Continuous monitoring of patients suffering from chronic diseases is always considered as proficient and cost-effective, hypothesised to minimize the liability on the elderly and their families as well as on government budgets. While considerable research and development is being undertaken in this field, most of the current state of the art reflects a lack of a concerted and cohesive approach to develop an integrated remote health-monitoring system.

Population ageing is being experienced in nearly all countries. As posited earlier, the two main contributors are enhanced life expectancy and declining fertility. According to a report published by the United Nations, the global share of older people (aged 60 years or over) increased from 9.2% in 1990 to 11.7% in 2013 and will continue to grow upwards reaching 21.1% of the world population by 2050. The number of older persons (aged 60 years or over) is expected to more than double, from 841 million people in 2013 to more than 2 billion in 2050 (Rafalimanana and Lai, 2013).

In most of developed countries, the population is older, results in low old-age support ratios, that is to say the number of working-age adults per older person in the population. In this respect, developing countries will also be heading in that direction within the next few decades (Rafalimanana and Lai, 2013). While at present, the old-age support ratio is favourable in developing countries, the absolute numbers are not. At present, over two-thirds of the world's older persons live in developing countries. The growth rate of the older population in less developed regions is rising more quickly than in developed regions and will continue to outpace them; hence, it is believed that by 2050, nearly 8 in 10 of the world's older population will live in less developed regions (World Population Ageing Report, 2013).

Modernity and rapid social change has affected society's social structure. Nowadays, the atomic family in UAE, for example, has become the dominant family structure and women are joining the workforce in ever-larger numbers. Such social change has, in many cases, weakened the bonds that used to be the hallmark of UAE's society. Caring for an ageing family member can be a very stressful responsibility and sometimes, entails a hefty financial burden, as well.

It is well understood that the prevalence of non-communicable diseases and disabilities increases as the population ages. Undoubtedly, an ageing population leads to an elevated burden on healthcare infrastructure, rendering effective and timely healthcare a pressing challenge the world over. Taken together, this all clearly underscores the need for a multi-faceted strategy to innovate within healthcare management. This will make it possible for healthcare services to be delivered in an effective and efficient manner in addressing the challenge of an ageing world population (World Population Ageing Report, 2013).

5.3 Related Work

Remote health-monitoring technologies are fundamentally implemented using sophisticated systems equipped with multiple sensors that are able to acquire, process and transmit medical data through a secured communication channel to a central processing unit for analysis and diagnosis.

The elementary architecture of smart health-monitoring systems consist of a user interface, clinical devices, a transmission medium and supporting software and hardware. The ideal healthcare technology user interface is achieved through a healthcare technology workstation (Coronato and Pietro, 2010), which may be a simple personal computer (PC), a PDA or a mobile device. The user can interface, for instance, through a telephone pad, mouse, touch screen, remote control, joystick or voice recognition system (Cattamanchi et al., 2011). Clinical devices are connected to the healthcare technology workstation for local healthcare providers to capture patient vital signs or other clinical data, like images and sounds.

It has been suggested that such systems may not require patients to expressly engage with any medical devices. The abstraction is accomplished through embedding sensors, such as those in mattresses, toilets, kitchen appliances and clothing. Such embedded sensors can determine sleep patterns, body weight, body temperature, pulse rate and so forth (Coronato and Pietro, 2010; Bardram and Christensen, 2007).

Currently, researchers are looking into advanced tele-sensing modalities that employ the Doppler radar technique to gather scattered vital signs from throughout the body (Ziefle and Rocker, 2010). These systems can gather multiple clinical parameters and are able to operate autonomously without disturbing the lives of patients. The various integral components of remote health-monitoring systems include a widely deployed wireless network and advanced computing technologies (Anderson, Valenzuela and Wittwer, 2011). Quite a few monitoring systems have been recommended for monitoring different clinical parameters, such as ECG, blood glucose, blood pressure and body temperature.

Application-based ECG monitoring systems include CardioNet's MCOT™, LifeSync's Wireless ECG System, AUBADE, the ICER system and Pinmed's Pelex-04. Among these, CardioNet's MCOT™ alerts a physician to take action promptly when needed (Hayes, 2014). While most of these require the sensors to be distributed on a patient's body and involve connections to a device using leads, LifeSync's Wireless ECG System is unique and has an edge over other devices by being able to acquire and transmit data wirelessly (Mattila et al., 2007). AUBADE does possess a basic framework for communication of clinical data over a network, however it does not have full-scale integration with different stakeholders involved in healthcare. There are sensor-based ECG monitoring systems, like Toumaz's Sensium™ Life Platform TZ2050 and Shimmer's Wireless ECG Sensor (Bohn et al., 2004; Hansen, Bardram and Soegaard, 2006; Ducatel et al., 2001; Bardram, Mihailidis and Wan, 2007). Soteras Wireless ViSi Mobile™ System serves as a mobile-based ECG monitoring system (Cruz-Correia et al., 2007; Muras et al., 2006; Lukowicz et al., 2004). The ICER system is quite different among these, though - it evaluates the severity level of parameters related to local hazards and vulnerability through a fuzzy expert system approach, and furthermore, offers recommendation on necessary capabilities for managing each local parameter (Hijji et al., 2015; Hijji et al., 2013) . The adopted methodology of the ICER system was used in this research.

Analogous monitoring systems have been put forward for other clinical parameters. Entra Health Systems' MyGlucoHealth, Vitalo Ltd.'s SmartLAB® Global Glucose Monitor - D10419-SmartLAB Global and FORA's D15b BG Plus BP Monitor (Bluetooth version) are examples of sensor-based blood glucose monitoring systems while AT&T's Diabetes Manager®, Agamatrix's iBGStar Blood Glucose Monitoring System and LG's KP8400 Cell Phone with a built-in blood glucose monitor are exemplary mobile-based blood glucose monitoring systems (Andre and Teller, 2005; Banerjee et al., 2003; Lee and Mihailidis, 2005; Sixsmith and Johnson, 2004; Camarinha-Matos and Afsarmanesh, 2004; Mahoney and Tarlow, 2006; Philipose et al., 2004; Schrooyen et al., 2006; Morris, 2005; Anliker et al., 2004; Scheffler and Hirt, 2005; Chen et al., 2005). Similar specific monitoring systems have also been conceived for monitoring blood pressure and body temperature parameters, among others.

While myriads of individual clinical parameter monitoring systems have been proposed in the literature, researchers have been making efforts to integrate different sensing modalities for developing systems that are capable of monitoring more than a single clinical parameter. To illustrate, systems like A&D's CP-1 THW Complete Wireless Software Connected Health Monitoring System, CareMatrix's CareMatrix Wellness System (CWS), HoneyWell's HomMed Genesis™ DM Remote Patient Care Monitor, Bosch Healthcare's Health Buddy System and Viterion's Viterion 100 Health Monitor & Viterion 200 TeleHealth Monitor. Thje majority of these cited examples are configured to monitor blood glucose and blood pressure levels in addition to a few other clinical parameters.

Of note is that with the emerging technology in the smart health monitoring, energy consumption and usage can be optimized. A recently proposed system called Advanced Metering Infrastructure (AMI) has a new application for monitoring e-health power consumption (Chalmers et al., 2015).

While intensive research efforts are underway in remote health-monitoring technologies, several challenges still remain. First and foremost, the initial cost is one of the strongest barriers to widespread adoption. The equipment currently costs several thousands of dollars and successful market penetration entails bringing down the setup fees and there are currently no clear guidelines related to reimbursement of costs through health insurance. The second major barrier is the lack of industry standardization in the field of remote health monitoring. Remote health-monitoring technologies invariably revolve around a combination of diverse devices. In the absence of standardization and regulatory guidelines, interoperability of individual components constituting the system poses an issue. Other hurdles are related to data transmission and data security. Remote health monitoring necessitates reliable wireless telecommunication infrastructure, which may not be available, especially in rural areas. Data security of private medical data of subjects being monitored is another problem. Another concern frequently voiced by healthcare professionals is that continuous monitoring systems would lead to an excessive influx of information, especially in institutional settings, where clinical data from a large number of subjects would be captured. In the absence of intelligent processing systems, the large amount of data would eventually require large teams just to handle the information load and may actually increase the workload (Benharref, Serhani and Nujum, 2014). One of the main reasons behind many of the issues described is the monolithic architecture-based approach to build remote health-monitoring systems.

To overcome the barriers to adoption of currently available remote health-monitoring systems, the proposed framework was introduced in this research, providing an integrated and scalable architecture that enables customization and flexibility in individual implementations based on the patient profile. It also supplies a framework for achieving interoperability between different monitoring products and, therefore, makes possible a reduction in patient hospitalization costs, standardization and interoperability between various platforms.

5.4 Integrated and Scalable Framework for Remote Health Monitoring:

5.4.1 Overview Description

The proposed healthcare monitoring system for the aged at home around the clock is non-intrusive. It assists the elderly to survive independently at their homes by supporting their ADL to make their lives easier and more manageable through consistent interactions across services. The system will enable physicians to support the aged community by providing advice, diagnoses and treatments. This will minimize the number of visits to the hospitals, diminishing the cost of elderly care and at the same time, decrease the burden on healthcare providers. In addition, it will allow access to advanced and specialized care to remote communities with no access to specialized medical centres, resulting in minimized durations of hospital stay and intensive caretaking in the comfort of an individual's home.

The key objectives of the proposed system are listed below.

a. Provides an integrated and customizable platform implemented using a set of sensors and actuators within the subject's home environment supporting medical data acquisition in a seamless and non-intrusive manner without disturbing the ADL of the subjects.

b. Provides healthcare professionals with access to medical data acquired at home, enabling healthcare professionals to monitor the medical conditions of the subjects remotely and pervasively (anytime and anywhere).

c. Generates real-time alerts for healthcare professionals to garner timely and effective intervention depending on the medical condition of the subject being monitored.

d. Outputs real-time advice related to treatment and medication depending on the health condition through suitable display devices.

e. Makes available real-time nutritional advice related to diet programs, sport practices and nutrition plans for preventive health management.

f. Enables time and cost-efficient administration of healthcare services to residents at home, in old-age care centres or remote communities.

g. Facilitates early discharge of non-vital cases to resume their normal lives at home in a reliable and safe environment while enabling continued monitoring of their health conditions for the desirable length of time.

h. Engenders health authorities with access to medical data of elderly individuals suffering from chronic diseases over a long-term period, fostering data analytics and establishing patterns regarding chronic diseases in a region and other statistics for health-related issues.

The key differentiator of the proposed system is the modular architecture with clearly defined interfaces between varying modules and standardization of communication protocols, leading to scalability and interoperability.

5.4.2 New Proposed Framework

The framework of Figure 5.1 (Alhemairy et al., 2016) depicts the monitoring of various clinical parameters. It involves data acquisition, processing and analysis of the acquired data using an artificial intelligence-based diagnostic engine. It displays the most appropriate recommendations to the concerned users on suitable display, i.e., visual display, screen, or through voice. While the framework exploits artificial intelligence to automate processing of large volumes of inflowing data, it also provides flexibility for manual intervention. Medical experts may initiate manual intervention on their own accord or in response following being prompted by the system. In the beginning, patient vital signs will be captured by various non-intrusive and wearable sensors and will be sent to the data acquisition modules. The data will then be filtered from the noise and invalid values and stored in the database. Data will also be obtained from other sources, such as knowledge databases and social networks. If there is an emergency, such as falling, the intervention module will be triggered immediately.

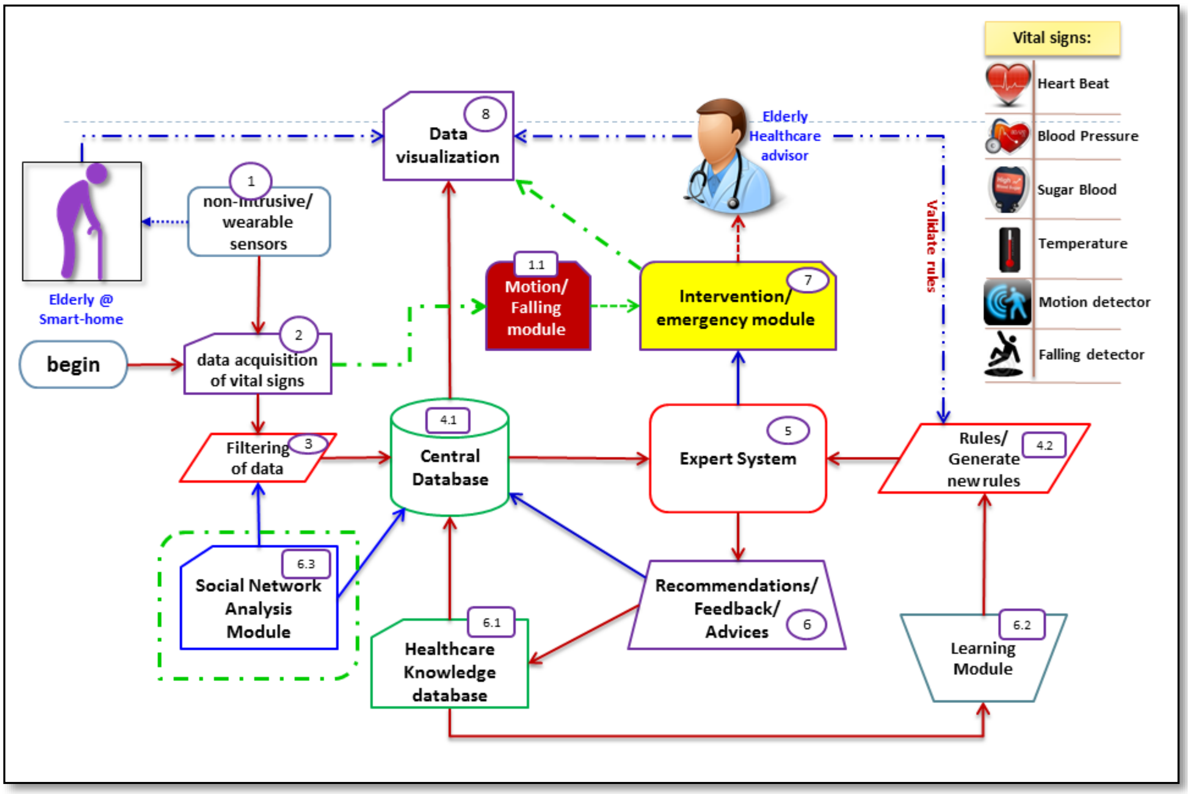


Figure 5.1: Framework for remote healthcare monitoring (Alhemairy et al., 2016)

The expert system will examine the obtained data from the patient and check the predefined rules for matching cases, taking the appropriate action accordingly. The action will be in the form of advice, recommendations or generating new rules in the case they were not defined in the knowledge base of the Leaning Module. To ensure rule validation and system accuracy, no new rules will be added without human expert validation. The system is supposed to display the information to both the patient and physician simultaneously in the form of warnings, alarms or medical advice.

The main modules of the proposed framework are listed below.

1) **Data Acquisition Module**: includes a network of sensors for acquiring clinical data of monitored subjects within their homes. Various examples of clinical

data include, but not limited to, heart beat rate, blood pressure, blood sugar, temperature and motion- and falling detectors.

2) **Data Filtering Module**: filters the acquired data to eliminate noise, errors or invalid values using filtering techniques/algorithms, including low-pass filters, high-pass filters and noise removal/cancellation, and can be used to pre-process sensory data before formal processing.

3) **Diagnostic Engine**: an expert system is implemented to effectively substitute for a human medical expert. The engine interfaces with a data repository containing, for instance, a set of rules related to diagnostics, alert generation and prompting manual intervention. A Bayesian network could be used for data classification. However, a novel algorithm for real-time diagnoses of medical conditions (diseases) was developed using new mathematical expressions (“Indicator Value”). The details are explained in chapter 6.

4) **Publication Module**: also known as, the Recommendation/Advice Module, will interface with the diagnostic engine and publish advice and/or recommendations on suitable target devices (monitored subjects, responsible healthcare professional or both).

5) **Intervention/Emergency Module**: deals with urgent and emergency cases where the captured signs were identified by the diagnostic engine as extremely abnormal. It will generate an urgent warning to the responsible healthcare professionals as well as trigger other actions, such as a request for dispatching an ambulance to the subject’s location. Additionally, the module

will allow the medical staff to review and validate or update the final advice for the patient.

6) **Learning Module**: will be configured to update the data repository with new rules whenever required. It learns from the new recommendations/feedback provided by the human medical expert and the previous experiences. It will continuously improve the knowledge base captured using a Bayesian classifier to generate accurate and valid medical advice, therefore arriving at the best possible decision.
7) **Data Visualization Module**: it is responsible for rendering the recommendations/advices generated by the diagnostic engine or provided by the medical expert through the Manual Intervention Module for both the elderly patient and healthcare staff.
8) **Motion/Falling Module**: deals with emergency scenarios and consists of detecting fall incidents. It has been separated from the other medical conditions as it requires immediate attention and heavy processing. It has been mapped directly to the Intervention/Emergency Module such that necessary action is taken immediately, such as calling an ambulance and alerting the responsible healthcare professional.
9) **Social Network Analytics Module**: will collect data from social networks, filter it and analyse the remainder to yield relevant insights that will aid in monitoring. The results of the analyses will also be used to enrich the knowledge base and possibly derive new rules. This module uses social networks APIs (e.g. twitter APIs for twitter) to search the network using

user's search keywords to extract data, build a structured model to describe this data, implement and populate the database using this model, then querying the database whenever needed to extract relevant additional information that might help in disease diagnosis, awareness, etc.

Other supportive components complement the roles of these modules including:

10) **Central Database**: this is the main database of the system where it used to store the medical data from various sources, which encompasses data from the sensors, Healthcare Knowledge database Module, Feedback/Advice Module and external databases, like social networks.
11) **Knowledge Database**: uses to store and analyse data from various external database sources, like, for example, patient medical history and records extracted from other external healthcare databases, and data collected from the Social Networks Analytics Module. For a better system architecture, the knowledge database was separated from the main system database.
12) **Generating New Rules**: process related to the Learning Module; if a new medical condition is detected, then a new rule will be generated after it has been validated by a human expert.

5.4.3 Social Network Sensing Module

This module is responsible of collecting health-related data from social networks, performing pre-processing and transformation activities (e.g., filtering, restructuration) on this data to derive relevant health-related information and augment the knowledge base. Data analytics could result in pattern detection, rule validation and, eventually, new rule deduction. As an example, for various diseases in UAE that are highly related to the cultural behaviours - such as Obesity and Diabetes. While scrolling the Social Networks information related to such diseases, relevant conclusion can be extracted from user's data as well as the community's data. It might include for example the following:

- Food habits that had impacted the youth generation in UAE enormously.
- Cultural commitments in various occasions such as family gathering on daily/weekly basis and the custom food style.
- Obesity and Diabetes are highly engendering vital health problems such as: cardiac vascular diseases, high blood pressure and others.

Figure 5.2 outlines the Social Network Module's components and the sequence of interactions among them.

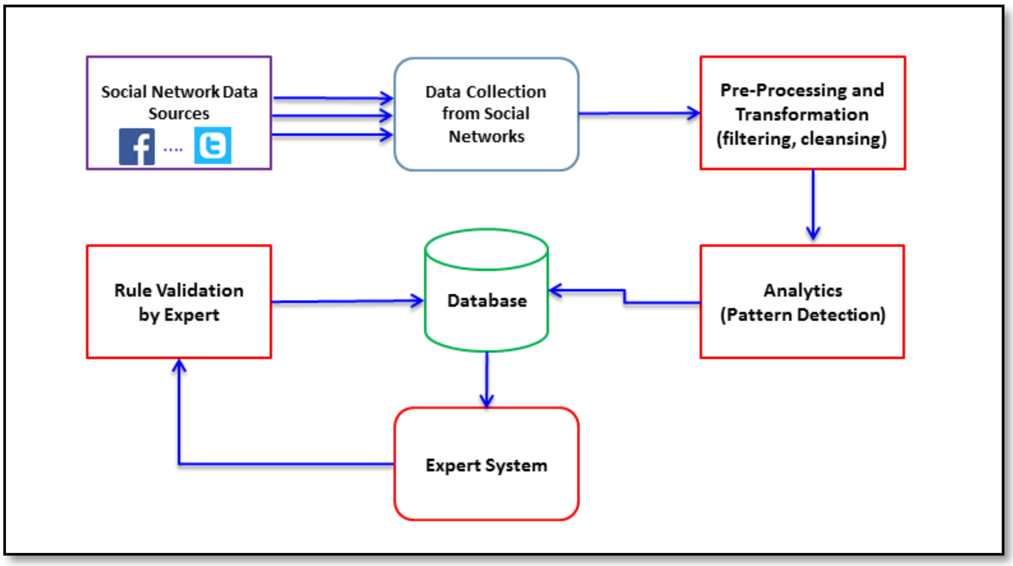


Figure 5.2: Detailed view of the social network health-sensing module

The social network module engages in the following:

1. Collect data from the social networks (i.e., Facebook, Twitter) as row data;

2. Filter the data to remove unwanted or invalid data (or information) and keep only the relevant structured health-related data in a specific format (i.e., XML, ERD);
3. Analyse the health data collected from the social networks and filtered in steps (1) and (2) and derive patterns and new rules;
4. Store the data in the central database.
5. Expert system will check the matching rules and take an appropriate action.
6. If there is a new rule detected, the expert system will consult a human expert to validate the new rule before adding it to the database.

5.5 Novel Algorithm for Disease Detection

Self-diagnosis of diseases is gaining traction nowadays, especially with the application of artificial intelligence techniques. It will permit early disease detection for an appropriate and prompt treatment. Furthermore, with the increasing spread of diseases and their corresponding symptoms, it has become impossible for a physician to recall all symptoms and medical conditions for all diseases. Hence, introduced here is an innovative algorithm that could be incorporated into a web-based platform to support a medical expert in diagnosing disease based on the vital sign values acquired from the wearable sensors on a real-time basis. The algorithm uses a single and unique "**Indicator**" value to search in a look-up table for the predefined corresponding diseases. Many existing expert systems use either sequential (or serial search) algorithms. The latter incorporates inference rules method for disease diagnosis, which is a very sophisticated process that requires many resources in terms of computational time and energy consumption. The process of detecting the diseases using the new algorithm is formally specified in Figure 5.3:

```
Algorithm 1 DISEASE SEARCH ALGORITHM
Input: smarEhealthSensor // Vital signs database table
Output: ehealthIndex , detectedDisease
procedure LOOKUPTABLEALGORITHM(smarEhealthSensor )
    eHealthIndex ← 0
    for all row ∈ smarEhealthSensor do
        val ← row[primaryValue] // vital sign value
        wf ← row[weightFactor]/100 // weight factor
        vsMin ← row[vitalSignMin] // min normal range
        vsMax ← row[vitalSignMax] // max normal range
// we include vital sign if its value is outside normal range
         if (val >=vsMin && val <=vsMax)
           subIndex ← 0
        else
           subIndex ← val * wf
         endif
         eHealthIndex ← eHealthIndex+subIndex // update ehealth index
    end for
    for all row ∈ smarEhealthSensor do
        dMin ← row[dMin]
        dMax ← row[dMax]
         if (eHealthIndex >=dMin && eHealthIndex <=dMax)
// a disease is detected add it to disease string
           detectedDisease ← detectedDisease.row[dName]
         endif
    end for
end procedure=0
```

Figure 5.3: Disease search algorithm (Al Hemairy et al. US Patent, 2016)

The disease diagnosing algorithm is described, implemented and evaluated in detail in the following chapter. The novelty discussion and analysis for the proposed algorithm is discussed in greater detail in section 6.6 in chapter 6.

5.6 Implementation

To explain the concept of the proposed framework, this section browses the implementation process. However, before delving into all details surrounding implementation, it is worth reviewing a sample set of rules that may be configured in the data repository in Figure 5.4.

Rules	Examples

Blood Sugar (BS)	IF (Fasting Blood_Sugar is >= 200) THEN (FBglucose is very *high*)
	IF (Fasting Blood_Sugar is >= 125) THEN (FBglucose is *high*)
	IF (Fasting Blood_Sugar is 50-70) THEN (FBglucose is *low*)
	IF (Fasting Blood_Sugar is >=70) THEN (FBglucose is *normal*)

Blood Pressure (BP)	IF (SysToLic is 90-120) AND (DiasToLic is 60-80) THEN (BP is *normal*)
	IF (SysToLic is <90) AND (DiasToLic is <60) THEN (BP is *low*)
	IF (SysToLic is >120) AND (DiasToLic is >80) THEN (BP is *High*)

Falling	IF (Falling_Sensor is = ON) AND (Voice_Command = Respond) THEN (False_Alarm is = ON)
	IF (Falling_Sensor is = ON) AND (Voice_Command = No_Respond) THEN (Un_Conscious is = ON)
	IF (Un_Conscious is = ON) AND (Call_Check is = Respond) THEN (False_Alarm is = ON)
	IF (Un_Conscious is = ON) AND (Call_Check is = No_Respond) THEN (Call_Emergency)

Motion	IF (Motion_Timer is= OFF >= 20 min) AND (Bed_Sensor is = OFF) THEN Motion_Module is = ON
	IF (Motion_Module is = ON) AND (Call_Check is = Respond) THEN (False_Alarm is = ON)
	IF (Motion_Module is = ON) AND (Call_Check is = No_Respond) THEN (Caregiver_Call)
	IF (Motion_Module is = ON) AND (Caregiver_Call is = No_Response) THEN (Call_Emergency)

Falling & Motion	IF (Falling_Sensor is = ON) AND (Motion_Timer is= OFF >= 10 sec) THEN (Call_Emergency)

Figure 5.4: Sample set of diagnostic and monitoring rules

5.6.1 System Technical and Non-Functional Requirements

The following are certain technical requirements for the monitoring system as well as a number of non-functional properties it is supporting:

1) **Application Server**: the system is hosted on a Glass Fish application server and RabbitMQ servers running on a Linux platform in a Cloud environment and connected to MySQL Database servers. Various technologies, like JSP, Servlet, EJB, MDB and JDBC were used to develop features of the monitoring system. All communication with the client complies with public HTTPS and TCP/IP communication protocol standards.
2) **Client**: users will be able to access the system through mobile application as well as via web applications browsers. HTML5 was utilised to support interoperability across mobile applications and provide high flexibility and dynamic features.
3) **Security**: access rights will be granted to any user accessing the application-landing page. Only an administrator user can add or remove other creators and perform other administrative tasks.
4) **Persistence**: we used a relational database for data persistence, and data management rules were enforced to ensure consistency and accuracy of the data.
5) **Performance**: there are no particular constraints related to system performance. It is anticipated that the system will respond to any request under standard database and web server script timeouts. Additionally, system performance may

depend on available hardware as well as network and internet connection capabilities.

5.6.2 Prototype Implementation

To demonstrate the applicability of the proposed framework, a mobile application as well as web application prototypes has been developed that can be used in experiments with the main framework's components and implement key processes in the monitoring scenarios, such as data acquisition, data processing, data analysis and data visualization. Table 5.1 describes the key technologies, devices, and sensors used to implement components of the framework. For example, the data acquisition process collects the data from the sensors via Bluetooth and sends it to the mobile application via Wi-Fi, and then stores it in the MySQL database. The sensor used for heart rate was Zephyr HxM, while for blood pressure and blood glucose, MyTech and iBGStar were employed, respectively. The diagnostic engine will test the captured values against rules and conditions that are predefined and generate advice/recommendation or trigger other actions, like the Emergency/Intervention Modules. The Data Visualization Module features charts, medical advice, warnings to the user via mobile. A further description and explanation for how each module works can be found in Section 5.4.2.

Table 5.1: System components and technologies to implement the framework

System	**Description & Use**	**Examples**
Database Server	Servers used to store data acquired by sensors, generated rules, medical advice and recommendations.	- MySQL - Oracle
Visualization Devices	Display information to patient and physician based on user role (system admin, physicians, patients, nutritionist, etc.)	- Tablet, Mobile Phones - LCD, Dashboard, Printout
Processing /Application Servers	Hosted locally (or on web server) to process data and analyse conditions using expert system.	- Cloud servers (hosting the expert system, process recommendations & learning module)
Sensor Devices	Set of sensors to capture different parameters from patients at home, i.e., wearable sensors.	- Zephyr HxM (heart rate) for Android & iPhone - MyTech (Blood Pressure) - iBGStar (Blood Glucose)
Diagnostic Engine	Expert system consists of set of rules and conditions based on medical case. It then processes the rules and generates advice or triggers Intervention/Emergency Module if needed.	- Expert system is developed using Java-based engine.

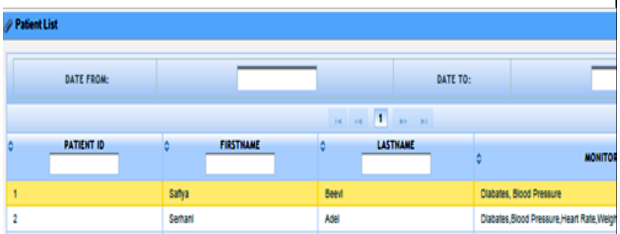
As mentioned previously, the healthcare-monitoring system, after collecting the data from various sources (sensors, knowledgebase, social networks, etc.) will verify that data against the set of rules stored in the system database. If the captured sensor value is within the abnormal range of a specific medical condition, then a matching case will be found and a set of actions (i.e., recommendations) will be generated and displayed to the patients and/or the medical staff. All these rules are set and validated by the medical human expert in advance.

5.6.3 Mobile Application Implementation

The mobile application was developed on the Android platform and deployed on different mobile devices including, tablet and mobile phones. Table 5.2 depicts different views of the monitoring system, including those for medical staff and patients from both the web application and mobile application perspectives.

Table 5.2: System views for monitored subjects and healthcare professionals

a. **Medical staff web application view**



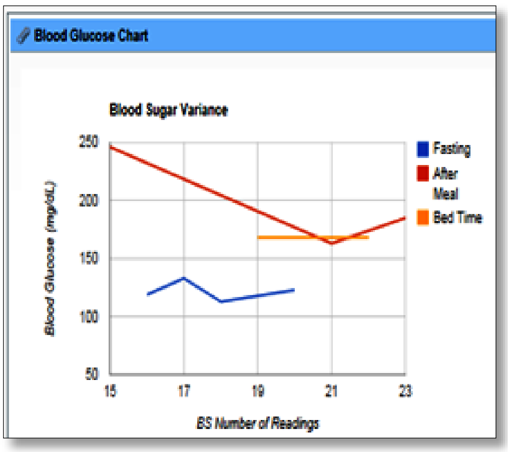
Real-time monitor for patient medical records

PATIENT DETAILS

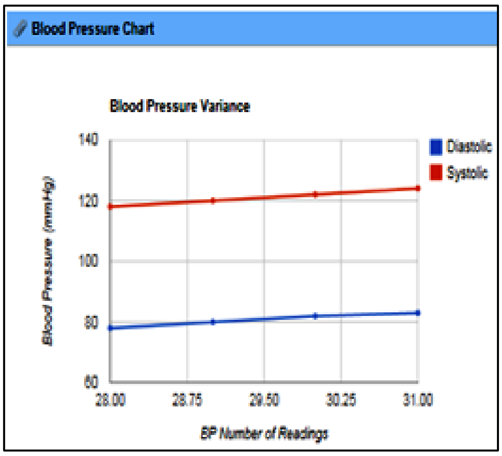
NAME	AGE	SEX
Abdulla	50	Male
Samad	45	Male
Muneer	35	Male
Rahman	30	Male

List of patients allocated to specific physician based on the medical case

Figures above are examples of captured data and how it is processed and analysed simultaneously to supply medical staff with up-to-date data and patient's history to provide the best medical advice.



Blood Glucose
Monitoring Screen



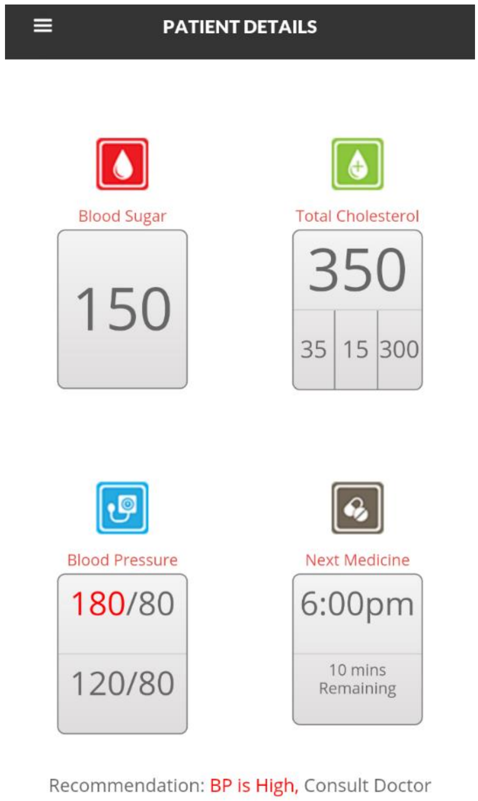
Blood Pressure
Monitoring Screen

b. Patient mobile application view

The following are examples of how the data captured by the system will be processed and analysed simultaneously to provide an up-to-date medical status for the patient.

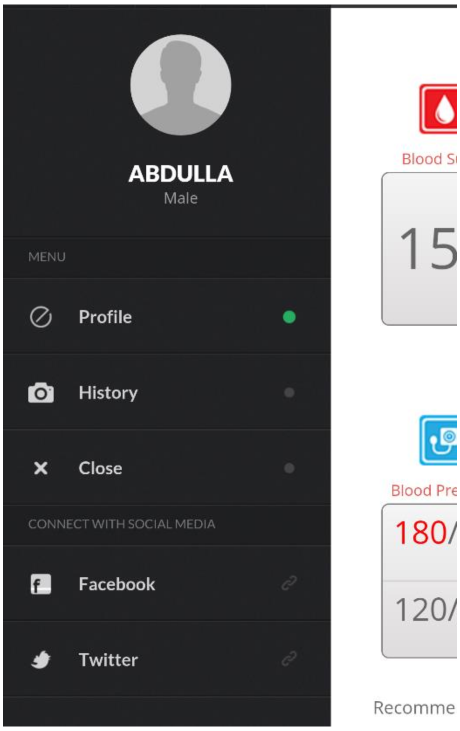
Smart-home eHealth System Home Page
Features two login options:

- **Physician View**
- **Patient View**



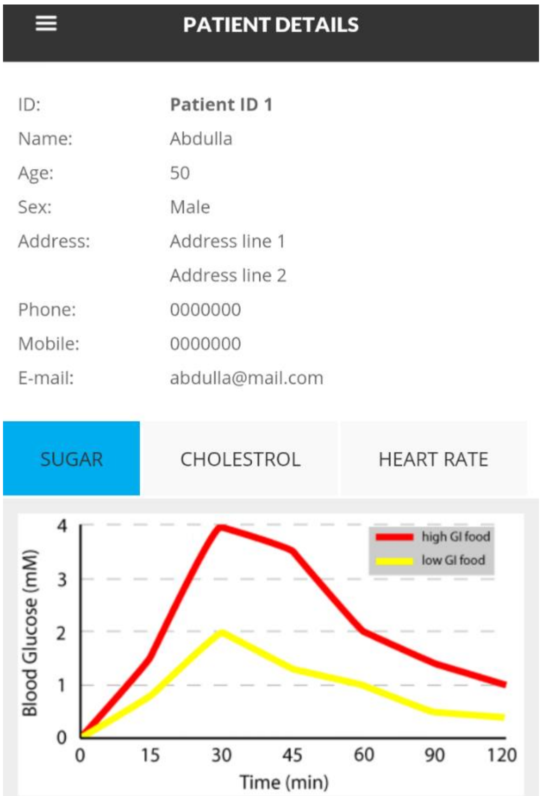
Simple and clear messages shown to patients.

The eHealth system uses mobile devices as the target devices for visualization. Sample screenshots of a mobile-based application to be used with the proposed system have been provided.

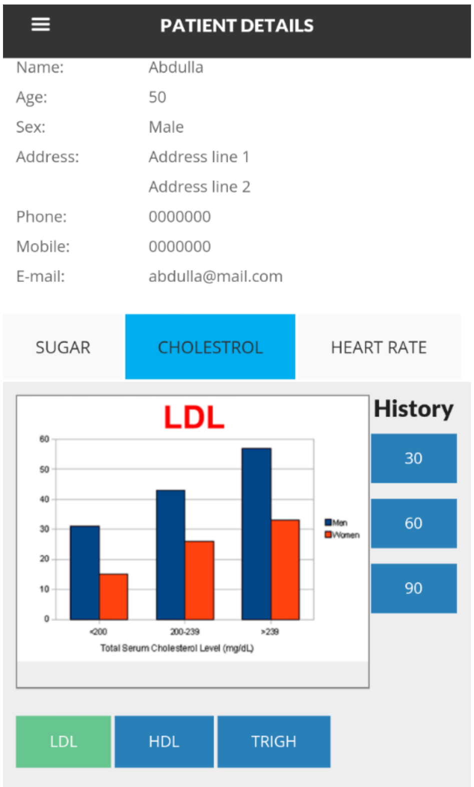


Patient View:
User profile and other tools with simple view

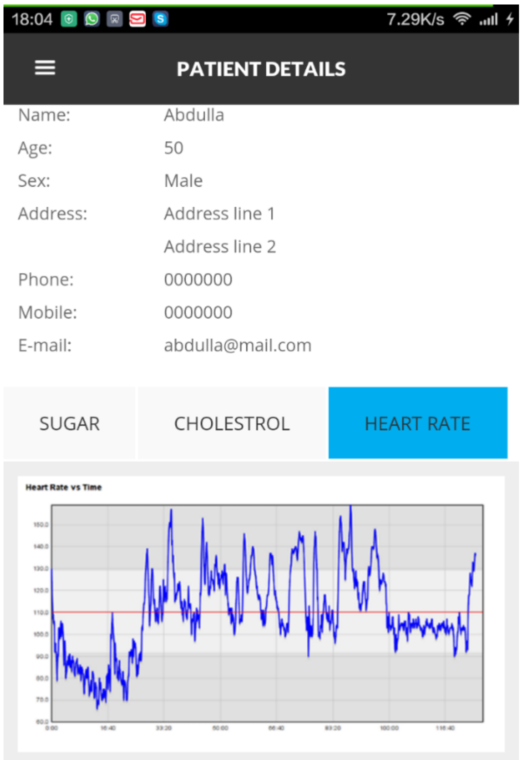
c. **Physician Mobile View**



Physician View:
Patient's blood Sugar records



Physician View:
Patient's cholesterol level records

Physician View: Patient's Heart Rate records	

5.6.4 Further novelty discussion for: "Framework for Remote Health Monitoring"

A literature review search was performed to find the most relevant reference publications and potential patents for a framework for providing remote healthcare-monitoring systems. The results of the search showed that the general concept of remote health monitoring is known, however, just nine patent references and three publication references (non-patents) were found interesting and relevant. In the following, it will be discussed and analyse these results and comment on the cited references. It is important to note that these cited literature references were based on the information available to us from the online search and to the best of our best knowledge are the extent of the published scholarly work at the moment of writing this thesis. Section 2.3 in Chapter 2; described the Search and Methods Strategy for identifying the novelty of our proposed framework related to a remote health-monitoring system employing multiple modules from the publication-literature.

The relevant references showed that the general concept of the framework for providing remote health monitoring was known. However, there are various novel modules here that would be novel relative to the literature, such as the combination of prompting manual intervention by a medical expert, generating urgent warnings in cases of emergencies, and obtaining further medical rules and data from the social network to be used in the knowledge database of the system. Therefore, it formed the basis of a potential patent application.

A. Non-patent related work

In the work of Vaidehi et al. (2012), an in-home health-monitoring system had moderate relevancy here. Based on a patient's vital parameters that are sensed, collected and sent by bio-sensors, abnormalities are identified so that an appropriate action can be taken. For example, if the patient forgets to take their medicine, a message notification is sent. As well, the system architecture has an image fall-detection module for detecting if the patient has fallen. Hence, it appears there is the idea of a diagnostic engine for generating alerts, including sending information to the patient. It also has a motion/falling module for detecting fall incidents. On the other hand, the authors did not disclose the idea of prompting manual intervention so that a medical expert could review and validate advice for the patient in the case of malfunction of the system or false assessment from the expert system. Furthermore, it did not contain any learning modules configured to update the diagnostic rules based on feedback provided by a medical expert or obtaining further medical data from a social network.

Another project (Benharref and Serhani, 2014) described a system in which data is collected using sensors and mobile applications. This data is then sent to a system that uses rules to generate a set of recommendations sent to the patient and a physician, who can then validate or update or expand on the advice through an interface. The knowledge retrieved from those recommendations is then used by a learning module to update the existing rules. The automated recommendations are displayed to both the physicians and the patients.

The ideas corresponding to data acquisition and filtration, diagnostic engine, learning module and display modules of the architecture were discussed. However, no emergency module for generating an urgent warning to a healthcare professional for triggering other actions such as a request for dispatching an ambulance to the monitored patient's location was found. Additionally, their work did not contain any motion/falling module for detecting fall incidents or utilizing the available medical data from social networks.

Forkan et al. (2015) devised a system for diagnosing abnormalities for the patient based on monitoring data about the patient. The authors claimed that a Naive Bayes learning technique could be used to train a dataset generated using diagnostic rules that were generated from vital sign data. Hence, it appeared that they were using a Bayesian network for data classification and a learning module for updating the diagnostic rules. However, their system did not adopt a manual intervention so that a medical expert could review, validate or advise the patient through an interventional approach. In addition, it contained neither a module motion/falling, detecting fall incidents, nor harvesting the social network for medical use.

In **Table 5.3**, there is a comparison between the relevant features between the proposed system and three selected references cited previously.

Table 5.3: Compared features: proposed system vs. three cited systems

	Features	Vaidehi et al.	Benharref et al.	Forkan et al.
Preamble	Framework for providing remote health-monitoring comprising:	Y	Y	Y
Data acquisition module	a) a network of sensors for acquiring clinical data of a monitored subject;	Y	Y	Y
Data filtering module	b1) a data filtering module for filtering the acquired data to eliminate noise, errors or invalid values	Y	Y	N
	b2) use different filtering techniques/algorithms including low-pass filters, high-pass filters, noise removal/cancellation etc.	N	N	N
Diagnostic engine	c1) a diagnostic engine interfaced with a data repository	Y	Y	Y
	c2) the data repository containing a set of rules related to diagnostics and alert generation	Y	Y	Y
	c3) alert generation prompts manual intervention	N	Y	N
	c4) Bayesian network for data classification	N	N	Y
Publishing module	d) publishing module interfaced with the diagnostic engine for publishing advice to the monitored subject and/or a healthcare professional	Y	Y	Y
Intervention/ emergency module	e1) an intervention/emergency module for generating an urgent warning to the healthcare professional	Y	N	Y
	e2) triggers other actions such as a request for dispatching an ambulance to the monitored subject's location	N	N	N
	e3) allows a medical expert to review and validate the advice for the monitored subject	N	Y	N
Learning module	f1) a learning module configured to update the data repository with new rules	N	Y	Y
	f2) learning module learns from feedback provided by the medical expert	N	Y	N
Display module	g) renders advice for the monitored subject and the healthcare professional generated by the diagnostic module or provided by the medical expert through the intervention/emergency module	Y	Y	N
Motion/falling module	h1) a motion/falling module for detecting fall incidents	Y	N	N
	h2) mapped directly to the intervention/emergency module	Y	N	N
Social network module	i1) use of big data from social networks (i.e., Twitter, Facebook) to extract medical knowledge	N	N	N

B. Patent related work

In this section, a few examples of published patents will be discussed that were found relevant during the novelty search on the proposed framework. In **Table 5.4**, a comparison drawn between the proposed system and nine USA patents cited during our exhaustive search on the proposed framework's novelty. Therein, we compared the prior art to the current key features.

Based on the comparison and the novelty of the system was endowed with, a successful patent application was filed at the USPTO. The patent holds the number **US 15/395,121** and a filing date of **December 30, 2016.**

Table 5.4: Compared features between: proposed system vs. nine cited patents

	Features	US2015025329A	US2015186777A	US2015356263A	US2015019259A	US2014108025A	US2011313789A	US2016180743A	US2016135755A	US2011144451A
Preamble	Framework for providing remote health-monitoring comprising:	Y	N	Y	Y	Y	Y	Y	Y	Y
Data acquisition module	a) a network of sensors for acquiring clinical data of a monitored subject;	Y	N	Y	Y	Y	Y	Y	Y	Y
Data filtering module	b1) a data filtering module for filtering the acquired data to eliminate noise, errors or invalid values	Y	N	N	Y	N	N	N	Y	N
Data filtering module	b2) use different filtering techniques/algorithms including low-pass filters, high-pass filters, noise removal/cancellation etc.	N	N	N	N	N	N	N	N	N
Diagnostic engine	c1) a diagnostic engine interfaced with a data repository	Y	Y	Y	Y	N	Y	N	Y	N
Diagnostic engine	c2) the data repository containing a set of rules related to diagnostics and alert generation	Y	Y	Y	Y	N	Y	N	Y	N
Diagnostic engine	c3) alert generation prompts manual intervention	N	N	N	Y	N	Y	N	N	N
Diagnostic engine	c4) Bayesian network for data classification	N	N	N	N	N	N	N	N	N
Publishing module	d) publishing module interfaced with the diagnostic engine for publishing advice to the monitored subject and/or a healthcare professional	Y	N	Y	Y	N	Y	Y	N	N
Intervention/emergency module	e1) an intervention/emergency module for generating an urgent warning to the healthcare professional	Y	N	Y	N	N	N	N	Y	N
Intervention/emergency module	e2) triggers other actions such as a request for dispatching an ambulance to the monitored subject's location	N	N	N	N	N	N	N	Y	N
Intervention/emergency module	e3) allows a medical expert to review and validate the advice for the monitored subject	N	N	N	Y	N	Y	Y	N	N
Learning module	f1) a learning module configured to update the data repository with new rules	Y	N	N	Y	N	N	N	N	N
Learning module	f2) learning module learns from feedback provided by the medical expert	Y	N	N	Y	N	N	N	N	N
Display module	g) renders advice for the monitored subject and the healthcare professional generated by the diagnostic module or provided by the medical expert through the intervention/emergency module	Y	N	Y	Y	N	Y	Y	N	Y
Motion/falling module	h1) a motion/falling module for detecting fall incidents	N	N	N	N	N	N	N	Y	N
Motion/falling module	h2) mapped directly to the intervention/emergency module	N	N	N	N	N	N	N	Y	N
Social Network module	i1) use of big data from social networks (i.e., Twitter, Facebook) to extract medical knowledge	N	N	N	N	N	N	N	N	N

5.6.5 Discussion of Results

Based on the aforementioned sample of monitoring results and after having seen different monitoring scenarios, the system demonstrates its efficiency reporting accurate readings of the vital signs from the sensors and visualize them on a mobile application. This shows how data are transferred from data acquisition stage to data visualization. Subsequently, it will be necessary to analyse the recorded vital signs and differentiate between the abnormal readings using an expert system that will be developed in the next chapter.

After a considerable period of monitoring a set of 100 anonymous patient's records, the system was able to detect health deterioration with a 100% detection accuracy most of the time. By scaling the size of the dataset by the number of anonymous patient's records with different parameters (blood pressure, cholesterol and blood sugar) the system remained stable and performed very well. No major issues or delays in communication or data transfer were recorded, and only a slight performance deterioration were observed based on network bandwidth and sensor calibration. For vital signs, blood sugar, cholesterol level and heart rate monitoring results were always accurate and reflected the actual situation. One of the key components of the healthcare monitoring framework is the diagnosing engine. In the next chapter, a novel algorithm is introduced for diagnosing and detecting diseases based on the change in the vital signs values that are captured continuously from the patient by a set of sensors, the algorithm utilizes a mathematical model developed for this purpose.

5.6.6 Summary:

As the world population ages and old-age support ratios diminish, innovative and intelligent healthcare administration is imperative. An important cornerstone of future healthcare administration is the adoption of remote health-monitoring technologies. While significant research and development work is currently being undertaken, several barriers related to costs, industry standardization, regulatory frameworks, user acceptance and data privacy and security, among others, have yet to be overcome. This proposed monitoring system exploits various emerging technologies, including biosensors, mobile technologies and communication media to generate a reliable, efficient and complete solution, which can easily scale with various users, sensors and homes. Thus, the proposed system addresses several key barriers related to widespread adoption of remote health-monitoring technologies.

In future work, it is planned to extend the monitoring model to cope with the varying number of vital signs and learn the correlation between them. It is also planned to implement and integrate the Social Network Analytics Module to retrieve data from social networks and compare it against sensory data to offer better insights. As well, it is intended to evaluate the model in a large-scale scenario involving a larger number of patients and consider different health situations.

Chapter 6

A Novel Algorithm for Disease Monitoring Based on Vital Signs

Chapter 6: A Novel Algorithm for Disease Monitoring Based on Vital Signs

6.1 Chapter Overview

Self-diagnosis of diseases is highly desired at present. It would not only permit early disease detection, but also will provide access to appropriate treatment quickly (Riches et al., 2016). Further, because of the increasing frequency of diseases, it has become difficult for the physicians to recall all symptoms and medical conditions for every disease type. This research has generated an innovative new diagnosis algorithm that could be integrated into web-based tools to provide an efficient online system for disease diagnosis using several wearable sensors. The system features many defined medical conditions composed of sets of vital signs with abnormal value ranges. Various scenarios were experimented with using the proposed system and a software simulator developed for evaluating and performance testing. As the algorithm accesses a database to acquire real-time vital signs and verify medical conditions, the time taken for calculation changes depending on server load. However, during all the tests conducted, it has been observed that the performance of calculating the health Indicator was faster by between 10% and 48% than the sequential search method.

6.2 Introduction

Vital signs, mainly body temperature, blood pressure, heart rate and breathing rate, are the most important reflections of the human body's basic functioning (Gatzoulis and Iakovidis 2007). They aid in assessing the physical health of a person, provide clues into potential diagnosis and verify treatment progress (Borson et al., 2000). Table 6.1 lists various common diseases (Papadakis and Rabow, 2015) along with their corresponding medical conditions and sensors used to measure associated vital sign modification. Detection and identification of diseases at an early stage can facilitate treatment success significantly (Etzioni et al., 2003). Self-diagnosis of diseases is highly desired and has become quite essential in monitoring human health. This kind of diagnosis not only permits early disease detection but also provides access to appropriate treatment promptly. Vital signs, such as temperature, blood pressure, heart rate and breathing rate, are the most commonly used for monitoring human body basic functioning. These indicators help in assessing the physical health of a person by providing a diagnosis of possible disease and verifying treatment progress. Detection and identification of disease at an early stage can facilitate treatment significantly. However, any abnormality or change in these vital sign's values can only be understood by the medical staff who can infer what disease the patient may have. Unfortunately, due to the load of their daily work, most people do not find enough time to visit the doctor and get the appropriate medical advice (Yarnall et al., 2003). On the other hand, due to the frequent increment of diseases nowadays, it becomes difficult for the physicians to recall all symptoms and medical conditions for all kinds of diseases (Eddy, 1984) and therefore, adequate assistive tools are necessary not only to help rapidly identify diseases but to also minimize medical mistakes as well as to avoid prescribing invalid medications or treatments (Fernandez-Millan et al., 2015). Online diagnosis system can be used to provide such diagnostic services (Garg et al., 2005). The accurate detection and identification of a disease is highly dependent on the method used for diagnosis (Mangiameli et al., 2004; Barnett et al., 1987). Although the current advancement in

MDDS systems that increased the accuracy of the medical diagnosing for remote healthcare (Yan et al., 2006), the disease diagnosis is a very sophisticated process and demands an advanced level of expertise, besides being expensive in terms of computational time and energy consumption.

Table 6.1: Sample of defined diseases & corresponding vital sign & sensors ranges

Disease	Description	Vital signs ranges	MIN Abnormal range	MAX Abnormal range	Sensor(s) detection
Bradycardia	Abnormally slow heart rate	< 60 beats/min	0	60	HR_SENSOR
Tachycardia	Abnormally fast heart rate	> 100 beats/min or > 120 beats/min	100	200	HR_SENSOR
Hypotension	Abnormally low blood pressure	BP < 100 mm Hg systolic	0	100	BP_SENSOR
Hypertension	Abnormal systolic blood pressure.	Mild to moderate hypertension (systolic blood pressure < 180 mm Hg)	0	180	BP_SENSOR
Hypertension	Abnormal diastolic blood pressure	Diastolic blood pressure < 110 mm Hg	0	110	BP_SENSOR
Hypertension	Severe hypertension /abnormal systolic blood pressure	Severe hypertension defined as a systolic pressure > 180 mm Hg	180	360	BP_SENSOR
Hypertension	Severe hypertension / abnormal diastolic blood pressure.	Diastolic pressure > 110 mm Hg	100	200	BP_SENSOR
Asthma Moderate 1	Chronic inflammatory disorder of the airways	90 < SPO2 < 95%, 100 - 120 beats/min, Tachypnea	90	95	SPO2_SENSOR
Asthma Moderate 2	Chronic inflammatory disorder of the airways	90 < SPO2 < 95%, 100 - 120 beats/min, Tachypnea	100	120	HR_SENSOR
Asthma Severe 1	Chronic inflammatory disorder of the airways but is severe	SPO2 < 90%, > 120 beats/min, Tachypnea	90	180	SPO2_SENSOR
Asthma Severe 2	Chronic inflammatory disorder of the airways but is severe	SPO2 < 90%, > 120 beats/min, Tachypnea	120	240	HR_SENSOR
Respiratory Arrest Imminent 1	Cessation of normal breathing because of failure of the lungs to function effectively	SPO2 < 90%, Bradycardia, PR > 30 breaths/min	0	90	SPO2_SENSOR
Respiratory Arrest Imminent 2	Cessation of normal breathing because of failure of the lungs to function effectively	SPO2 < 90%, Bradycardia, PR > 30 breaths/min	30	60	BR_SENSOR

According to an early study in the field; a highly selective and efficient web-based clinical expert system has not yet been developed in spite of the ongoing and existing trials and available systems (Miller, 1994). Existing expert systems incorporate inference rules (Basilakis et al., 2007; Lovell, 2009; Basilakis et al., 2010). Those rules play a significant role in suggesting specific methods for disease diagnosis and treatment. Currently, there have been several reports on eHealth management systems that employ various diagnostic tools (Al-Absi et al., 2011; Kumar, 2015). There is ongoing scientific discussion and debate about which kind of diseases should be included in medical diagnosis expert systems along with their symptoms (Hayashi, 1991; Celler and Sparks, 2015). Furthermore, which factors should be considered in diagnosis for such system and what approach should be followed are also concerns (Kaplan, 2001).

This work presents a systematic procedure that will be applied to diagnosing any kind of disease. The developed algorithm incorporates mathematical expressions used to determine the “**Indicator**” variable (it’s also called an “eHealth Indicator”) and its minimum and maximum interval values. The system then uses this value to search within a look-up table for the predefined corresponding disease. The proposed system was evaluated in various scenarios and a software simulator was created for performance testing.

6.3 Data and Methods: System Architecture and Algorithm

An overview of the proposed online system architecture is portrayed in a workflow diagram in Figure 6.1.

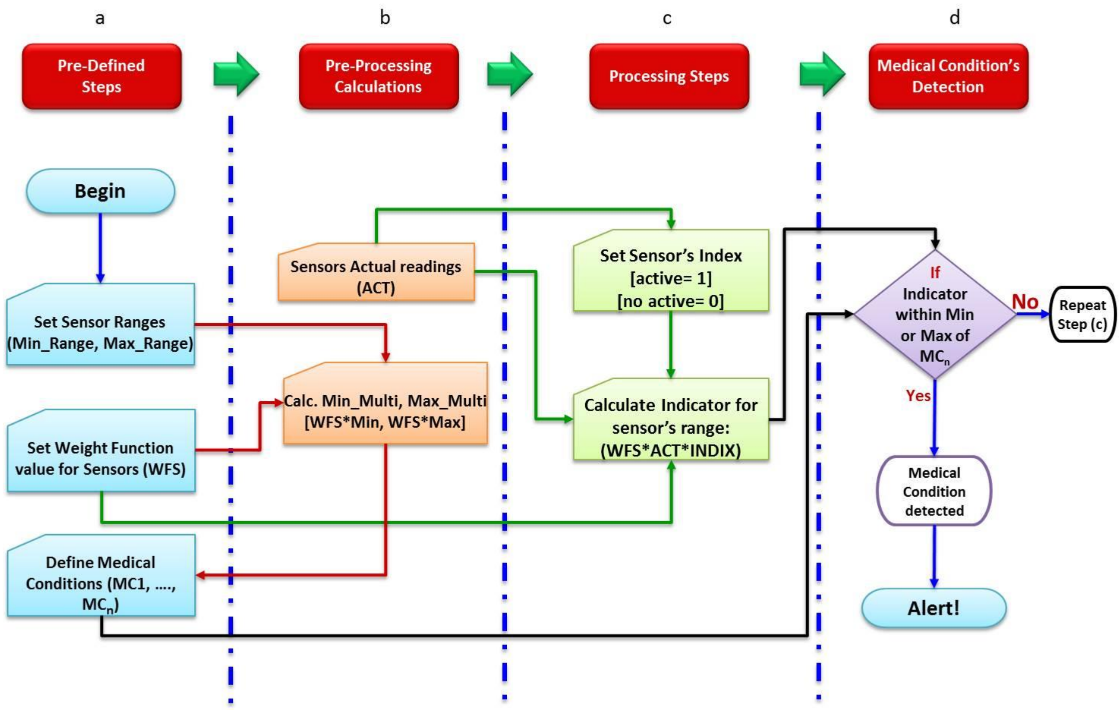


Figure 6.1: Proposed system overview

The workflow has four stages (a, b, c and d):

a. Pre-Defined Stage: where sensor ranges will be set up with their corresponding minimum and maximum ranges and weighting factors (WFs) as well as medical conditions.

b. Pre-Processing Calculation Stage: the sensor values are captured and stored, and the minimum multiplication for each sensor is computed using the WFs defined from the previous stage.

c. Processing Operations Stage: the control value for each sensor [0, 1] is set depending on its normal and abnormal value, while the Indicator factor will also be calculated based on WF, ACT & control values, where ACT refers to the sensor actual reading.

d. Medical Condition Detection Stage: final phase where the medical condition is determined based on the Indicator value falling within the minimum and maximum ranges of the defined medical condition.

The system incorporates quite a number of defined medical conditions. Usually, a disease is constructed as a medical condition associated with specific symptoms and vital signs. Vital signs normally vary with age, weight, gender and overall health (Chester and Rudolph, 2011; Agelink, 2001). Measuring the vital signs for a person will paint an accurate picture of physical status and health condition. With the sophistication of biological sensors, there have been developed dedicated sensors for each vital sign (Pantelopoulos and Bourbakis, 2010). The majority of standard human diseases are related to the status of vital signs and if their values are within or outside normal ranges. To accelerate the development of the system, a commercial product was used: **eHealth Sensor Platform, v2.0** (Hacks, 2016). The platform consisted of nine different wearable sensors, which measure 11 vital signs and a shield to connect the sensors. A schematic of the sensors and shield is shown in Figure 6.2.

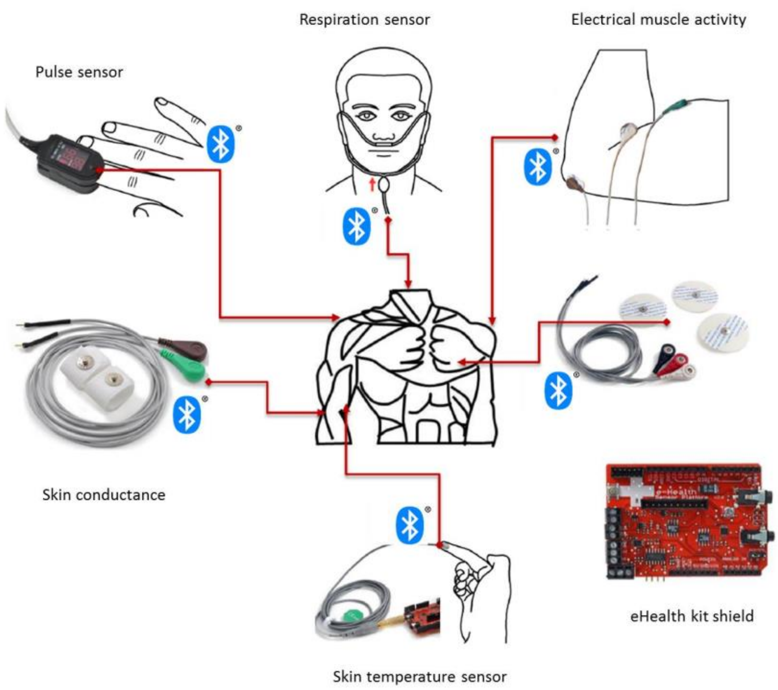


Figure 6.2: eHealth Sensor Platform, v2.0 (Alhemairy et al., 2016)

A description of the nine sensors and the biometrics they assess can be found in Table 6.2. The proposed system measures 11 different biological signals, and those signals have normal ranges such that if a value outside the normal range has been detected, then the physiological status of the person is established as abnormal and interpreted as likely the result of a medical condition. The ranges for these signals change according to many factors, like age and location. For example, normal heart rate ranges for an infant, if they are awake, is between 100 and 190, but while they are sleeping, that range is 90 to 160. On the other hand, the normal heart rate of a sleeping adult is between 50 and 90, though if awake, is 60 to 100 (Hacks, 2016).

Table 6.2: Wearable health sensors and the biometric they measure (Hacks, 2016)

Sensor	**Biometric measured**
Pulse and SPO2 sensor	Heart Rate (HR)
	Arterial oxygen saturation (SPO2)
Airflow sensor	Respiratory rates (RR)
Body temperature sensor	Body temperature (TEMP)
ECG sensor	Assess the electrical and muscular functions of the heart
Glucometer	Approximate concentration of glucose in the blood
Sphygmomanometer	Systolic blood pressure (SBP)
	Diastolic blood pressure (DBP)
Galvanic skin response (GSR) sensor	Measures electrical conductance of the skin, which varies with moisture levels
Accelerometer	Patient positions
Muscle/electromyography (EMG) sensor	Electrical activity of muscles

6.4 Theory and Calculation

6.4.1 Medical Condition-Detection Algorithm

Figure 6.3 describes the algorithm used for the medical condition detection system, which includes detecting a medical condition or a disease from a list of defined medical conditions (diseases) based on the calculation of the **Indicator**.

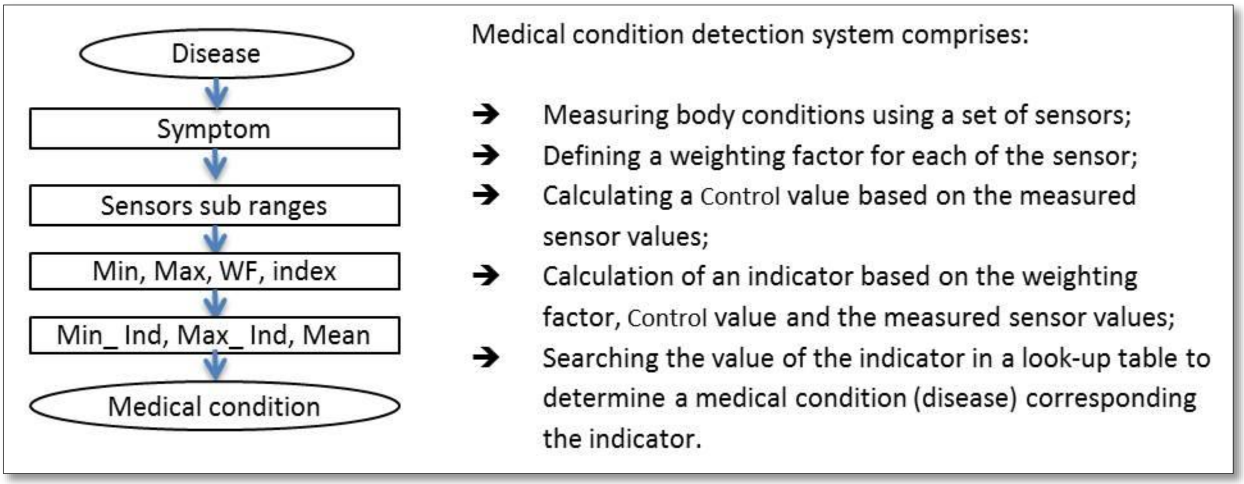


Figure 6.3: Medical condition-detection system formation algorithm

Herewith how the algorithm works; initially a disease must first be identified in a look-up table. Next, the symptoms of the disease should be specified and the involved sensor sub-ranges are defined. Following that, the maximum and the minimum value for the involved sensors are established and the corresponding control value for the involved sensors will be set to ‘1’. A WF value is introduced at this point, and it should be a unique value assigned to each sensor. This value determines the significant contribution of the corresponding sensor. The WF value varies from “0” to “1”, and is concurrent with the frequency of use of a specific kind of sensor in several medical conditions. In other words, if there are 100 defined medical conditions based on 10 kinds of sensor readings and the temperature is included in all of them, then its corresponding WF is 1, and if it is included in 85 conditions, its WF is 0.85 and so on. This factor will be used later in the computation of the Indicator value used to identify the corresponding medical condition. As the WF depends on the total number of defined diseases in the database, every time a new disease was added, the WF for the involved sensors is updated. Finally, the maximum and minimum “**Indicator**” values for the disease are computed and attached to the relevant medical condition in the disease look-up table 6.1. The below table 6.3 features the weighting factors for a number of the sensors employed according to the defined medical conditions in the database.

Table 6.3: Sample of the sensors used with their corresponding WF

WFS	Sensor type	sensor Abbreviation
0.7	Heart Rate Sensor	HR_SENSOR
0.9	Blood Pressure Sensor	BP_SENSOR
0.2	Spo2 Sensor	SPO2_SENSOR
0.6	Temperature SENSOR	TEMP_SENSOR
0.5	Respiration Rate Sensor	RR_SENSOR
0.2	Glucose Level SENSOR	GLOCOSE_SENSOR

It is worth mentioning that each sensor has a specific sensing range that can be divided into small ranges. Table 6.4 presents the sub-ranges for human temperature sensor readings as an example. The sensor has four intervals, each with its unique range values. For instance, when the body's temperature falls below 35.0 °C, the subject probably has hypothermia (which happens when human's body loses heat faster than it can produce it), causing a critical low body temperature. The normal range of internal human body temperature varies between 36.5 and 37.5 °C.

Table 6.4: Defined human temperature classification ranges*

Ranges	Symptom	Interval
STR1	Hypothermia	< 35.0 °C (95.0 °F)
STNR	Normal	36.5 – 37.5 °C (97.7 – 99.5 °F)
STR2	Fever	> 37.5 or 38.3 °C (99.5 or 100.9 °F)
STR4	Hyperpyrexia	> 40.0 or 41.5 °C (104.0 or 106.7 °F)

* Sources: (Rotheray and Cattermole, 2010; Hutchison et al., 2008; Axelrod and Diringer, 2008; Laupland, 2009; Trautner et al., 2006).

In Table 6.5, a sample of seven sensors for known vital signs, their corresponding minimum and maximum normal ranges and pre-defined WFs are found.

Table 6.5: Sensors with min/max normal ranges and weighting factors

No.	Sensor type	WFS	Min	Max
1	Heart Rate Sensor	0.7	60	100
2	Blood Pressure (Systolic)	0.9	90	120
3	Blood Pressure (Diastolic)	0.9	60	80
4	Body Temp. Sensor	0.6	36	37
5	Respiration Rate (Breathing)	0.5	12	16
6	SpO2 Sensor	0.2	95	100
7	Glucose Level Sensor	0.3	70	99

6.4.2 Indicator Computational Algorithm

As stated previously, the proposed expert system begins whenever subject sensors measurements are available. For each sensor, three parameters were defined, namely their WF, minimum values and maximum values. The proposed system utilises these values to compute the related minimum and maximum range values of the **Indicator** parameter. Table 6.6 is updated by adding to it a new column that represents the actual measured value. If the actual measured value lies within the normal range, the corresponding control value is set to “0”, otherwise to “1”. Based upon this, if all the sensors’ readings are within their normal ranges, then the Control value will be “0”, and as it will be shown later, no medical condition is detected (diseases-free case). Table 6.6 depicts the Indicator computation matrix.

Table 6.6: Indicator computation matrix

Sensor rule	**WF**	**Min**	**Max**	**Actual**	**Control**
S1R	WF1	Min1	Max1	A1	C1= “0” or “1”
S2R	WF2	Min2	Max2	A2	C2= “0” or “1”
S3R	WF3	Min3	Max3	A3	C3= “0” or “1”
S4R	WF4	Min4	Max4	A4	C4= “0” or “1”
S5R	WF5	Min5	Max5	A5	C5= “0” or “1”
S6R	WF6	Min6	Max6	A6	C6= “0” or “1”
S7R	WF7	Min7	Max7	A7	C7= “0” or “1”

The developed algorithm incorporates mathematical expressions used to determine the Indicator and its minimum and maximum interval values. The system then uses this value to search within a look-up table for the corresponding disease. The Indicator for a specific disease is computed using the formula:

$$\text{Indicator} = \sum_{i=1}^{12}(WF_i)(A_i)(C_i) \qquad (6.1)$$

and the corresponding minimum and maximum for the indicator values for a specific disease are computed using the equations:

$$\text{Min\_Ind} = \sum_{i=1}^{12}(WF_i)(Min_i)(C_i) \qquad (6.2)$$

$$\text{Max\_Ind} = \sum_{i=1}^{12}(WF_i)(Max_i)(C_i) \qquad (6.3)$$

where WF_i, A_i, C_i, Min_i, Max_i and i are the WF, the actual reading of the sensor, control, minimum range values, maximum range values and the number of the sensor, respectively. The Min_Ind and the Max_Ind values are computed and saved in the disease look-up table. Each disease has an interval to identify it as appropriate and this interval is defined by the Min_Ind and the Max_Ind values. Every time a new disease is added to the database, its 'Indicator' interval is defined using equations 2 and 3. The disease look-up table is implemented as a binary search tree (BST). BSTs facilitate and accelerate the range searching processes.

6.4.3 Disease-Detection Algorithm

A detailed disease diagnosis algorithm overview can be located in Figure 6.4. First, the user's vital sign readings are inputted into the system. The sensors with readings in the normal range will have their index (control) value set to zero and the other sensors' control values will be set to 1. Then, the Indicator value is computed from the actual sensor reading's value, the sensor control value and the sensor WF value. If the calculated Indicator value equals zero, the user's vital signs are within the normal range, but if the Indicator value is greater than zero, this mean the user is suffering from a specific disease. The Indicator value is then employed to search the disease look-up table for the corresponding disease and present it as a suggested diagnosis to the patient and his/her physicians.

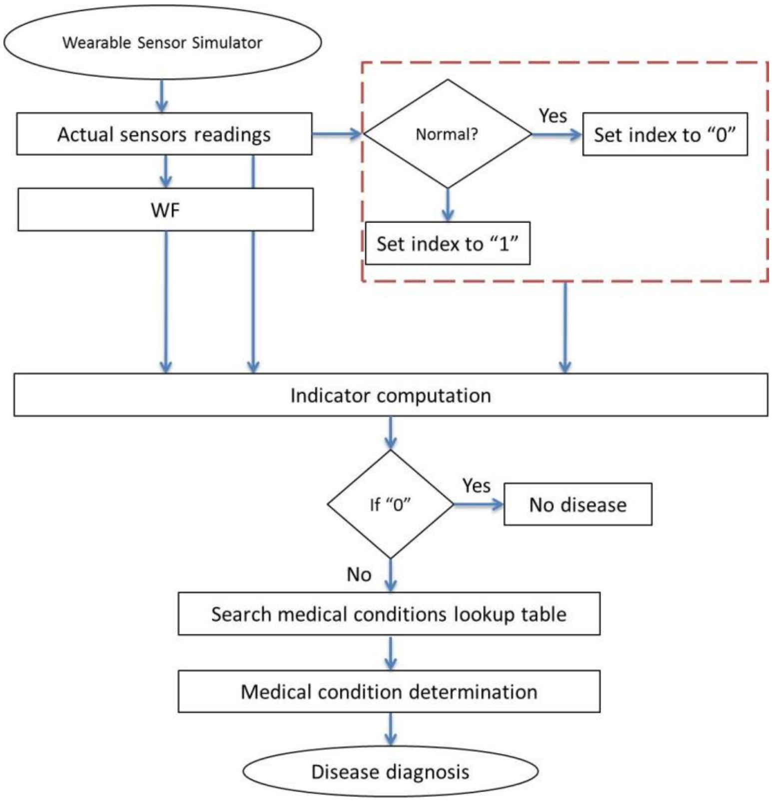


Figure 6.4: Disease diagnosis algorithm

Table 6.7 outlines the structure of the disease look-up table for four medical conditions for the sake of demonstration. As revealed through equations (2) and (3), the calculation of the corresponding disease's minimum and maximum Indicator values is independent of the actual real-time sensor reading. Indeed, all parameters for determining Min_Ind and Max_Ind have predefined values.

Table 6.7: Disease look-up table for diagnosis and identification

Disease	Min_ Ind	Max_ Ind
MC1	Min_ Ind1	Max_ Ind1
MC2	Min_ Ind2	Max_ Ind2
MC3	Min_ Ind3	Max_ Ind3
MC4	Min_ Ind4	Max_ Ind4

The proposed expert system does not require any medical information to be provided and entered by the user manually. Rather, all that is needed is to connect the sensors to the subject's body. This may require a one-time training for the user to teach them where and how to place the sensors. In fact, this is what makes the system novel versus traditional web-based medical diagnostic tools where the user needs to type his symptoms in manually provided they know the medical term for the symptoms and their correct spelling. Also, with traditional diagnostic tools, symptomless diseases will not be identified, such as hypertension without a proper sensor in place.

6.5 The Disease Search Using the Algorithm

The process of discerning the diseases using the new algorithm is depicted as a pseudocode in Figure 6.5

```
Algorithm 1 DISEASE SEARCH ALGORITHM
Input: smarEhealthSensor // Vital signs database table
Output: ehealthIndex , detectedDisease
procedure LookupTableAlgorithm(smarEhealthSensor )
    eHealthIndex ← 0
   for all row ∈ smarEhealthSensor do
       val ← row[primaryValue] // vital sign value
       wf ← row[weightFactor]/100 // weight factor
       vsMin ← row[vitalSignMin] // min normal range
       vsMax ← row[vitalSignMax] // max normal range
// we include vital sign if its value is outside normal range
        if (val >=vsMin && val <=vsMax)
          subIndex ← 0
       else
          subIndex ← val * wf
        endif
        eHealthIndex ← eHealthIndex+subIndex // update ehealth index
   end for
   for all row ∈ smarEhealthSensor do
       dMin ← row[dMin]
       dMax ← row[dMax]
        if (eHealthIndex >=dMin && eHealthIndex <=dMax)
// a disease is detected add it to disease string
          detectedDisease ← detectedDisease.row[dName]
        endif
   end for
end procedure=0
```

Figure 6.5: Pseudocode for search algorithm (Alhemairy et al., US Patent, 2016)

In the next chapter, an expert system for disease detection will be implemented encompassing the proposed algorithm above, in order to demonstrate the concept and evaluate the performance.

6.6 Further Novelty Discussion on "Algorithms for Systems based on Vital Signs"

A systematic literature review was conducted to find the most relevant publications and patents related to algorithms for detecting medical conditions from vital signs. In particular, our search focused on the following subject matter: *"***A diagnostic algorithm utilizing monitored biosensor information associated with a user's vital signs, wherein the ranges of the measurements of the vital signs could be used to diagnose a patient; the diagnosis system could be accessed via a mobile device***"*. The results of the search, analysis of those results and comments on the cited references are set out in what follows. It is worthwhile noting that these cited literature references are based on the information available to us and to the best of our knowledge, they were the extent of the published scholarly work at the moment of writing this thesis. As mentioned earlier in the Search and Methods Strategy (Section 2.3), the search concentrated on the relevancy to our proposed system from the publication-literature, where 11 cited references were identified and discussed in addition to 15 patent-literature references.

A. Non-Patent Related Work

Tia et al. (2005) proposed a system for monitoring a patient's vital signs in real-time using sensors. The system allowed remote monitoring of patient status using ad-hoc networking and web portal technology. The data from the sensors could be transmitted to a tablet device and would then be processed to detect abnormalities. The sensor thresholds were used to define particular abnormalities such that when a vital sign was outside the normal range, an alert was triggered.

The Sotera Project (Mddionline.com, 2017) introduced a platform for continuous and non-invasive monitoring of a patient's vital-signs through wearable sensors. **Sotera** is a commercial product developed by Devin McCombie and allows physicians to continuously and remotely monitor their patients at home by measuring patients' temperature, heart rate, respiration rate and blood oxygenation levels. The sensor data is transmitted wirelessly via WiFi and viewed remotely on a mobile device or a PC. Real-time notifications and alerts can be triggered when an emergency case is detected. There were no specific details provided as to how patient emergencies are detected or interventions encouraged. However, it is likely that alerts are generated when a vital sign reaches above or falls below a particular threshold. Frederick and Robert (2005) put forth intelligent agents called "Reflex Agents" that detect certain medical conditions based on the input of particular symptoms. The reflex agent essentially looks up in a list of rules in a table and responds to given input with a pre-programmed response.

Madkour and Roushdy (2004) described a fuzzy expert system for medical diagnosis, where a diagnosis decision for a particular disease was obtained based on symptoms of the patient. The symptoms were verified physically and fed into the program. Sensors could also be used to collect patient data and feed it automatically into the fuzzy expert system, which makes use of a set of 'm' diseases and defines a collective set of some features 'f' relevant to these diseases. The symptoms of a patient will be verified against all features and a fuzzy value is assigned to them. Further, the diagnosis decision for a particular disease is calculated on the basis of fuzzy value for the feature, 'f', of the input symptoms, a WF, etc. The WF used in their system was to specify that certain features could have more or less significance than others when diagnosing a disease. However, each feature will not have a weighting that would correspond to the frequency of use of that feature in several medical conditions. The input symptoms are obtained by physically inspecting the patient and manually feeding the input to the program.

In the work of (Wu et al., 2011), a system consisting of a set of intelligent physiological sensors and control nodes (internet-enabled PDA or mobile phone) was introduced. They proposed a base station and a network of remote healthcare servers and related services (e.g., caregivers, physicians). Sensors were used to gauge body vital signs and forward the readings to the control node. The control node provides a human computer interface where it communicates with the medical remote server through the base stations and hence provides specific recommendations to the patient. Further, the transmissions of sensors in different users will interfere with each other when they operate in the same region and communicate concurrently. This said, the system could not operate fully independently by itself without cooperating with other sensors used by nearby patients.

Another project from Vaidehi et al. (2012) describes an architecture for a platform based on low-power integrated circuits and lightweight medical sensors (i.e., temperature, heart rate and respiratory rate) placed on patients for non-invasive and continuous health monitoring enabled with web browsers or mobile devices. Data is transmitted in real time to a monitoring station and is displayed on a user graphical interface on the screen. The system features a premature diagnosis tool through a set of algorithms (mainly C/C++-based algorithms) to determine the vital sign values and present them to a medical human expert for their evaluation, but does not predict any disease or abnormality in the patient conditions independently apart from that of the physician.

Forkan, 2015 discussed a health-care monitoring system based on two stages. The first stage comprised collecting patient data using sensors and transmitting this data to an Android application. The second stage was the transmission of the patient data over a Femto-LTE network. In the first stage, the patient data is classified into three categories, critical, chronic and normal, while in the second stage, a scheduling decision tree schedules the data between the Femto-cell and LTE base station. The scheduling decision is based on the sensors' WF wherein the weighting factor is based on the patient's status data, i.e., critical, chronic or normal. However, each sensor will not have a weighting factor, which corresponds to the frequency of use of that sensor in several medical conditions

Gomathi Sachin (2014) reported a medical diagnosis system that provides output indicating a disease. It consists of entering some symptoms as an input to the system and the system will then perform symptom matching and calculate a probability of the disease occurring. However, it does not use sensor WFs, which, as mentioned earlier, corresponds to the frequency of use of that sensor in several medical conditions.

Hasan et al. (2010) introduced a fuzzy expert system for human disease diagnosis based on its knowledge. The user or the patient selects a problem area and the system provides the user with a set of symptoms from which they must select. Based on the selected symptoms the system asks the patient questions and based on the answers, calculates probabilities of diseases employing a total weight of a disease based on the selected symptom and total weight of unselected major symptoms of a disease as well as a catalyst factor based on patient history. The system mainly depends on the interaction between the patient and the system, where the patients will be given a number of symptoms and they have to select the symptoms that apply to their individual medical case. This system does not rely on vital sign values that are captured by the sensors directly and processed by the algorithm or check these values in the look-up table to detect the diseases automatically on a real-time basis without further intervention from the patient.

Manukov et al.'s (2016) expert diagnostics system featured a knowledge base, a database and a processor. The knowledge base system diagnosed corresponding to the inputted symptoms of a patient. The expert system processor then calculates a confidence coefficient. However, the sensor does not have a WF corresponding to the frequency of use of that sensor across multiple medical conditions.

The Clinical Decision Support System (Anooj, 2012) possesses a clinical decision support system for prediction of heart diseases. It works in two phases - an automated approach for the generation of weighted fuzzy rules and developing a fuzzy rule-based decision support system. However, the sensor does have a WF corresponds to the frequency of use of that sensor in several medical conditions.

6.6.1 Analysis and Summary:

Athorough revision and search among the most relevant systems and algorithm was conducted for "*medical condition detection from vital signs and an online disease detection expert system*" and compared the proposed system with 11 other relevant systems in terms of the key features identified. It seems that using vital sign sensor data to alert healthcare professionals of abnormalities based on sensor thresholds is quite common. However, none of these systems employed an algorithm for calculating an Indicator value to diagnose a disease. Thus, it's anticipated that calculating an Indicator using the particular formula developed and searching for that value in a look-up table to diagnose a disease would be novel and considered a potential patent application. The key features are highlighted below:

a. A predefined stage, which comprises:

1. Setting up the minimum and maximum ranges for all the sensors to be used in measuring the body vital signs;

2. Defining a weighting factor for all the sensors wherein the weighting factor of a sensor corresponds to the frequency of use of that sensor in several medical conditions;

3. Defining all the medical conditions (diseases);

b. A pre-processing calculations stage, which comprises:

1. Measuring and storing the body vital signs using the sensors;

2. Minimum multiplication for each sensor is calculated using the weighting factor;

c. A processing operations stage, which comprises:

1. setting up an index value for each sensor based on the actual measured sensor, wherein the index value is set to 0 if the actual measured sensor readings are in normal sensor ranges and the index value is set to 1 if the actual measured sensor readings are in abnormal sensor ranges;

2. calculating an indicator value, wherein:

i. the indicator value for each sensor is calculated using the weighting factor, the actual measured sensor values and the index value;

ii. Minimum and maximum interval values corresponding each indicator value are calculated;

iii. the indicator value for all the sensors is calculated using the following formula, wherein WFi, Ai, Ii, and i are the weighting factor, actual measured sensor readings, index, and the sensor reference number respectively;

$$\text{Indicator} = \Sigma_{i=1}^{n}(WF_i)(A_i)(I_i)$$

iv. minimum and maximum interval values corresponding the indicator value for all the sensors are calculated using the following formula, wherein WFi, Ai, Ii, Mini, Maxi, and I are the weighting factor, actual measured sensor readings, index, minimum value, maximum value and the sensor reference number respectively;

$$\text{Min\_Ind} = \Sigma_{i=1}^{n}(WF_i)(Min_i)(I_i)$$

$$\text{Max\_Ind} = \Sigma_{i=1}^{n}(WF_i)(Max_i)(I_i)$$

d. A medical condition detection stage, which comprises:

1. detecting a medical condition or a disease based on the indicator value, wherein the medical condition or the disease is identified by searching the indicator value in a look-up table;
2. identifying the corresponding disease using a binary search.

6.6.2 Further assessment on the literature:

From the literature review and subsequent discussion, it has been identified that the first two references were the most relevant to our proposed system and algorithm, specifically the Vital Signs Monitoring System of Tia (2005) and the Sotera Wireless Continuous Monitoring System from SOTERA (Mddionline.com, 2017). Moreover, for ease of comparison with the two relevant systems, key features of the proposed system were reviewed the in the previous section with the features mentioned and described in the most relevant references in Table A3.

Table 6.8: Compared features between: proposed system vs. two cited references

Common Features	Feature Description	Tia (2005)	SOTERA System
Pre-defining stage	A medical condition-detection system for detecting or identifying a disease comprises:	N	N
	a1) Setting up the minimum and maximum ranges for all the sensors to be used assessing body vital signs	Y	(Y)
	a2) Defining a WF for all sensors wherein the WF of a sensor corresponds to the frequency of use of that sensor across several medical conditions;	N	N
	a3) Defining all the medical conditions (diseases)	N	N
Pre-processing stage	b1) Measuring and storing body vital sign readings from the sensors;	Y	Y
	b2) Minimum multiplication for each sensor calculated using the WF	N	N
Processing operations	c1) Setting up an index value for each sensor based on the actual measured sensor, where the index value is set to 0 if the actual measured sensor readings are in the normal sensor ranges or the index value is set to 1 if the actual measured sensor readings are in abnormal sensor ranges	N	N
	c2) Calculating an Indicator value	N	N
	c2i) the Indicator value for each sensor is calculated using the WF, the actual measured sensor values and the index value	N	N
	c2ii) minimum and maximum interval values corresponding to each indicator value are calculated	N	N
	c2iii) the indicator value for all the sensors is calculated using the following formula, where **WF_i, A_i, I_i,** and **i** are the WF, actual measured sensor readings, index and the sensor reference number, respectively; $\text{Indicator} = \sum_{i=1}^{12}(WF_i)(A_i)(I_i)$	N	N
	c2iv) minimum and maximum interval values corresponding to the indicator value for all sensors are calculated using the following formula, where WFi, Ai, Ii, Mini, Maxi, and i are the WF, actual measured sensor readings, index, minimum value, maximum value and the sensor reference number, respectively; $\text{Min\_Ind} = \sum_{i=1}^{12}(WF_i)(Min_i)(I_i)$ $\text{Max\_Ind} = \sum_{i=1}^{12}(WF_i)(Max_i)(I_i)$	N	N
Medical Condition detection	d1) detecting a medical condition or a disease based on the Indicator value, where the medical condition or the disease is identified by searching the Indicator value in a look-up table	N	N
	d2) identifying the corresponding disease using a binary search	N	N

Clearly, although there is commonality between the references, they are distinct in the mechanism and our proposed algorithm has a number of unique features. For example, Tia (2005) and Sotera (2016) had several common features, such as **a1** and **b1** when referring to **Table 6.8**. However, as per the comparison, these features are very broad used frequently in most eHealth diagnosing systems. Apparently, the core features for the pre-processing and the processing operation stages were not used. For instance, setting up an index value for each sensor and calculating a unique I**ndicator** for each sensor to diagnose the medical condition is a simpler and faster method compared to a standard searching algorithm based on the captured vital signs.

B. Published Patent-Literature (Patent References)

The following **Table 6.9** corresponds to the most 11 relevant patent references from the prior-art and literature for the proposed algorithm and expert system. Apparently, none of these systems in the patent-literature made use of an algorithm for calculating an Indicator to diagnose a disease. Hence, it has been anticipated that calculating an Indicator with the particular formula developed and searching for the value in a look-up table to diagnose a disease was novel and, therefore, a patent application at the USA Patent and Trademark Office (USPTO) has recently filed. The patent holds the number **62/377,223** and a filing date of August 19, 2016, along with patent application no. **US 15/383,341** filed on December 19, 2016.

Table 6.9: Compared features between: proposed system vs. 11 cited references

	Features	**WO16095691A**	**US2014257058A**	**US2008171916A**	**SG193032A**	**US2008235058A**	**US2005010087A**	**US2015112607A**	**US2016058379A**	**US2015257654A**	**US2001029322A**	**US2002107452A**
Preamble	A medical condition-detection system for detecting or identifying a disease comprises:	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y
Pre-defining stage	a1) setting up the minimum and maximum ranges for all the sensors to be used in measuring body vital signs	N	Y	N	N	Y	Y	N	Y	Y	N	N
	a2) defining a WF for all the sensors where the WF of a sensor corresponds to the frequency of use of that sensor across several medical conditions	N	N	N	N	N	N	N	N	N	N	N
	a3) defining all medical conditions (diseases)	(Y)	Y	Y	N	N	(Y)	Y	(Y)	(Y)	Y	Y
Pre-processing stage	b1) measuring and storing body vital signs using the sensors	Y	Y	(Y)	Y	Y	Y	Y	Y	Y	Y	Y
	b2) Minimum multiplication for each sensor calculated with the WF	N	N	N	N	N	N	N	N	N	N	N
Processing operations	c1) setting up an index value for each sensor based on the actual measured sensor, where the index value is set to 0 if the actual measured sensor readings are in normal ranges or the index value is set to 1 if the actual measured sensor readings are in abnormal sensor ranges	N	Y	N	N	N	N	N	N	N	N	N
	c2) calculating an indicator value	N	Y	Y	N	N	N	Y	Y	N	Y	Y
	c2i) Indicator value for each sensor is calculated using the WF, the actual measured sensor values and the index value	N	N	N	N	N	N	N	N	N	N	N
	c2ii) minimum and maximum interval values corresponding to each indicator value are calculated	N	N	N	N	N	N	N	N	N	N	N

	c2iii) the indicator value for all sensors is calculated using the following formula, where WFi, Ai, Ii, and i are the WF, actual measured sensor readings, index and the sensor reference number, respectively $\text{Indicator} = \sum_{i=1}^{12}(WF_i)(A_i)(I_i)$	N	N	N	N	N	N	N	N	N	N	N
	c2iv) minimum and maximum interval values corresponding the Indicator for all the sensors are calculated using the following formula, where WFi, Ai, Ii, Mini, Maxi, and i are the WF, actual measured sensor readings, index, minimum value, maximum value and the sensor reference number, respectively $\text{Min\_Ind} = \sum_{i=1}^{12}(WF_i)(Min_i)(I_i)$ $\text{Max\_Ind} = \sum_{i=1}^{12}(WF_i)(Max_i)(I_i)$	N	N	N	N	N	N	N	N	N	N	N
Medical condition detection	d1) detecting a medical condition or a disease based on the Indicator value, where the medical condition or the disease is identified by searching for the indicator value in a look-up table	N	N	N	N	N	N	N	N	N	N	N
	d2) identifying the corresponding disease using a binary search	N	N	N	N	N	N	N	N	N	N	N

6.7 Summary:

The chapter has introduced a novel algorithm and mathematical model for disease diagnosing based on biological vital signs values captured by set of wearable sensors. The experiments conducted to test the efficiency of the algorithms showed that it was more efficient to search for a diagnose for a disease using the proposed algorithm rather than using the conventional methods by 10% to 48%.

Chapter 7

System Implementation and Evaluation

Chapter 7: System Implementation and Evaluation

7.1 Chapter Overview

This chapter presents the proof-of-concept results to evaluate the proposed system and perform an accuracy test following the assessment of the expert system and novel algorithm in a simulated real-time environment. In Sections 7.2.4 and 7.2.5; the algorithm performance is discussed and benchmarked with the conventional algorithm using sequential search method.

7.2 System Testing and Evaluation

In order to prove the applicability of the expert system and the algorithm in real-life situations, the main functions and components were developed and various experimental tests were performed. Afterwards, several measurements to evaluate the system's performance using the novel proposed algorithm were also conducted.

7.2.1 System Testing Setup

To validate the eHealth architecture and disease-detection algorithm, a test bench was created that consisted of three elements as presented in Figure 7.1: wearable Bluetooth sensor simulators, the medical gateway and the eHealth remote server.

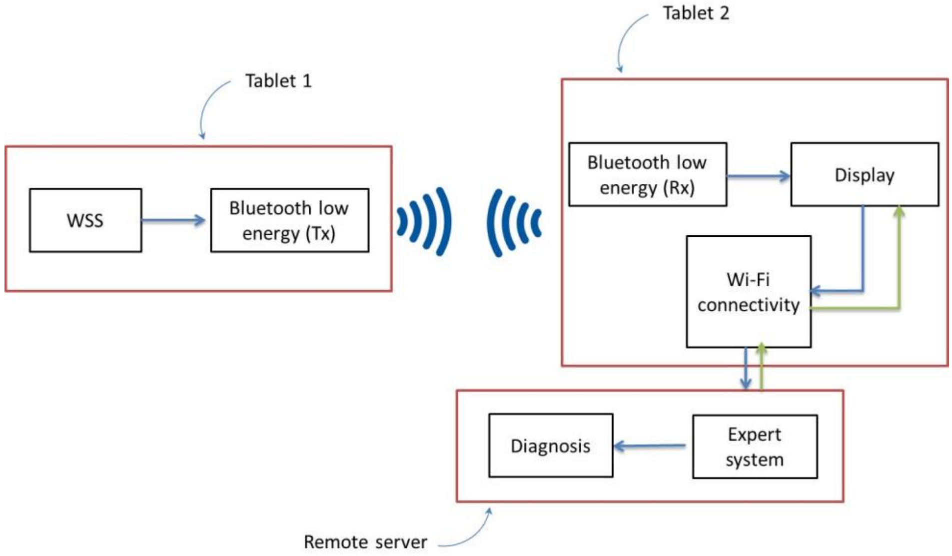


Figure 7.1: eHealth test bench

The simulator enables simulation of various medical sensors' output, and it was installed on a tablet. In the actual system, the simulator will be replaced by a set of wearable medical sensors mounted on the patient (depicted in Figure 7.2). Digital values of vital signs are sent from the simulator to the medical gateway using Bluetooth low energy wireless network technology. The medical gateway (an Android application running on a tablet) gathers vital sign readings and displays them in real-time, while simultaneously, these values are transferred to the eHealth server for further analysis and disease detection. The eHealth server analyses vital sign values using the proposed algorithm for disease detection. Once a disease or medical condition have been determined, the server transmits a notification to the patient (this notification will be displayed in real-time on the tablet) and an email alert will be forwarded to the doctor. An overview of the system design and key components are portrayed in Figure 7.2,

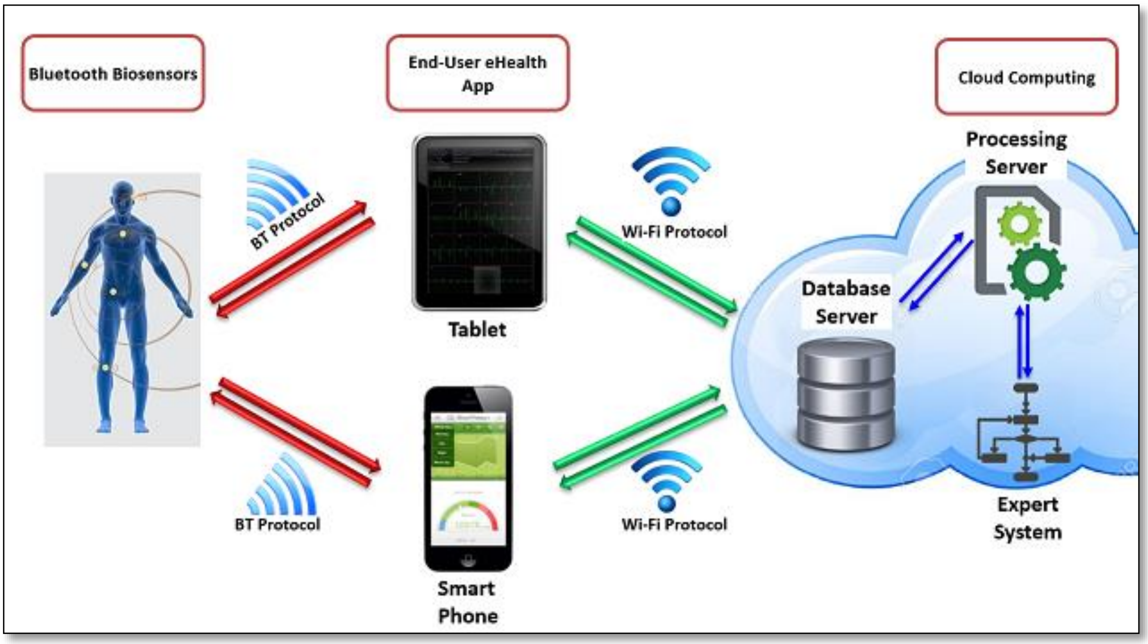


Figure 7.2: System overview and design

A software simulator with a set of virtual wearable sensors was designed to simulate specific medical conditions. The simulator's set of virtual sensor output is adjustable to correspond to a specific disease for demonstration purposes. The designed simulator can be seen in Figure 7.3.

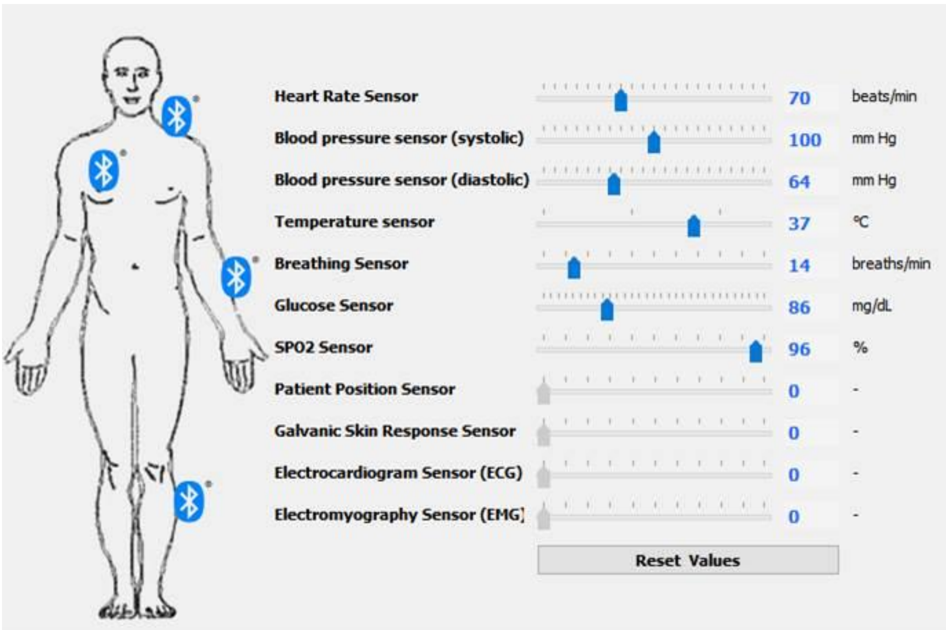


Figure 7.3: Wearable sensor simulator

The hybrid simulator sensors' configuration framework was developed to simulate the continuous transition of human vital signs from biosensors. Medical conditions can be simulated by adjusting the slider to a particular value. A decision was made during the conducted experiments to use just the first seven sensors. The remaining sensors can be activated whenever there is a need to expand the scope of disease diagnostic and scale up the system. With this, the listed medical conditions in Table 6.1 can be simulated by configuring the first seven sensors exclusively, in addition to the simulator potentially being updated to include further types of sensors. Figure 7.4 shows the sensor Normal Range Configuration form, where the physician must set up the initial normal ranges for each sensor for a patient based on their unique situation, age and gender. Once these values are configured, the online diagnostic system will immediately begin to detect any abnormal values captured from the vital sign sensors.

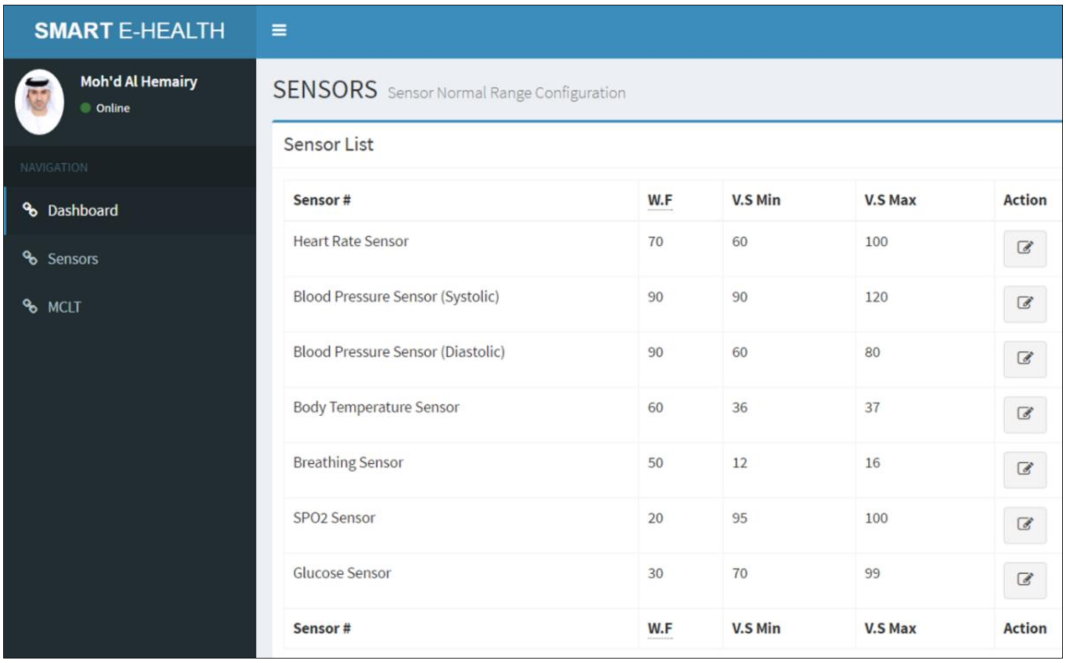


Figure 7.4: Sensor normal range configuration interface

Different communication protocols are used to transmit the collected data to the storage and processing servers, i.e., Bluetooth, Smart Ready and WiFi. The Bluetooth protocol was employed because of its short-range connectivity, low power consumption, high connectivity bandwidth and lightweight receiver/transmitter load. The WiFi protocol was chosen to connect the gateway to Cloud servers via the internet based on liability and wide-range (approx. 50 meter) connectivity. The Cloud environment was opted for because of its availability, huge processing capabilities as well as its large storage resources. The test bed for the experimental setup is depicted in Figure 7.5. The purpose of the experiment was to examine the performance of the novel algorithm detecting medical conditions. Those tests should demonstrate the efficiency of the algorithm in comparison with conventional and linear algorithms. The experiments were also to evaluate system performance in terms of data transfer rate and computational time.

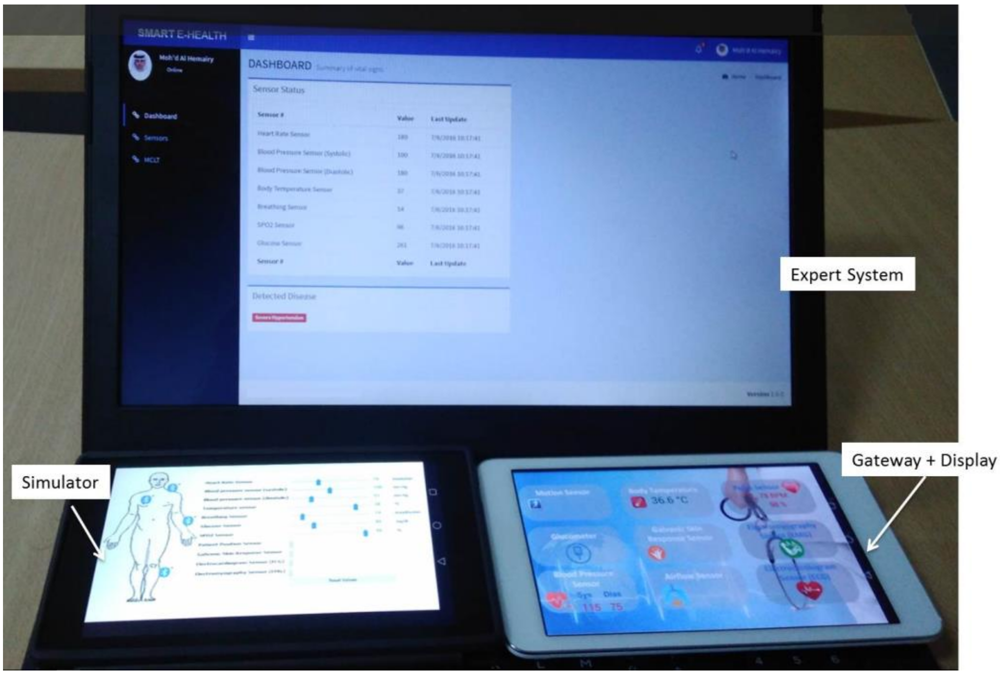


Figure 7.5: Designed system for evaluation: simulator, gateway and display

7.2.2 Bluetooth Data Transfer Time

Figure 7.6 describes the data transfer from the sensors simulator (peripheral device) to the medical gateway (called 'central'). The peripheral has an advertised interval of 300 milliseconds (ms); however the advertised time was fixed by the software to 100 ms. The Central has a scan window of 50 ms and a scan interval of 100 ms.

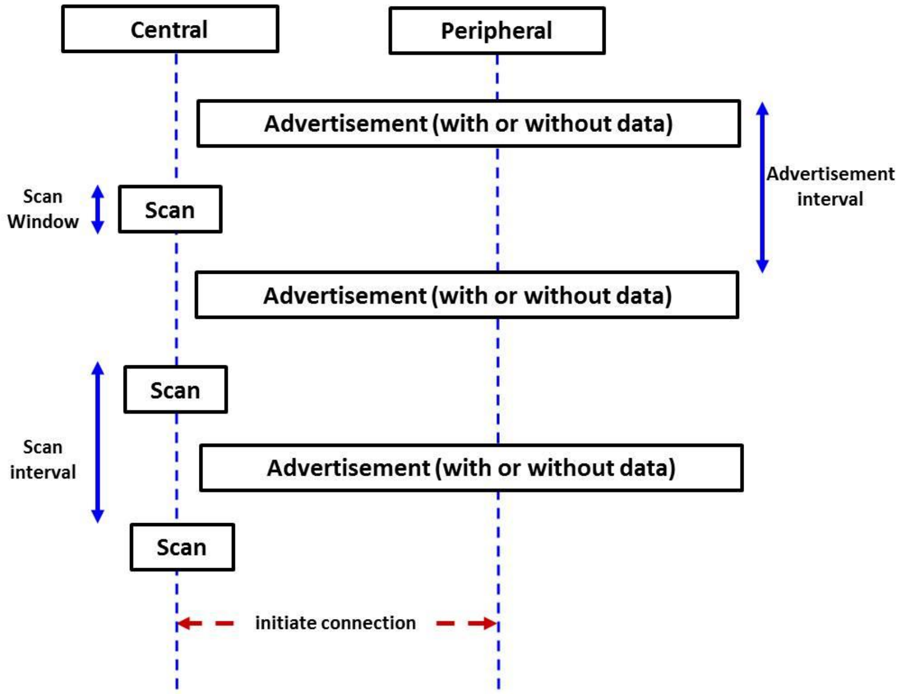


Figure 7.6: Bluetooth Smart Advertisement and scan flowchart

7.2.3 Data Transfer from the Gateway to the Server

The second test evaluated the data transfer time needed for sending data from the medical gateway to the server. Figure 7.7a shows the transfer time from the medical gateway to the server over several evaluations, while Figure 7.7b represents a comparison of time transfer performance between the eHealth Indicator and sequential search methods over a number of tests. The results in Figure 7.7a are an average of 155 ms. The x-axis represents the number of tests ran and the y-axis represents time in ms.

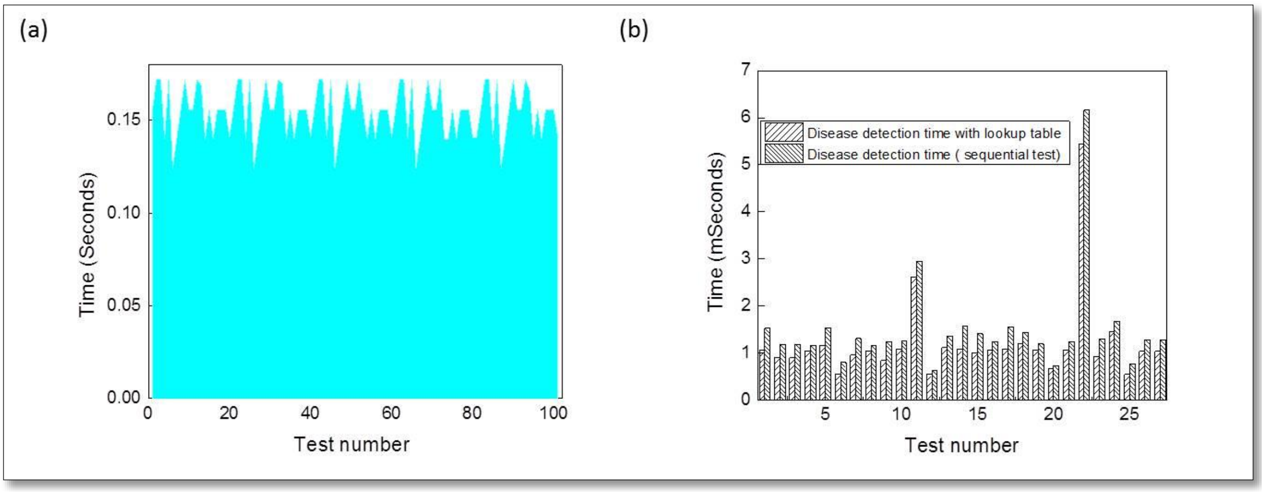


Figure 7.7: Algorithm evaluation and efficiency

7.2.4 Disease-Detection Algorithm Evaluation

The last test was primarily designed to evaluate the performance and efficiency of the proposed algorithm (Figure 6.5 in previous chapter) to detect disease. To establish the time required for disease detection, a custom script was created similar to that executed on the eHealth server to assess the differences between the proposed algorithm and any conventional algorithm by searching in a normal look-up table sequentially as exhibited in the pseudocode in Figure 7.8.

```
Algorithm 2 SEQUENTIAL ALGORITHM
Input:
heartRateValue, BPSystolicValue, BPDiastolicValue,
bodyTemperatureValue, breathingValue, SPO2Value, glucoseValue
Output: detectedDiseases
procedure SEQUENTIAL ALGORITHM( )
    detectedDiseases ← ""
     // Bradycardia: Heart Rate Sensor (abnormal ranges) min:0 max:60
    if  (heartRateValue < 61)
       detectedDiseases ← detectedDiseases + "Bradycardia"
    endif
     // Tachycardia: Heart Rate Sensor (abnormal ranges) min:100 max:200
    if  (heartRateValue > 99) && (heartRateValue < 201)
       detectedDiseases ← detectedDiseases + "Tachycardia"
    endif
    ...
    ...
     //Moderate Hypertension:
 // Blood Pressure Sensor(abnormal ranges) min:0 max:180,
 // Blood Pressure Sensor (Diastolic) min:0 max:110
    if  (BPSystolicVal < 181) && (BPressureDiastolicVal < 111)
       detectedDiseases ← detectedDiseases + "ModerateHypertension"
    endif
     // Severe Hypertension:
 // Blood Pressure Sensor (abnormal ranges) min:180 max:360,
 // Blood Pressure Sensor (Diastolic) (abnormal ranges) min:100 max:200
     if  (BPSystolicVal < 361) && (BPSystolicVal > 179) &&
 (BPDiastolicVal < 201) && (BPDiastolicVal > 99)
       detectedDiseases ← detectedDiseases + "SevereHypertension"
    endif
    return detectedDiseases
end procedure=0
```

Figure 7.8. Pseudocode for a sequential search (Alhemairy et al., US Patent, 2016)

The script included measurement functions that gauged the time required to execute the following tasks:

- eHealth Indicator calculation time;
- Disease search time in the look-up table;
- Total disease detection time using eHealth Indicator and a look-up table.

- Disease-detection time with conventional sequential algorithm (Gurevich, 2000) (vital signs are compared with the normal and abnormal ranges of each sensor)

In Table 7.1, disease-detection time using the eHealth Indicator values and the look-up table are presented. It is clear that the algorithm is much faster than the conventional sequential algorithm. The algorithm makes use of an access to the database in order to garner real-time vital signs and to verify medical conditions, with the time needed for calculation changing depending on server load. Therefore, some tests were conducted on a dedicated local host instead of a Cloud-based server to avoid the server load factor. During all the tests that were conducted; the performance observed of the method utilised in the algorithm for calculating the Indicator; **was faster by between 10.66% and 48.26%** compared with other search techniques, such as Sequential Search (Gurevich, 2000).

Table 7.1: Computation time lapsed over different tests (all times in seconds)

TEST N°	eHealth Indicator Value (seconds)	eHealth Indicator Calc. Time **(A)**	Time to Search for Disease in Look-up Table **(B)**	Disease-Detection Time Using Indicator **C = A+B**	Disease Detection Time Using Sequential Test **(D)**	Delta Time % Δ= (D * 100/C) - 100	Detected Diseases
1	376.900	0.000898	0.00015800	0.001056	0.001527	44.63%	Severe Hypertension
2	48.500	0.000786	0.00011500	0.000901	0.001184	31.42%	Hypotension / Diabetes / Moderate Hypertension
3	176.400	0.000786	0.00011500	0.000901	0.001184	31.42%	Asthma Severe / Moderate Hypertension
4	189.200	0.000816	0.00021900	0.001035	0.001165	12.53%	Asthma Severe / Moderate Hypertension
5	0.000	0.001005	0.00015300	0.001158	0.001534	32.43%	// No Disease Detection
6	111.400	0.000473	0.00008300	0.000556	0.000795	43.04%	Tachycardia / Asthma Severe / Moderate Hypertension
7	132.300	0.000804	0.00014800	0.000952	0.001305	37.10%	Tachycardia / Asthma Severe / Moderate Hypertension
8	21.700	0.000816	0.00021900	0.001035	0.001165	12.53%	Bradycardia / Hypotension / Respiratory Arrest Imminent / Moderate Hypertension
9	35.000	0.000688	0.00014500	0.000833	0.001235	48.26%	Bradycardia / Hypotension / Pre-Diabetes / Respiratory Arrest Imminent / Moderate Hypertension
10	111.300	0.000898	0.00018400	0.001082	0.001252	15.69%	Tachycardia / Asthma Severe / Moderate Hypertension
11	133.000	0.002494	0.00012700	0.002621	0.002945	12.37%	Tachycardia / Asthma Severe / Moderate Hypertension
12	221.000	0.000461	0.00007900	0.000540	0.000632	17.09%	Moderate Hypertension
13	53.800	0.000868	0.00024200	0.001110	0.001351	21.67%	Hypotension / Diabetes / Moderate Hypertension
14	64.200	0.000919	0.00015000	0.001069	0.001561	46.00%	Hypotension / Diabetes / Moderate Hypertension
15	94.800	0.000847	0.00015600	0.001003	0.001403	39.93%	Tachycardia / Asthma Moderate / Moderate Hypertension
16	71.400	0.000873	0.00019300	0.001066	0.001245	16.80%	Tachycardia / Hypotension / Diabetes / Moderate Hypertension
17	30.500	0.000889	0.00019500	0.001084	0.001554	43.32%	Bradycardia / Hypotension / Prediabetes / Respiratory Arrest Imminent / Moderate Hypertension
18	376.900	0.000994	0.00019600	0.001190	0.001434	20.49%	Severe Hypertension
19	48.500	0.000899	0.00016300	0.001062	0.001190	12.02%	Hypotension / Diabetes / Moderate Hypertension
20	21.700	0.000559	0.00010300	0.000662	0.000733	10.66%	Bradycardia / Hypotension / Respiratory Arrest Imminent / Moderate Hypertension
21	166.500	0.000873	0.00019300	0.001066	0.001245	16.80%	Asthma Severe / Moderate Hypertension
22	8.800	0.005223	0.00020700	0.005430	0.006163	13.49%	Bradycardia / Hypotension / Hypoxaemia / Tachypnea / Moderate Hypertension
23	195.300	0.000780	0.00013800	0.000918	0.001296	41.15%	Asthma Severe / Moderate Hypertension
24	241.300	0.001247	0.00021000	0.001457	0.001674	14.89%	Moderate Hypertension
25	221.000	0.000461	0.00007900	0.000540	0.000775	43.43%	Moderate Hypertension
26	221.000	0.000878	0.00015100	0.001029	0.001284	24.74%	Moderate Hypertension
27	264.600	0.000878	0.00015100	0.001029	0.001284	24.74%	Severe Hypertension

When compared to the conventional linear (sequential) search method for finding the target rule in a list and triggering its action, which checks each and every rule in the list until it finds the matching rule or all the rules are searched without finding a match, the online tool developed to test the algorithm's performance in real-time in detecting disease showed certainly improved performance as best possible. Figure 7.9 is a screenshot of the online test; where the time to search in the lookup tables for a matching record to determine a disease for both methods are compared. The sequential search method requires further time to search in a huge lookup table and involving firing a larger number of rules. The experiments showed that the search using the proposed algorithm is faster due to use of the e-Health Index that checks a matching interval for each disease; while in the sequential search methods; the larger number of diseases are; the slower the system will be in detecting the disease.

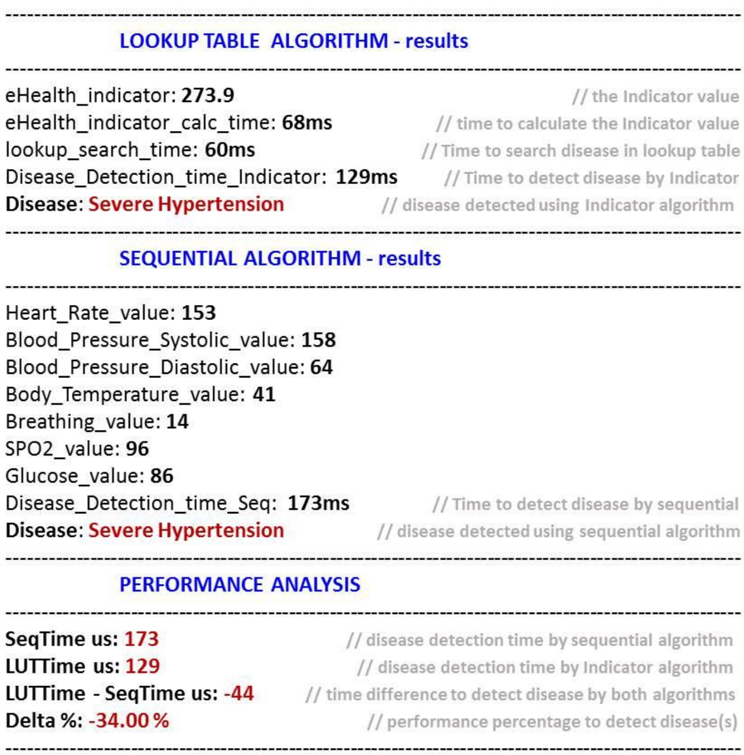


Figure 7.9: Real-time algorithm testing for disease detection performance

While, in the proposed method where the calculated Indicator value will be matched with the matching value in a lookup table to find the corresponding disease. For example, to detect "**Severe Hypertension**" with both algorithms based on the given vital signs from the sensors, the sequential search algorithm took **173** ms to detect it while the Indicator algorithm needed only **129** ms. Following this process raised the performance up **34%** for this particular medical condition. So for example, if there are 1,000 various medical conditions in the searching database; then using the algorithm will reduce the time required to find a match by 34% from 173,000 ms (about 2.8 min) to 129,000 ms (2.1 min), which means a huge impact on the system's performance and response time – given that there are hundreds or even thousands of patients registered in the system that are waiting for their diagnosing of their vital signs readings on the fly.

7.2.5 Disease-Detection Algorithm: Accuracy Test

To measure the accuracy and efficiency of the proposed algorithm, a set of medical conditions were defined for certain selected diseases, where those diseases were the type to be reflective of vital sign value changes, not simply have visible effects on the body, such as skin rash, swelling or red eye. The reason is because the algorithm is dependent on medical sensors to measure vital signs and therefore, only the diseases that are associated with a change in vital signs' values can be detected.

The set of selected diseases associated with vital sign changes were adopted from "Current Medical Diagnosis and Treatment" (Papadakis, McPhee and Rabow, 2016). Roughly 18 diseases were selected. A sample of the predefined diseases, corresponding vital signs with abnormal ranges and the type of sensors that capture the vital signs are described in the look-up table 6.1.

For each of the diseases, two medical conditions were defined with two different sets of vital sign values (total 36 medical conditions). For example, Bradycardia (abnormally slow heart rate) can be defined by the following two data sets:

1- **Heart rate = 58, blood pressure - systolic = 110, blood pressure – diastolic = 65, SPO2 = 99, temperature = 36, respiration rate = 17, glucose = 100; and**
2- **Heart rate = 52, blood pressure systolic = 116, blood pressure diastolic = 70, SPO2 = 98, temperature = 37, respiration rate = 15, glucose = 101.**

In other words, heart rate could be below 60 while all other vital signs are within normal ranges. In addition to the 36 medical diseases defined, 4 normal cases were also defined where all vital signs were within normal range. In total, a set of 40 medical conditions were used to test the accuracy of the algorithm. The other four medical cases represent some normal health status, where no significant change in the vital signs are observed, and are used to test if the algorithm can differentiate between normal and abnormal cases.

One of the challenges of applying the developed algorithm was that it supplied multiple diagnoses for completely different medical conditions. This was because the Indicator range for several diseases in the look-up table is overlapping. To resolve this, the intersection between these diseases are need to be eliminated, using the following technique:

- **Adding the measurement unit of the sensors to the disease set (i.e., beats/min for blood pressure). The unit is represented as a binary number of seven digits, each digit representing a sensor; where a value = 0 meant the vital sign was normal and**

1 if it was abnormal. For example, the set, "1 000 000", meant that the heart rate was abnormal, while "1 100 000" signified that both heart rate and respiration rate were abnormal, and so on. Consequently, if two diseases represented two different medical conditions with the same Indicator value, the algorithm should be able to differentiate between them.

The algorithm accuracy in identifying the 40 medical cases uniquely was nearly 92.5%. In other words, the algorithm was able to identify correctly and uniquely 37 cases out of the 40 (37/40% = 92.5%). Only three medical conditions were not identified independently by the algorithm, meaning that for only three medical cases, the algorithm gave more than one possibility for the detected disease. These three medical conditions were asthma moderate, asthma severe and respiratory arrest imminent. The challenge with the aforementioned diseases is that they rely on exactly the same set of vital signs, and as such, the same disease unit is generated for them while there is also an intersection between their Indicator ranges. As described above in this section, in case of there will be more than one detected disease for two different medical conditions; a new technique was implemented to use a "measurement unit" to differentiate between the two or more cases, were each unit is consisting of 7 digits (either 1 or 0). Therefore, this high combination technique can differentiate between numerous number of diseases in case there is an overlapping or intersection between various symptoms.

7.3 Discussion

There were no human subjects involved in this study. The simulator shown in Figure 7.3 was set up to record the virtual sensor readings. In order to demonstrate the applicability of the expert system's algorithm in real situations, the main functions were developed and various experimental tests were also performed. After, we conducted several measurements to evaluate the system's performance using the new algorithm in comparison with the conventional linear (sequential) method. The search method outperformed the sequential search method, which checks each and every rule in the list until it finds the matching rule or all the rules are searched without finding a match. The eHealth Server is hosted and accessed on the Cloud and involves the eHealth expert system. It is connected with the gateway through the internet using a WiFi network. The server stores the vital signs for disease detection. Different communication protocols are employed to transmit the collected data to the storage and processing servers, i.e. Bluetooth, Smart Ready and Wifi. The Bluetooth protocol was chosen based on its short-range connectivity, low power consumption, high connectivity and its lightweight receiver/transmitter, while the WiFi protocol connected the gateway with the Cloud servers via the internet because of its liability, and wide range (approx. 50 m). Figure 7.10 shows the eHealth Dashboard for online disease detection based on vital sign changes in real-time. As can be observed, two diseases were detected, Asthma Severe and Moderate Hypertension, based on the changes in the sensor values (body conditions).

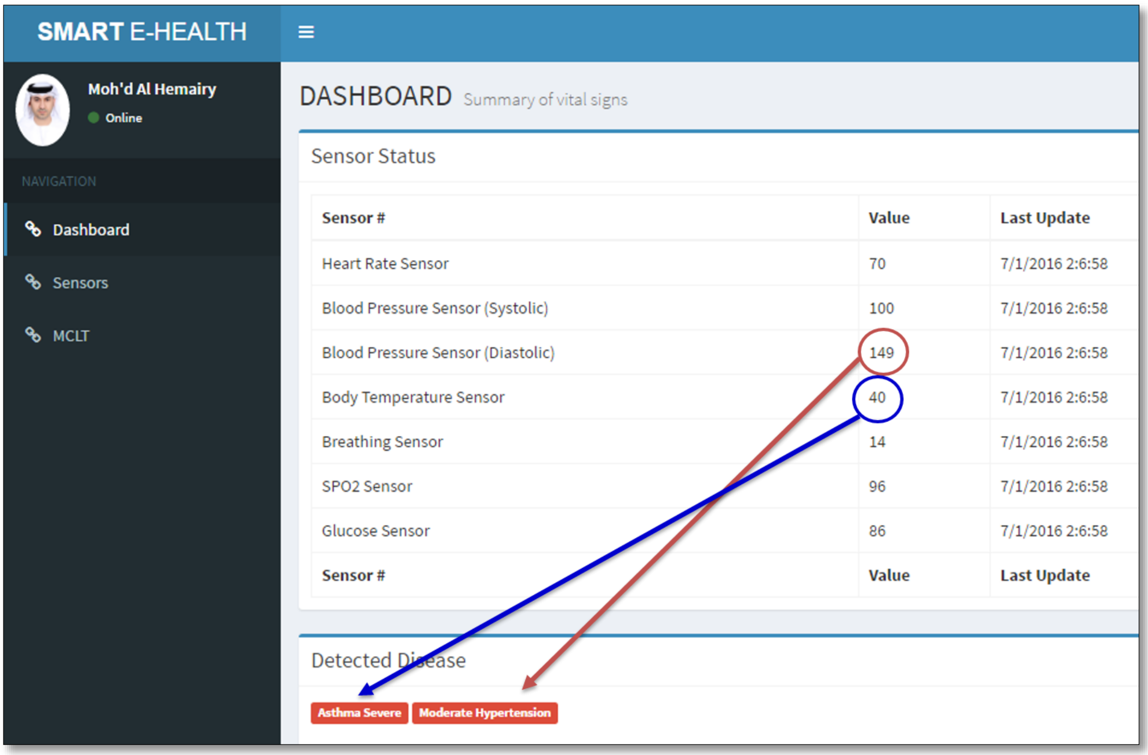


Figure 7.10: Detected disease based on changes in vital signs in the simulator

7.4 Summary:

In summary, a systematic procedure for a self-diagnosis disease support system was developed and tested. The system incorporates several medical conditions, and each is associated with specific symptoms and vital sign values that are mapped directly to several kinds of sensors and their readings. The proposed disease diagnosis approach begins with reading the user's real-time vital signs through a wearable sensor system. Two variables were introduced - the control to account the sensor output range and whether it is normal or not, and the weighing factor (WF) to determine the significance of the contribution of the corresponding sensor. As explained, the developed algorithm incorporates new mathematical expressions used to determine the Indicator and its minimum and maximum interval values. The system then uses this value to search for predefined diseases in a look-up table. This system aids in assessing the physical health of a person by providing a diagnosis of possible diseases and checking treatment progress. The evaluation process was performed exhibit the superiority of the algorithm over traditional techniques. However, there are still more improvements that can be made to increase the performance of the algorithm, rendering it a more effective technique for medical expert intelligent systems with fewer CPU resources needed and accordingly enhanced energy consumption savings.

Chapter 8

Conclusions and Future Work

Chapter 8: Conclusions and Future Work

8.1 Chapter Overview

This chapter provides an overall summary of the work reported here and assesses the efficiency of the proposed model and algorithms (Section 8.2). What the contributions are to the knowledge gaps filled and the innovative achievements of the study are also highlighted in Section 8.3. At last, future research opportunities are discussed in Section 8.4.

8.2 Conclusion

As the world population ages and the old-age support ratios diminish, innovative and smart healthcare administration is necessary. The foundation of future healthcare delivery is through the adoption of remote health-monitoring technologies. While significant research and development efforts are currently underway, several barriers related to costs, industry standardization, regulatory frameworks, user acceptance, data privacy and security and others have yet to be addressed. The proposed monitoring framework leverages various emerging technologies, including biosensors, mobile technologies and communication media to develop reliable, efficient and complete solutions that can readily scale based on the number of users, sensors and homes. Moreover, the proposed algorithm for disease diagnosis introduced a new numerical method for calculating a single digital value for diagnosing diseases based on abnormal vital sign values. This will open the door to further development in continuous healthcare monitoring systems and resolve the challenge of dealing with large numbers of patient records and numerous medical conditions and symptoms, facilitating the widespread adoption of remote health-monitoring technologies in our lives.

8.3 Findings with regards to Research Questions:

This research provided answers to the following research questions:

Question 1: How can existing healthcare solutions be classified and compared? What comparison criteria should be used?

Answer: from the literature survey conducted on the existing classification of healthcare systems, few references were located that could be classified under healthcare systems. For example, a comparison of the approaches was been carried out against certain features, i.e., security enabled, mobile aware and integration support (Kenny, 2006). Another study (Orwat et al., 2008) reviewed healthcare systems with features such as mobile devices, stationary devices, implanted devices, wearable sensors and context awareness. In this work, two common types of PHT solutions were chosen: (1) non-commercial academic solutions (prototypes); and (2) industrial applications. Alternative sets of criteria were selected based on features equipped within the systems and were used to differentiate significantly between healthcare solutions that have been developed lately.

The features in question were: *non-intrusive, security enabled, mobility aware, support integration and context awareness*.

Q1.1 Which comparison criteria will discriminate between health-monitoring solutions?

Answer: as stated earlier, existing healthcare solutions can be discriminated by having the following features: non-intrusive, security enabled, mobility aware, support integration and context awareness. Herewith a brief on each feature:

Non-intrusive healthcare solutions are characterized by their ability to be used without disturbing the normal life and activities of a patient under observation i.e. wearable sensors, while a **Security Enabled** system secures patient's information and privacy. The **Mobility-Aware** system includes using the mobile device to update the physicians of the patient's status and activities while they are anywhere and anytime by connecting the biosensors to backend systems i.e. Wi-Fi, 3G, 4G, and Bluetooth. **Integration Support** platforms are devices having features that enable the communication and interoperation across heterogeneous Healthcare platforms regardless of their infrastructure and architecture, which in turn provides the patients with highest level of care and quality treatment, using the standard protocols. Finally, a **Context-Aware** device collects contextual data from different sources and provides the physicians with hints about patient's profile trends while it ensures the integrity and confidentiality of the patient's information at the same time.

Q1.2 How to provide comprehensive categorization and comparison between different healthcare solutions?

Answer:

A comprehensive framework for health monitoring and disease diagnosis should exhibit the following features:

i. Provides an integrated and customizable platform implemented using a set of sensors and actuators within the subject's home environment supporting medical data acquisition in a seamless and non-intrusive manner without disturbing the ADL of the subjects.

j. Provides healthcare professionals with access to medical data acquired at home, enabling healthcare professionals to monitor the medical conditions of the subjects remotely and pervasively (anytime and anywhere).

k. Generates real-time alerts for healthcare professionals to garner timely and effective intervention depending on the medical condition of the subject being monitored.

l. Outputs real-time advice related to treatment and medication depending on the health condition through suitable display devices.

m. Makes available real-time nutritional advice related to diet programs, sport practices and nutrition plans for preventive health management.

n. Enables time and cost-efficient administration of healthcare services to residents at home, in elderly care centres or remote communities.

o. Facilitates early discharge of non-vital cases to resume their normal lives at home in a reliable and safe environment while enabling continued monitoring of their health conditions for the desirable length of time.

p. Engenders health authorities with access to medical data of elderly individuals suffering from chronic diseases over a long-term period, fostering data analytics and establishing patterns regarding chronic diseases in a region and other statistics for health-related issues.

Question 2: Does the existing healthcare-monitoring framework offer an efficient and comprehensive solution?

Answer:

Generally, healthcare monitoring systems introduced either from academia or industry are disease oriented platforms. They are very specific in monitoring certain health issues, such as heart failure and blood pressure, as well as warning the patient or the physician of any detected abnormalities. This may reveal certain limitations in terms of integration, interoperability and scalability. Other systems have attempted to be more comprehensive but they lack intelligence or decision support algorithms. In this research, a comprehensive framework has been introduced that covered most of the required features for monitoring patients (remotely) clustered in a modular structure, making it flexible and scalable by adding or removing further modules or features without affecting the other modules or interrupting the platform’s core operations. Besides, a new concept was also introduced for collecting medical knowledge from external databases, like social networks, and utilizing it in decision support of the expert system and learning techniques.

Q2.1 What are the main features of the new proposed framework in this study beyond the current state of the art?

Answer:

The key differentiator of the proposed framework for providing remote health monitoring is the **modular architecture** with clearly defined interfaces between the various modules and standardized communication protocols, enabling scalability, interoperability and smooth integration, creating a very comprehensive solution. Moreover, it was found that the proposed framework comprised distinctive concepts and novel features versus existing solutions in the prior art. Although the general concept of health-monitoring architecture is known, the combination of prompting manual intervention by a medical expert and generating urgent warnings – in cases of emergencies – are novel.

In addition, the decision to employ different **filtering techniques**, including **low-pass filters**, **high-pass filters** and **noise removal** to eliminate noise, errors or invalid values was considered different from other remote health-monitoring systems. Also, the integration of the **Social Network Analytics Module** to acquire health data from social networks (i.e., Twitter, Facebook) enhanced the knowledge base of the expert system and enriched the overall framework with a huge amount medical data available nowadays.

Q2.2 Do the exiting healthcare classification models capture all possible key features, such as non-intrusive, security-enabled, mobility-aware, support integration and context-aware?

Answer:

To the best of our knowledge, there was no comprehensive classification model from the literature that addressed and compared all the key features mentioned. Therefore, such a model will be very helpful for the interested stakeholders in this research area (academia and industry). However, in this study, interesting relationships and patterns were present in commercial and non-commercial pervasive healthcare solutions as well as common features. For further details on the outcomes of the comparison between healthcare solutions and the classification criteria, refer to Section 4.5.

Q2.3 To what extent should a healthcare solution posses smart features? What are the key barriers that challenge their implementation?

Answer:

The features already described can increase the efficiency of healthcare solutions. However, there is an innovative trend to integrate advanced smart features, such as:

a) Smart behaviour;

b) Data intensive management.

These smart features will characterize the next generation of healthcare solutions and eventually add value to the sustainability of healthcare solutions. Herewith a brief on smart features:

A. Smart Pervasive Healthcare

Smart healthcare solution refers to an end-to-end architecture that intelligently implements unique features such as: self-adaptation of services in different contexts and reacts proactively to critical situations. They behave autonomously to respond to different conditions and requirements in three cases: Self-adaptive, Proactive, and Autonomous behaviours.

B. Data Intensive Management:

Apparently, Healthcare Monitoring Systems generate a huge amount of data resulting from executing different types of operations, including monitoring and gathering health related data continuously and instantaneously, which require high performance data centres, powerful servers and advanced data analytics tools. Therefore, a healthcare solution utilizes today the new technology revolution evolving Cloud infrastructure for high performance, scalable and reliable healthcare services. Advanced processing and analytics tools could be used for intensive health data processing; for example; *NoSQL* and *Hadoop* platforms.

Question 3: What are the main features of the new proposed algorithm for health diagnostics in this study that are beyond the current state of the art?

Answer:

The novel algorithm that is developed within this study has distinctive features that can be used to develop a medical condition detection system; the following represents the key features of our proposed algorithm:

- **Measuring body conditions using a set of sensors;**
- **Defining a WF for each of the sensors;**
- **Calculating an index value based on the measured sensor values;**
- **Calculation of an Indicator based on the WF, index value and the measured sensor values;**
- **Detecting a medical condition (disease) based on the Indicator by searching for the indicator value in a look-up table.**

Following this process raised the performance up 48.26% for a particular medical condition over conventional methods.

Q3.1 Can expert healthcare systems based on vital signs data collected from sensors provide high efficiency such that it is beyond the current state of the art?

Answer:

Expert systems for healthcare is thought to be an established area of research, and there are numerous industrial products and prototypes available nowadays. Most of these existing prototypes claim efficiency and high performance. However, they are not necessary fulfilling the purpose of their use. In this study, a novel algorithm was developed for implementation in an online platform for disease diagnosis based on vital sign data captured from a set of wearable sensors to be used for continuous monitoring and in real-time.

It was also found that the proposed diagnosing algorithm was faster and more efficient over conventional search methods for calculating the health Indicator value and diagnosing the medical condition(s), with an average between 10% and 48% efficiency than the sequential search methods.

Moreover, the accuracy of the algorithm considering more than 40 medical conditions reached 92.5% if the diseases did not intersect with the abnormal ranges of other vital signs or the Indicator's ranges.

8.4 Future Work

This thesis proposed a comprehensive framework for health monitoring and an algorithm for disease diagnosis. What is proposed in this thesis addressed several problems discovered in the literature and offers an efficient and scalable solution to be adopted by healthcare providers and industrial manufacturers.

With respect to future work, there is still room for a number of research endeavours that would enrich the contributions of this work. The following are is a list of such directions:

- Explore social networks together with sensory data and retrieve health information that may expand the monitoring system with new situations, potentially leading to the development of new rules.
- Implement and integrate the Social Network Analytics Module to retrieve data from social networks with sensory data to offer better insights.
- Implement and evaluate the model on a large-scale and within a real environment where stakeholders are involved. This would include large numbers of patients considering varied health situations and target elderly care centres, hospitals and physicians at hospitals.
- Extend the healthcare monitoring framework and diagnosing algorithm to work with more vital signs and learn the correlation between them.
- Resolve the accuracy issue concerning diagnosing more than two diseases relying on the same set of vital signs, having the same disease's unit and overlapping in their Indicator value ranges.
- Conduct further clinical trials on in-patients at elderly care centres and outpatients within their homes to validate the holistic healthcare monitoring framework and the novel diagnosing algorithm proposed in this study in a real environment.

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Appendixes:

APPENDIX [1]: US Patent Application #1

SYSTEM AND METHOD FOR REMOTE HEALTHCARE

APPENDIX [2]: US Patent Application #2

DIAGNOSTIC METHOD AND SYSTEM