IoT Enabled Mobility Based Healthcare Monitoring and Implementation of Prediction Model

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Dedication

I dedicate this thesis to Lord Sai Almighty my creator, my strong pillar, my source of inspiration, wisdom, knowledge and understanding. He has been the source of my strength throughout this program. This dissertation is also dedicated to my family members, particularly my son who encouraged me to pursue my dreams and finish my dissertation. They were good source of inspiration in these six years long journey in completing my work. This work is also dedicated to mother who has always loved me unconditionally and whose good examples have taught me to work hard for the things that I aspire to achieve.
Thank you.

DECLARATION

I **Smt Suneeta Sadanand Raykar**, hereby declare that this thesis represents work which has been carried out by me and that it has not been submitted, either in part or full, to any other University or Institution for the award of any research degree.

Place: Taleigao Plateau
Date: **Suneeta Sadanand Raykar**

CERTIFICATE

I certify that the work was carried out under my supervision and may be placed for evaluation.

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Suneeta Sadanand Raykar

Thesis Approval

This thesis entitled **"IoT Enabled Mobility Based Healthcare Monitoring and Implementation of Prediction Model"** by Name is approved for the degree of **Doctor of Philosophy in Electrical and Electronics Engineering.**

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Supervisor:

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Principal:

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Abstract

Significant advances in technology in medical science lead to the enhancement of virtual patient monitoring and prediction of health status. As per the statistics gathered 71% of the elderly population reside in rural areas while 29% in urban areas of India. Rural residents often encounter barriers to avail of good healthcare facilities. Due to nonavailability of services, awareness about health parameters and afford to bear high costs in getting medical service will limit their ability to obtain the care they required. There is a need to provide sufficient preventive care to the elderly people of rural India to improve their healthcare facilities. As there is a rise in health problems, providing health assistance to every member is important. But the ratio of doctor to patient is significantly low (1:1000). The time required in scheduling appointments, waiting time in queue, traveling a long distance to consult the physician results in the several challenges in hospital centric system.

Internet of Things(IoT) has become most productive in the area of healthcare to improve the quality care of the patient health. IoT drives the hospital centric system towards patient centric system. IoT aims to reduce human intervention in the decision and decrease the involvement of human operators. Today it is acknowledged that a body area sensors network (BAN) assists in increasing the quality of life (QoL) and reduces major catastrophes by alerting the patient at an early stage. In traditional healthcare most of the patients had to stay in the hospital throughout their treatment period. This increased the cost of treatment and also strained the facility at rural and remote locations. Technological advancement has now allowed health monitoring using simplified hardware devices. Digitization of healthcare services helps the elderly patient to seek advice from medical experts remotely, thus reducing the difficulty of staying in the hospital for a longer duration.

This research work explores the innovative idea of bringing the patient closer to the doctor during the inaccessibility of expert doctors in their locality. However, an existing method used many sensors to record the patient's condition, which can be costly and inconvenient. The features required to be integrated in the healthcare unit used in monitoring the health parameters should be affordable in its cost. It should have a wearable unit able to carry along with the patient without affecting person's regular activities and free from any surgical intervention. Research work was carried out to design an IoT assisted hardware framework with the integration of machine learning prediction model using mobile application. This application supports in obtaining the timely diagnosis of disease.

The prediction model is analyzing a patient's biological data sensed by a smart medical IoT device ("ALERT") developed in this work. Sensors share the vital parameters of the

human body without personal participation.

A hardware unit that can collect data from the patient and send real-time information to the doctor/physician helps in virtual monitoring. Advancement in sensor technology and connectivity technology will make the device to collect, record, and analyze the data, that was not accessible in the traditional healthcare system. Regular monitor and recording of data can be used in the preventive care of the patient. Machine learning algorithm was developed to build the prediction model which helps the doctor to analyze the patient data and determine the likely chances of the disease.

The user-friendly graphical interface application for prediction model was developed on desktop and mobile terminals. The application assists medical experts to quickly predict the chances of getting cardiovascular and diabetes disease. The proposed system used the newly proposed Random Forest algorithm with Lasso Regularization method for feature selection to construct the prediction model. The dataset was retrieved from Cleveland and Mendeley data repository. The user interface designed using application gave 90.16% accuracy rate in predicting heart disease. The system was also added with the diabetic prediction model to predict the chances of getting diabetes and it responded with an accuracy of 95.83 %. Comparison of the different machine learning techniques were carried out. Performance analysis carried out assisted in deciding which algorithms were more suitable to predict the chances of diabetes/ heart disease.

A smart application assists the health experts to provide suggestions and advice to the patients remotely. Various sensors such as the ECG, temperature, oxygen saturation, and pulse rate sensors with a microcontroller terminal has been implemented. Sensor data validation was performed to avoid the risk of anomalies in the sensor data or false triggering. Smart mobile application was designed to monitor the patient's data virtually by looking into the details of health parameters, and report the readings collected from the sensors. Doctor's and Patient's lounges were developed to monitor, analyze and report the health conditions using the mobile application.

Keywords:**Healthcare, Internet of Things, Prediction model, Wearable sensor, Mobile applications.**

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List of Abbreviations

API Application Programming Interface

BAN Body Area Network

B-MAC Baseline Media Access Control

CSV Comma Separated Variable

CAC Controller Application Control

CTS Clear To Send

DSS Decision Support System

EHR Electronic Health Record

GTS Guaranteed Time Slot

HR Heart Rate

IoT Internet of Things

IoMT Internet of Things in Medicine

JSON Java Script Object Notation

MAC Media Access Control

QoL Quality of Life

RTS Request to send

VSMS Vital Sign Monitoring System

WBAN Wearble Body Area Network

WSN Wireless Sensor Network

XMPP Extensible Messaging and Presense Protocol

Chapter 1

Introduction

1.1 Overview of the Internet of Things

The Internet of things (IoT) is set to transform many aspects of our lives. Development of biomedical sensors and the availability of high bandwidth, mobile health (mHealth) systems are now offering a wider range of new services. New technology helps and provides a solution for in-home health monitoring. The IoT enabled connectivity has the potential to catapult the present ailing healthcare system into an integrated, efficient, and patient-centric system. With the pervasiveness of mobile devices across the country, communication digitally is now available in the remotest of the rural areas. This provides establishing connectivity between different healthcare settings [1]. The use of electronic health records (EHRs) is also gaining momentum. This chapter includes existing healthcare facilities and their shortcomings, the need for a smart health framework, and the research motivations.

As the health consciousness is increased among the people, the medical healthcare industry has become an emerging area of research. This realizes the need for a smart and interactive healthcare system, that will provide more cost-effective and efficient treatment [2]. Demographic aging is changing the demands on healthcare services, and older people are increasingly self-managing their long-term conditions with the increased use of mobile phones and technologies [3]. Thereby secure smart healthcare system is gaining more interest among the physicians and the patients.

1.2 Healthcare scenario in India and its challenges

According to the World Health Organisation (WHO), healthcare embraces all the goods and services designed to promote health, including “preventive, curative and palliative interventions, whether directed to individuals or to the populations” [4]. Due to the increase in the doctor-to-patient ratio, the time required in treating and diagnosing the disease is getting delayed. People do not prefer to visit hospitals because the more time they need to spend waiting in a queue, lack of transportation facilities, and negligence about the health-related issues. This further results in many health problems. Good affordable support of a low cost system is expected by the patients in the present smart healthcare system.

This makes healthcare sector should be considered the most important area that societies should develop through innovative technology. Indian healthcare situation gives a spectrum of complementary scenarios. When we visualize this spectrum in terms of facility, services, and availability; it is observed that on one side of the band, the extravagant structures are delivering high-tech medicare to the well-heeled, on the other side, there is the very scanty availability of the medical facility to the most of remote parts of rural India. With the rapid pace of change currently being witnessed, this spectrum is likely to widen further, presenting even more complexity in the future [5]. The present statistical study on the population and medical facilities available in India is illustrated using the chart shown in the figure 1.1.

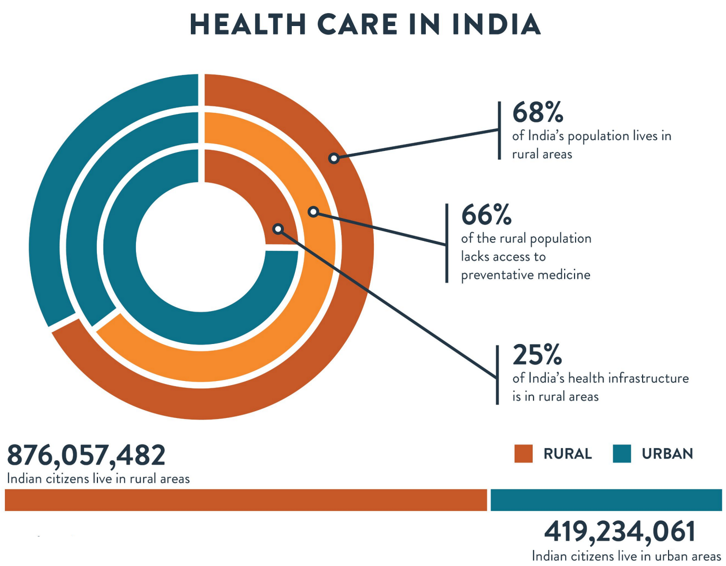

Figure 1.1: Rural vs Urban healthcare system

The chart in figure 1.1 indicates the population in rural India is larger than urban regions. But the infrastructure and access to a medical facility available are marginal. The main reason for poor health in the rural region of India is probably due to the following reasons [6].

1. Awareness or the lack of knowledge: Consequence of poor knowledge in understanding the health status of an individual is due to poor functional literacy, low accent on education within the healthcare system, and low priority for taking the early healthcare measures.

2. Access to healthcare: Access to the healthcare facilities is becoming complex due to physical reach, being one of the basic determinants of access, defined as "the ability to enter a healthcare facility within 5 km from the workplace" [7]. Even if the healthcare facility is available, the quality of care and continuous accessibility to the service is questionable.

3. Absence or the human power crisis in healthcare: A Rural area in India has a shortage of medical professionals. 74% of doctors are in urban areas that serve the 32% of urban population. This is a major issue for rural access to the healthcare. The lack of human resources causes citizens to resort to fraudulent or ignorant providers. Doctors tend not to work in rural areas due to insufficient housing, healthcare, education for children, drinking water, electricity, roads, and transportation. As per the statistics collected it is learned that allopathic doctors comprising 31% of the workforce, nurses and midwives 30%, pharmacists 11%, AYUSH practitioners 9%, and others 19% [8]. The density of doctors, nurses and midwives per 10,000 population is 20.6 according to the national service scheme (NSS) and 26.7 based on the registry data. Health workforce density in rural India and states in eastern India is low. In general, the areas of Northern and Central India has lower densities of health workers compared to the Southern states [9].

4. Affordability or the cost of healthcare: Healthcare in India is not uniformly distributed due to several reasons. The cost involved in getting medical treatment is high, the time involved in reaching the places for testing purposes, and transportation facility to reach the destination is not affordable to all people. The

public sector offers healthcare at low or no cost but is perceived as being unreliable, of indifferent quality, and generally is not the first choice unless one cannot afford the private care. In private care the cost of healthcare is very high, owing to the lack of regulation in the private sector and the consequent variation in quality and costs of services.

The above mentioned challenges need some solutions to improvising the healthcare system. Traveling long distances, lack of transportation and availability of services are the major barriers to avail proper healthcare for every individual. The healthcare sector needs innovations and applications to provide a proper and efficient healthcare system. Hence new applications are mandatory for handling the rising number of patients and providing better heathcare services.

1.3 Challenges in the existing system.

The traditional hospital centric and doctor centered health management model appears to be incapable of adequately dealing with the increasing number of patients and diseases [10]. In the traditional healthcare system data collected from the patient is analyzed traditionally, hence they are not helpful in the early prediction of complex health conditions.

In this regard, this research aims towards finding a solution to the traditional healthcare system. In the traditional healthcare systems, the lack of medical staff causes late diagnosis of the diseases and inadequate treatment process for the patients. Self-monitoring of parameters in healthcare helps to get help or assistance remotely from medical experts. Deferment in the diagnosis of disease causes a delay in treating the patient. Alerting the patient about their future health condition at the early stage is the main challenge faced in traditional healthcare. Regular monitoring of vital parameters, discussing with the family doctor, avoiding frequent visits to the clinics, and getting early assistance is the main goal of the smart healthcare system. The eminent aim of this research is to build patient centric rather than hospital centric healthcare monitoring system.

1.3.1 Benefits in building the smart healthcare model

Internet of Things not only save time but also money. The benefits of IoT in healthcare are summarized as below.

1. Reduced expenses: Patient monitoring can be done in real-time, drastically cutting down the need for doctors to go out and make visits.

2. Time saving and reduced errors: IoT allows for the accurate collection of data, and automated workflows, but most importantly it reduces the time for processing and analyzing and also reduces the risk of error.

3. Personal care of patients: A connected healthcare system creates an environment that meets each patient's needs. Dedicated procedures, enhanced treatment options, and improved diagnosis accuracy make for a better patient experience.

4. Monitoring health conditions with real-time data: Healthcare providers can continuously monitor patients. This means that they can spot any disease before it spreads and becomes serious.

5. Medical notification: With the help of sophisticated applications the regular monitoring of patient's vital parameters can be recorded and notification can be sent about medication, alert messages, and suggestions from medical experts or caretakers.

1.4 Virtual patient monitoring system

As the health consciousness is increased among the people, the medical healthcare industry has become an emerging area of research and realizes the need for a smart and an interactive healthcare system that will provide more cost-effective and efficient treatment.

A virtual patient monitoring system helps to the individual in getting regular health checks, and virtual consultations with the doctor. This system avoids the delay in obtaining doctor's suggestion. Timely monitoring of patient data prevents causalities and negligence. The regular monitoring of vital parameters like body temperature, heartbeat, oxygen saturation level, blood pressure, ECG waveform, and many more based on the type of sensors used can be stored securely over the cloud. If there are any drastic changes in these parameters then immediately an alert message is generated. The alert message or notification assists the patient in taking precautionary measures or scheduling an appointment with the doctor immediately.

Connected health has evolved into smart health wherein conventional mobile devices (such as smart phones) are used together with wearable medical devices (such as blood pressure monitors, glucometers, smart watches, smart contact lenses, and others) and the internet of things (IoT) based gadgets to enable continuous patient monitoring and treatment even when patients are at their homes. Thereby smart healthcare system in a secure manner is the need of the hour. Artificial intelligence can be also added to the healthcare system. This research also explores the impact of IoT technology and machine learning algorithm in the development of healthcare. Internet of Things (IoT) and Machine Learning were added in the design to make the system smarter. Based on the knowledge gained from the previous experience using the trained model, the machines can be trained to predict the health condition of a patient. The prediction model is designed using a machine learning algorithm that can assist the doctor to predict the chances of disease by using his/her knowledge. This model helps the medical practitioner to analyze the current data from the sensor and take decisions quickly.

Today there is a shift in patient monitoring systems from hospital to home with regular medical data gathering from available sensors and gadgets. Virtual patient monitoring system become easier for the doctors and patients. The interactive healthcare system must predict the disease of the patient through proper training with experience shared by the doctor. They should be able to predict probable diseases that a patient may suffer in the future. This type of model assists the doctor in making the decision quickly and avoiding the delay in treatment. There is an excellent relationship between the prediction model and medical data quality. The prediction model helps to minimize treatment variation and unexpected costs [11]. The use of a securely designed healthcare system and a mobile application makes virtual monitoring of the patient. Mobile application helps the doctor in treating the patient by prescribing medicine, checking the laboratory result online, comparing with previous test results of patient's history, chatting with the patient, or advising to take proper care. The complete design of a such system is a boon to mankind.

1.5 Research Motivation

Internet of Things is an emerging area, and many companies want to enter the market. Wide possibilities and a huge target audience make the healthcare segment extremely profitable. It is difficult to investigate the present situation before the development of any product and planning because the project should be able to meet the technological and economical requirements. The target audience study would show interest in the field.

If people are ready for smart health devices and what they expect from new technology is to be analyzed to fulfill their requirements. The main motivation for the design of IoT enabled mobility based health monitoring system is to help and assist the elderly people to have regular monitoring of body parameters and reporting it to the physician to know or detect the early symptoms of disease in the initial stage. Also, this system helps the people staying in the rural part of the country who are finding it difficult to meet the doctor physically.

Alerting the patient at an early stage of any chronic diseases like heart disease, or diabetes helps to reduce complications in the health status. Elderly patients who stay in the rural part of the country find difficulty in traveling to the clinics for regular monitoring of their vital parameters, and getting a piece of advice from the physician. To assist the people staying in an area where medical facilities and expert physicians are not scanty, this smart healthcare system is very helpful. The patient can get benefit from this new innovative solution.

If the system detects any abrupt changes in the patient's heartbeat, oxygen saturation, body temperature, and ECG waveform, the system automatically sends a notification to the doctor and respective caretakers. With an available technology "Sensor nodes", "Gateway nodes", "Internet of Things", "Data Analysis using machine learning" and "Mobile application" provides more opportunity to build an efficient smart healthcare system for mankind.

1.6 Research Objectives

The research objectives were carried out in four phases. They were

* The selection of an appropriate wearable sensor node to measure vital parameters

of the human body. Interfacing the sensors to the gateway node with a suitable communication module. Comparing the performance of various gateway, for the selection of gateway node. Storing the sensor information with a valid ID and secret key to the cloud was attained.

* Various simulation analysis of wireless sensor network, communication protocol, placement of sensor nodes, power consumption of nodes, latency rate, and the priority of data packets were performed.

* Prediction of heart disease and diabetics using machine learning algorithm was carried out to finalize the prediction model for smart healthcare. Datasets selection, mining algorithm, feature selections, and performance analysis of the model were carried out to achieve the desired response.

* Developing a user interface using the web interface and mobile interface for regular monitoring of patient data in the prediction of disease was carried out. Integration of hardware module containing sensor units and software module used in detecting chances of having a disease was embedded to complete working prototype of the healthcare model.

* Interactive mobile applications were developed to use as a virtual patient monitoring unit and alert notification. The application provides a dedicated service to the user in uploading the reports, and the images of medical meter data. The application enables in sharing of sensitive and valuable information securely with the registered doctor.

The designed system allows people to stay at home comfortably rather than staying in an expensive healthcare center such as hospitals or nursing homes. It thus provides an efficient and cost-effective alternative to on-site clinical monitoring. In this direction, the research work was carried out to help the society. This model will assist in regular monitoring and alerting under critical conditions. Applications of the designed system are also useful for continuous monitoring of the patients suffering from typical diseases such as diabetes, asthma, and heart attacks. By measuring changes in patient's vital signs, a body area network can inform the medical professional, even before they have a heart attack or any other serious conditions. Connecting the rural area with good healthcare system is the main criterion of this research work.

1.7 Organization of the Report

The organization of the thesis is mentioned as below,

- Chapter 2 provides an extensive overview of the literature, and commercial developments relevant to the research. Literature comprises of introduction to IoT, IoT in medicine, design of IoT based healthcare system, analysis of machine learning model used in prediction of various disease, Existing user interface in remote monitoring and prediction of disease are reviewed.

- Chapter 3 introduces to the various simulation software tools used in configuration of wearable sensor nodes, protocol used, energy consumption of the nodes and analysis in the placement of a sensor nodes. Simulation software used in analyzing the power consumption of wearable sensor nodes, packets transmission rate, and priority of the data packets are included.

- Chapter 4 presents the research methodology used in the design of the proposed framework, which includes criteria used in the selection of hardware unit. Describes the proposed hardware model designed for healthcare system, it also briefs about the sensor data validation algorithm for anomaly detection, and discussed the experimental results.

- Chapter 5 discusses the design of proposed prediction model using machine learning algorithms. This chapter covers the approach used in the design of prediction model, analysis of machine learning methods, and comparative performance of machine learning algorithms. It also discusses the design of web based and mobile based user interface developed for the prediction of heart disease/diabetes. It presents the mobile applications developed to assist in the virtual patient monitoring system. The evaluation of the constructed model is also covered in this chapter.

- Chapter 6 summarizes the conclusions drawn from the research project, which include outcomes, and the deployment carried out. These findings are evaluated to communicate healthcare benefits to the community. Also, the scope for the future directions of this work is presented.

Chapter 2

Literature Review

In the present scenario implementing smart health, smart grid, and other smart technologies using IoT applications helps to fulfill the requirements of the society. This chapter is devoted to a literature review for the Internet of Things (IoT) assisted smart healthcare, and the prediction for heart and diabetes modeling aspect. Literature of related works in the area of IoT in medicine, prediction models using machine learning, and mobile applications in healthcare has been carried out to identify the research challenges. It can be noted that the term 'prediction of disease' and 'smart healthcare' are used throughout this thesis. Comprehensive information on IoT assisted mobility based healthcare model approaches presented by the various researchers and the challenges are discussed in this chapter.

2.1 Overview of smart healthcare

Healthcare solutions are based on the IoT, Big Data, and Predictive data analytic using machine learning is the emerging research area to enhance healthcare services. The smart healthcare monitoring framework is the fusion of wearable sensor nodes, and a mobile communication. This kind of system enables the patients and doctors to communicate with each other and remotely exchange the information.

A basic requirement of the healthcare is to serve anybody at anytime and anywhere using a good health management system. This can be achieved by deploying IoT components into the healthcare system. Most of the paper's preliminary study was focused on improvising the existing healthcare system, in terms of expanding service time, space beneficiaries, and type of services offered [12]. The Internet of Things (IoT) enabled connectivity has the potential to catapult this ailing healthcare system into an integrated, efficient and patient-centric system.

2.1.1 Internet of Things

In order to understand the Internet of things, first we have to glance upon the definition of IoT, its application in the medical field. The internet has now become a staple food of modern life. The invention of the Internet took fifty years with the hard work of countless researchers. Internet of Things is an emerging technology that lets humans and things interconnect anywhere and anytime. The scope of IoT is not only constrained to connecting things, it allows devices to interact and exchange their data associated with users.

IoT enables to acquire the contextual information, and technology to improve security and privacy. The IoT is the connection of heterogeneous objects embedded with intelligence (e.g. computing capabilities, a unique identifier, and communication abilities) which allows them to interact and exchange the data [13]. This interaction and data exchange may be performed by different communication channels and it can be direct or indirect communication. This process is autonomous; thus, it works without human intervention.

2.1.2 Architecture of IoT

The three main building blocks of IoT architecture are represented in the figure 2.1. The perception layer receives the signals from smart things. The network layer or connectivity layer enables data transmission. The processing layer (middleware) accumulates, stores and processes the data to get meaningful information. The application layer seeks the information from the previous layer and is analyzed to provide the final answers to the key business questions [14]. Healthcare using wireless sensor network is broadly classified into three main domains. They are

1. Sensor network used in healthcare consists of various sensors, selection of type of sensors, placement of sensors, storage of sensor information and communication protocols used.

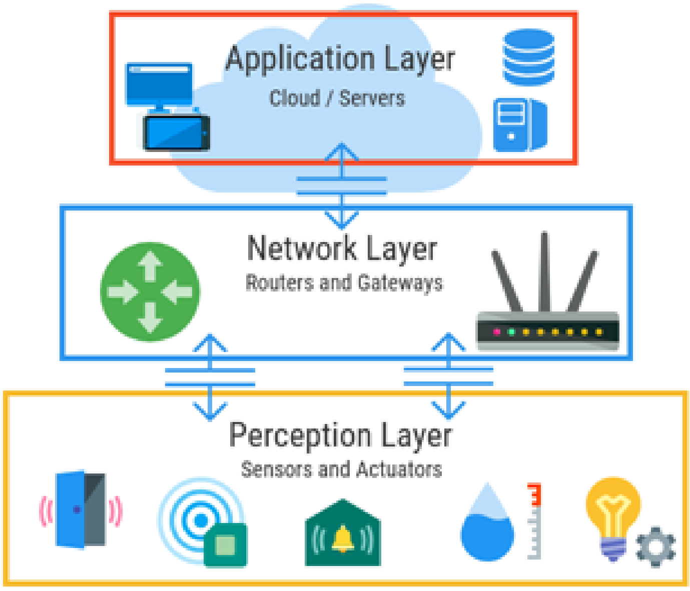

Figure 2.1: Architecture of IoT

2. Data analytic in healthcare assist in early detection of disease. Knowledge of machine learning is used in predicting chances of disease.

3. Virtual patient monitoring using mobile devices are used to track and report the health status.

2.1.3 Internet of Things in Medicine (IoMT)

Internet of Things (IoT) merges telecommunication and information technology for providing better medical services. By means of IoT, patient information can be exchanged from one location to another to diagnose the diseases and arrange for proper medications to improve the patient's health conditions even in rural locations. This technology enables to deliver healthcare services over a long distance and also minimizes the cost of allied services. It assists the people in managing the chronic diseases with less hospital stay, less travel time and get association with the doctors by sharing the information. IoT offers its greatest promise to deliver excellent progress in healthcare domain.

The figure 2.2 illustrates the data flow sequence in IoMT. The figure illustrates the direction of flow of data from sensor end to the physician end. The sensors captures the current reading and stores them in the cloud. The data stored in the cloud can be accessed using mobile or web interface. The physician can utilize this service in the patient monitoring system. If any distinct changes in the parameters occurs patient will able to get early assistance from the physician or caretakers.

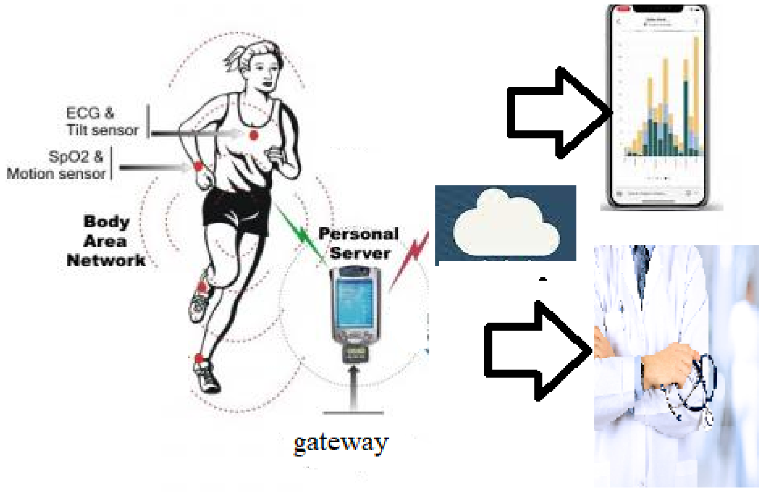

Figure 2.2: WBAN communication

There are people all over the world whose health may suffer because they don't have ready access to an effective health monitoring. With an aid of small, powerful wireless solutions connected through the IoT are now making it possible for monitoring and assisting the patients. These solutions can be used to securely capture the patient's health data from a variety of sensors, apply complex algorithms to analyze the data and then share it with medical professionals. Further doctors can make appropriate health recommendations based on their knowledge.

Today there are many challenges in delivering healthcare which includes,

1. Scarcity of trained personnel.

2. Overworked providers.

3. Unpredictable numbers of patients.

4. Demographic shifts, an aging population and their healthcare issues.

These challenges give an opportunity in the development of mobile applications to better serve the increasing number of patients.

A conceptual representation of a system for remote monitoring using WBAN sensor is represented in the figure 2.3. It represents data from the sensor are fetched (1) and transmitted to the cloud (2). The doctor can access the data (3), by providing a web interface (4) or mobile interface (5). Doctor can analyze and advise the patient about his/her health condition.

Figure 2.3: Data flow sequence in IoT enabled system

2.2 Classification of wearable sensors

The wearable body area sensors are classified into three main types. They are represented in in the figure 2.4.

Wearable sensors are deployed on human body to monitor vital signs are categorized

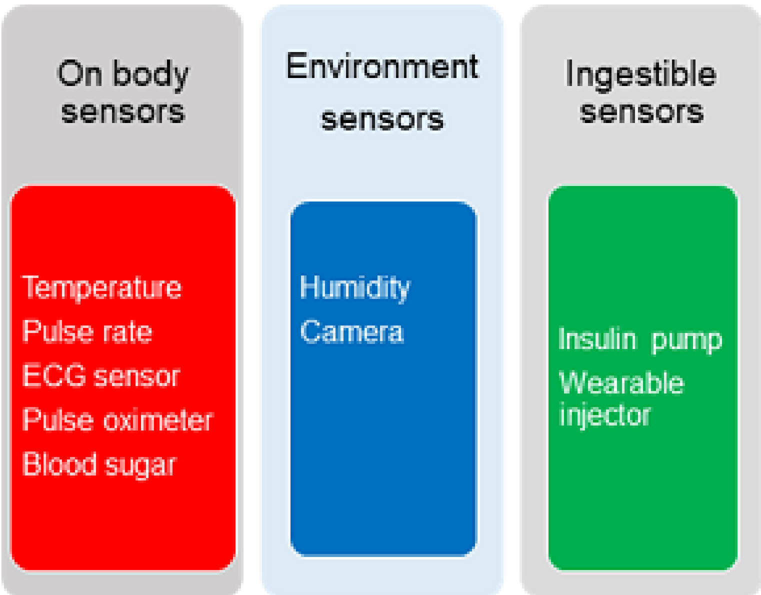

Figure 2.4: Classification of wearable sensors

as body sensors, or surface mounted sensors, environment sensors and ingestible sensors. Body sensors are placed using either wrist worn watch, head mounted type, finger ring shape or smart textile type. The size of the sensor is compact and light in weight. They can be placed in contact with the body to collect the vital parameters.

Environment sensor are used in a place near to the patient at least 10 cm away from the human body. They are used to record surrounding condition of the place where the patient is staying (home or hospital).

Ingestible sensors are inserted inside the human body under the proper supervision of medical experts. These sensors are placed inside the human body for continuous recording of a most critical parameter.

Sensor nodes are acquiring data from the patient. The selection criteria for sensor nodes are taken utmost importance. The main criteria for acquiring data depends on the health status of the user. The mobility of the user is to be seen while placing the sensor on the body. Implant sensor nodes can be inserted either underneath the skin or inside the body tissue to monitor and diagnose the symptoms at an early stage. The mounting of the sensor node and the antenna is the main constraint in using implant sensors. The replacement of the battery to the sensor node might involve surgical operation [15][16]. Such kind of nodes requires careful design although they are more beneficial. The body surface node is either placed on the surface of the body or 2 cm away from the human body.

The external node sensor is not in contact with the human body and is rather a few centimeters to 5 meter away from the human body. Sensors that measure health parameters such as vital signs for disease management and prevention may include six sign parameters. They can be electrocardiogram (ECG) signal, oxygen saturation (SpO_2), heart rate (HR), blood glucose (BG), respiratory rate (RR), and blood pressure (BP). The sensors used in human health monitoring should satisfy the following features [17][18].

- Unobtrusiveness: Sensors should be lightweight and miniature in size. They should allow both non-invasive and unobtrusive continuous monitoring of health parameters. The size of the battery used should also be light in weight.
- Security: Wearable Body Area Network (WBAN) based healthcare system should provide the security of patient's information. Sensor's data integrity must be ensured, which implies that sensors must fulfill the privacy requirements provided

by the law. Sensor data should be made accessible to the authorized experts in remote locations without affecting their privacy.

- Interoperability: Interoperability in healthcare is the extent to which various systems and devices can interpret data and display it in a user-friendly way. Data collected from various sensors are able to accessible regardless of the vendor or type of sensor.

- Reliable Communication: Sensors should be able to communicate to the monitoring station using a suitable communication protocol. Latency and data loss are to be considered while selecting a protocol. Range and power consumption capability are to be addressed before the selection of the communication model.

2.3 Commercially available smart healthcare devices

An initial study was conducted to determine the types of vital signs that are routinely measured during a visit to a doctor. These vital signs are: body temperature, pulse rate, respiration rate (rate of breathing), blood pressure, and blood sugar. Some of the existing devices used in monitoring these vital signs and their features are highlighted.

1. LifeGuard [19]: helps to monitor ECG, respiration, activity, temperature, heart rate, SpO_2, and blood pressure. Used for multiple applications and designed for extreme environments. It can send data to a computer via Bluetooth, provides short range communication service. Other drawbacks of this are, sensors are hard to put on and somewhat intrusive, can only log up to 8 hours of data. These devices are not available for sale.

2. Spot Vital Signs LXi [20]: It measures the temperature, respiration rate, pulse rate, blood pressure, and Body Mass Index (BMI) of a human body. They are very expensive and have a complex system which is difficult for home-based monitoring purposes.

3. ALARM-NET [21]: Assisted-Living and Residential Monitoring Network (ALARM) for pervasive, adaptive healthcare solutions. Protection of medical information is very important, so IP and WSN communication is secured with SRP and

SecureComm, a hardware accelerated security suite for Chipcon CC2420-based devices was implemented. Alarm-Net introduced a heterogeneous network architecture made by body sensor networks and environmental sensors. With the help of the circadian activity rhythm module, Alarm-Net adjusts the context aware power management and privacy policies.

4. eCAALYX [22]: Complete Ambient Assisted Living Experiment. eCAALYX system is composed of three main interconnected subsystems, customer-premises equipment, a set top box and interactive TV. eCAALYX system increases older people's autonomy and self-confidence by developing a wearable light device for measuring particular vital signs of the elderly, detecting falls, and communicating automatically in real time with his/her care provider in case of an emergency,

5. TeleCARE [23]: Integrates the Internet with an agent and mobile-agent technologies to develop a configurable common infrastructure so that the elderly people and those responsible for providing care and assistance can get the best out of the technologies developed;

6. CHRONIC[24]: Understanding home care is an efficient alternative to conventional institutional care for chronic patients. An efforts are made to improve quality of life and reduce costs. An innovative information environment based on two elements: a chronic care management network (the entry point to any requirement for health resources) and a patient monitoring environment (to capture and process at home all relevant information) was developed. They will contribute to the growth of health-related new business and industries.

7. MyHeart [25]: Is an intelligent system for the prevention and monitoring of cardiovascular diseases using smart electronic and textile systems and appropriate services that enable the patients to take control of their health condition. The system uses wireless health devices and a mobile application on the patient's end. A rule-based expert system, and a dashboard on the clinician's end to facilitate the exchange of information about the vitals, symptoms, and the health risk.

8. OLDES [26]: Older People's at home brings a novel concept of an innovative low-cost technological platform, which provides a wider range of services to elderly

people.

The cost and features of the commercial available devices are not satisfactory. Analysis of data collected from the sensor at the server end needs revisions.

2.4 IoT assisted framework in healthcare monitoring

Shahzad, Aamir et al.[27] have proposed Cloud-I/O design, which enabled three important services. They are tele-monitoring, location identification, and communication service. In order to access and monitor the heart patients residing in the hospital premises, a private computing platform is built. However, there are still several challenges, such as to carry the remotely located information and the remote connectivity issues, mainly present in the healthcare systems. Alongside with this, the cost is also a big issue, there are difficulties in updating the existing systems with the new developments. Therefore, the cloud computing platform is one of the best solutions in the current age to fight against the issues. Moreover, the study will be updated with the newly used technology in the arena of information technology called the Internet of things (IoT), which provides automated communication services over the Internet access and will be helpful for the development of new advanced medical systems.

Shivakumar et al.[28] proposed a design of vital sign monitor based on wireless sensor networks and tele medicine technology. They have explained that even after the heart attack the patient needs continuous monitoring and care. But all this needs to be at a very affordable cost, thus developing a quality, secured and cost effective system is the requirement. So they have designed a mini patient monitoring system which measures the vital parameters like ECG, heart rate and respiration rate. The system uses Bluetooth technology which is embedded with the sensor for faster transmission.

Alaseel et al.[29] developed a Vital Signs Monitoring System (VSMS) that can be used to control and monitor vital signs of the patients such as blood pressure, body temperature, and heart rate pulse. The main purpose of this proposed system is to keep all patients under 24 hour monitoring and be able to alert the staff in case of any abnormalities. The system is built on distributed control system (DCS) architecture. Initially, they proposed the system architecture and its subsystems in detail along with all functions. As a continuation, they discussed data historians, how to store and handle the aggregated “Big Data” that resulted from continuous monitoring. The VSMS is based on a wireless sensor network and telemedicine technology. The power utilized by the entire system is low due to the intelligent algorithms that control the system. The system was designed to take preventative measure of only cardiac patient.

Wang et al.[30] have developed a real-time patient monitoring system based on the third generation (3G) cellular standard and General Packet Radio Service (GPRS). This was developed for emergency care and response management. Besides the vital signs of patients, such as ECG, SpO_2 and Non Invasive Blood Pressure (NIBP), the system simultaneously transmits videos, voice and geographical position. This is required throughout the pre hospital procedure. Moreover, a hand-held ID card reader can automatically record the patient’s personal information, and the patient care software received the real-time patient data from the sensor and processes the data to detect anomalies.

Zhang et. al[31] presented a model that allow doctors to monitor the physical parameters of the patient’s body in real time and to understand the changes in their condition. This medical remote monitoring system is based on the Internet of Things. From the perspective of practical application of hospital wards, a medical health monitoring system was designed with the help of CC2430 microcontroller, human information sensor, microelectronic, and modern wireless communication technology. The experimental result proved that the network node was reliable and the data transmission was accurate. It is concluded that the medical monitoring system basically meets the design requirements. They also analytically derived expressions for fuzzy membership functions that should facilitate a system theoretic approach to mathematically design the medical expert systems.

Abdullah et al.[32] have discussed the implementation of the Wireless health monitoring system and its components. They have demonstrated using various sensors. It consists of ECG device. in which electrical impulses of heart beats are recorded on a piece of paper. LM35 temperature sensors whose output voltage is linearly proportional to the temperature in Celsius. Blood pressure sensor is a device that measures the pressure of the blood in the arteries as it is pumped around the body by the heart. Blood glucose sensor is a medical device uses to calculate the blood glucose level. Microsoft Pro Tablet is a mobile computer which includes display, battery and circuitry in a single unit.

Gelogy et al.[33] developed U-healthcare system architecture. The system is mainly utilizes the Body Area Network (BAN). In this system sensors are attached to body area to capture bio-signals, blood pressure, body temperature, pulse and breathing. It also divided into two parts that is, Wireless Body Area Network (WBAN) and Personal Monitoring Devices (PMD). The patient's PMD can be a personal computer or mobile phone. It gets information from WBAN and it contains logistics to determine whether to send this information to Intelligent Medical Server (IMS) or through internet. Intelligent Medical Server (IMS) is a backbone of the entire system and serves as a hub between the patient and hospital. Based on the data received from the BAN an agent determines whether patient is in a critical or normal condition. If it determines the patient is in a critical condition, the data is transferred to the hospital system. If it is not an emergency, the data is simply stored in the IMS. Data stored in the IMS will be deleted after certain period of time unless there is an emergency and the necessary data is regularly saved to the central database of the hospital. This data is available to doctors and support staff in the hospital.

Yehia et.al constructed a security for Healthcare Systems [34] They have discussed about security for healthcare techniques. It plays an important role in healthcare applications. Introducing new technologies in healthcare system causes patient privacy vulnerable. The physiological data or report of an each and every individual patient is highly sensitive and should be secured. The wireless medical sensors produce or collected large amount of data which must be secured from security attacks. To overcome from this problem by applying various algorithms or techniques, and can prevent many malicious attacks of data when transmitting to the remote locations. The success of healthcare applications mainly depends on patient security and privacy.

Konstantinidis et al.[35] have discussed about age-friendly healthcare system. It consists of two distinct components, namely Controller Application Communication (CAC) framework and an extensible Messaging and Presence Protocol (XMPP) network. Both components enable real-time communication between different entities. The CAC framework integrates multiple controllers and provides input to the systems and applications such as exergaming platforms. On the other hand, it contains medical devices, software components, disease management, and an elderly support services such as Decision Support System (DSS). It communicate with each other using the XMPP protocol. The design and various aspects considered in the survey shows most of the system are open ended they collect the information and transmits them further for processing. In order to understand and analyze the data there is a requirement of integration of an Artificial Intelligence model.

2.5 Predictive analysis of healthcare system

The primary focus of this research work is in the development of smart healthcare system for the people who finds difficult in accessing the medical facilities. After gathering the statistics in terms of rural population of India, mortality rate, reasons for lack of healthcare, and several important factors led to the development of low-cost alert system in healthcare.

Various systems existing in the healthcare monitoring are broadly classified into two categories. Hospital centric, and Home centric.[36] [37].

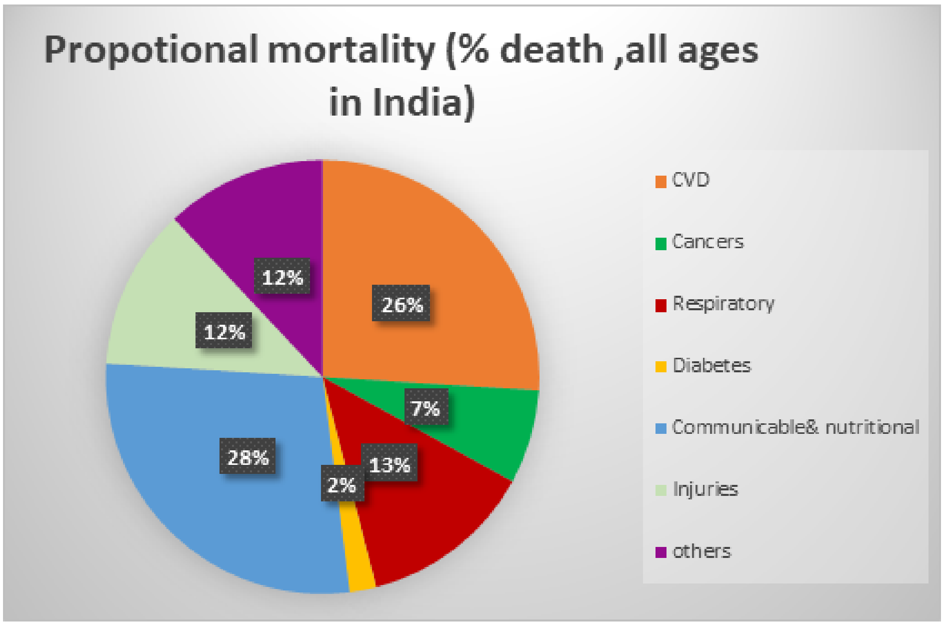

Figure 2.5: Mortality rate in India

According to a report by the Institute for Health Metrics and Evaluation, University of Washington states that the diabetes rate had increased by 45% globally, whereas it has increased by 123% in India (1990 and 2013).

The predictive analytics can be applied in data mining for predicting the future events especially in the medical sector, business, education, and crime detection. A medical data of large size needs powerful data analysis tools for processing. Data mining techniques can also be used for the diagnosis and predictive analysis. Heart or cardiovascular diseases refer to a medical condition that affects the heart and blood vessels. The extreme outcome of the disease is a heart attack or stroke [38]. This is the major culprit for mortality all around the world and has claimed more lives than other diseases.

According to World Health Organization, the heart disease account for nearly 17 million which is approximately 30% of death occurring annually. It is proven that half the victims die within one hour of the beginning of the symptoms. Most of them don't make it to the hospital in time subsequently they die. In this case Wireless body area sensors provide a real-time monitoring of heart problems by constantly sensing, processing and transmitting data from the sensors to the server. Using this data, the physician can track his/her patient's health progress every day and timely intervene for the anomaly in the readings.

Diabetes describes a group of metabolic diseases in which the person has high blood glucose either because insulin production is inadequate, or because the body's cells do not respond properly to the insulin. The WHO projects that diabetes will be the 7^{th} leading cause of death by 2030 [39]. India currently represents 49% of the world's diabetes cases. It is also estimated that 7.8% of the population above 18 years of age has raised blood glucose level or they are on treatment for diabetes. However, a large section of the population remains unaware of the this disease. Statistical report presents, TamilNadu has highest death rate (53/100,000) from diabetes followed by Punjab and Karnataka state [40]. Diabetes directly or indirectly accounts for 2% of deaths in India annually.

Diabetes is a disease which is detected on a blood test when the blood sugar is higher than normal blood sugar. Normal blood sugar fasting levels lies between 70 and 99 mg/dL, whereas a person with diabetes sugar level higher than 126 mg/dL. There are 3 categories of diabetes Type1, Type2, and gestational diabetes. The implications of diabetes are terrifying. It could be blindness, amputation, high blood pressure, kidney disease, heart disease. Recent studies have manifested an increasing trend in number of diabetic patients and their deaths across the globe. Current healthcare systems incorporate multidisciplinary technologies which encompass growth of sensing technologies like Radio frequency Identification (RFID), and its integration with Information technologies.

2.5.1 Available data mining tools

Prediction models can be designed using data mining tools. Cognitive analysis using data mining tool is to simulate human thinking into an automated model. The ability of solving problems without the assistance of experts is used in healthcare services. Cognitive analysis can solve complicated problems without the intervention of medical person. In order to implement cognitive analysis on the data collected from data repository, various simulation tools are used. The main features included in cognitive analysis are adaptive, interactive, stateful and contextual. It has the ability to think and adapt from surroundings. Cognitive systems should interact bi-directionally. System should recollect prior knowledge gained in a process and return results for new input which helps in making decision. They can collect information, including both structured and unstructured digital information, as well as real time data. The available data mining tools used are [41]

- KNIME Knostanz Information Miner (KNIME) is free software for creating data science applications and services. KNIME primarily used for data preprocessing, data extraction, transformation, and loading. KNIME is a robust tool with graphical user interface contains the network of data nodes.

- Weka is a workbench developed by university of Waikato, a group of machine learning algorithms for data mining tasks. The algorithms can either be useful directly to the dataset or called from Java code. Tools in Weka includes, data pre-processing (missing data entry, filters), classification (based on function, tree, meta), regression (logistic, linear), clustering (K means), association rules, and visualization (plots). Weka is suitable for developing hybrid machine learning schemes.

- RapidMiner is data mining tool used in cognitive analysis. It is initially called as YALE (Yet another Learning Environment). It is used for data preparation, machine learning, and model deployment. Rapid Miner consists of multifaceted data mining functions for pre-processing, visualization, predictive analysis, and can be easily integrated with Weka and R-tool.

- R-tool is freely available software. R provides environment for statistical computing and graphics. R tool has open source command line driven statistical package. Visualization of the results and well designed publication quality plots can be produced using R. R-studio has Integrated Development Environment (IDE) designed for R language. One of the popular tool used to conduct data mining tasks. R-tool has packaged with hundreds of libraries built specifically for data mining.

- Orange is machine learning and data mining toolkit. It is open source tool which has visual programming front-end for data analysis and interactive graphical output. Orange initial released in 1996 and stable version released in 2019. Orange has widgets for data prepossessing, classification, regression, and evaluation. Orange provides add-on facility to handle upcoming data analytics.

- Tanagra is an open source data mining tool for research purposes. It proposes several data mining methods from exploratory data analysis, statistical learning, machine learning and database.

The data mining algorithm is an interesting topic to the researchers as it classifies the patterns efficiently. The performance analysis of various datasets are tested using tools to understand the significance of parameters to be considered.

2.5.2 Early detection of heart disease using machine learning

An extensive amount of work has been done in the area of smart health monitoring system for the prediction of various health conditions. Data mining is widely used in the medical field to study predictive models. Machine learning based classification methods are being proposed to predict heart disease and alert the patient in early prediction of heart disease. Machine learning algorithm such as logistic regression analysis, decision trees, artificial neural network algorithms, and many others are used in the prediction model.

Ehteshami A. Rezaei et al.[42] revealed that early disease prediction is the most required area of research in healthcare sector. By integrating computer-based patient records with clinical support could reduce medical errors, enhancement of patient safety, minimize undesirable laboratory tests, thereby improves the patient outcome. Data analysis involves more computational resources and devours much time when dataset is of vast size. Therefore, feature selection procedure is used to eradicate the irrelevant or noisy features from the data, in order to reduce the time and the resource usage [43].

Shanta Kumar B. Patil[44] obtained important patterns from heart disease database for heart attack prediction. They have developed an algorithm Maximal Frequent itemset Algorithm (MAFIA) using Java. The data is pre-processed first, then clustered using K-means algorithm into two clusters and the cluster significant to heart attack is obtained. Then frequent patterns are mined from dataset to know significant feature to be chosen. Features of the dataset are given some ranking to understand its significance in determining the output variable.

G. Purusothaman et al.[45] has surveyed and compared different classification techniques for heart disease prediction. Hybrid model of machine learning algorithm is used instead of using single algorithm such as Decision tree, Naive Bayes, Artificial Neural Network. Authors have demonstrated the effectiveness of hybrid models. The performances of single models such as Decision tree, Artificial Neural Network and Naive Bayes gave prediction accuracy rate of 76%, 85% and 69% respectively. However, hybrid approaches produced an accuracy of 90%. Therefore, hybrid models lead to reliable and promising classifiers for predicting heart diseases with the good accuracy. Feature selection in medical diagnosis helps to improve clinical decision quickly. Heuristic methods help to resolve the problem of selecting the best features.

Song et al.[46] proposed a feature selection approach using filtering the signal to noise ratio (SNR) score and Particle Swarm Optimization (PSO) algorithm. Clustering dataset using K-means and SNR score is used to rank genes. SVM, KNN, and Probabilistic Neural Network (PNN) classification methods are used for testing the performance.

Ambarasi et al.[47] enhanced the prediction of heart disease with feature subset selection based on a Genetic algorithm. Genetic algorithm is used to determine the attributes which contribute more towards the diagnosis of heart ailments which indirectly reduces the number of tests which are needed to be taken by a patient. Thirteen attributes are minimized to six attributes using Genetic search. Subsequently, three classifiers like Naive Bayes, Clustering and Decision Tree are used to predict the diagnosis of patients with the same accuracy using fewer attributes.

Nahar Jasmine et al.[48] proposed various methods like Bagging, Boosting, Stacking in prediction model and achieved 84.15% accuracy by applying stacking technique. Rajagopal et al.[49] presented a classification of cardiac arrhythmia using five different linear and non-linear unsupervised methods. They have demonstrated the dimensionality reduction techniques combined with a probabilistic neural network (PNN) classifier. The PNN classifier and the fast-independent component analysis (fastICA) obtained the best result.

2.5.3 Early detection of Diabetes using machine learning

Various researcher contributed in the prediction model of diabetes using machine learning algorithm. Machine learning based classification methods are being proposed to test patient data to provide early prediction of diabetes.

T. Santhanam et al.[52] proposed a method using K-means, Genetic algorithms and, SVM to achieve higher accuracy for diabetes diagnosis. Data cleaning was achieved by substituting the missing values with the meanvalues . K-means is used to eliminate noisy data and genetic algorithms to is to find the optimal set of features for classification with Support Vector Machine (SVM). Outcome of this research are in the collected 768 instances of the dataset. K-Means selected 511 samples as correctly classified and 257 samples were detected as outliers. The outlier detection is 33.46%. The minimum number of attributes selected using Genetic algorithm is 3 and maximum is 6. The minimum and maximum classification accuracy using SVM is method improved using feature selection component.

Saba et al.[53] proposed use of multiple ensemble assessment techniques for diabetes datasets. Two diabetes datasets are adapted from the UCI and Bio-Stat databases. Three types of decision trees ID3, C4.5, and CART are used as basic classifiers. As the base classifiers, three decision trees with specific splitting criteria, i.e. information gain, gain ratio and gini index, are used. Experimental results and assessment indicate that the technique of the bagging ensemble shows better performance than the other ensemble methods. Pradeep et al.[54] suggested J48 for the diagnosis and prevision of diabetes, developed by Ross Quinlan. J48 takes less time for training and can handle missing values in diabetes data.

Chen et al.[55] proposed a hybrid prediction model to aid diagnosis of Type 2 diabetes. All the researcher using pima indian database in the prediction of diabetes. The data set was handled without anomaly removal. The output of the prediction model represents the outcome using binary classifier.

2.6 Simulators in the performance analysis of the sensor nodes

Simulation tools are used to understand the behaviour of WBAN. The analysis of various features can be carried out using freely available simulation tools. The simulations tools are Cooja, and Omnet++. They can be used in the simulation of channel modeling, network traffic etc.

Cooja simulator is a network simulator used for wireless sensor networks. A simulated Contiki mote in Cooja is an actual compiled and executing on Contiki operating system [50]. The system is controlled and analyzed by Cooja. Contiki is an open source operating system for the Internet of Things. It is designed to work with all kind of hardware devices that are severely constrained in memory, power, processing, and communication bandwidth. Contiki connects tiny low-cost, low-power microcontrollers to the Internet. Contiki is a powerful toolbox for building complex wireless systems. The simulator MSPsim is an additional add-on that can be integrated into COOJA for WSN nodes with TI MSP430 microcontrollers. MSPsim also provides a Java-based Graphical User Interface (GUI) for sensor board visual representation, break point setting, stepping, data tracking, etc. Similarly, MPLAB SIM(one of the emulation engines from Microchip's MPLAB IDE), can be used to emulate WSN nodes with 8/16/32 bit based PIC microcontrollers.

OMNET++ framework is an extensible, segmental, component based C++ simulation library, predominantly employed for developing simulators and emulators for wireless network[51]. OMNET++ proposes an eclipse based IDE, graphical runtime atmosphere and a presenter of additional tools. There are extensions available for real time simulations, network imitation, and database integration. Castalia-3.2 is an OMNET++ based simulator is extensively used for wireless sensor network (WSN), Body area network (BAN), and for network of low power embedded devices. Researcher can make use of Castalia for evaluating their distributed algorithms and techniques in credible wireless channel and radio models. The main features of Castalia are,

- Progressive Channel model grounded on real time data.
- Channel model explaining path loss map.
- Complete provision of mobility of nodes.
- Accessibility of MAC and routing protocols.
- Aimed for adaption and extension.
- Compressive sensing and modelling abilities.

Based on studies of evaluation tools, it is easy to conclude that Contki Cooja simulator can be used for analysis of sensor nodes in placement of sensor, assigning priority to the packets and determining latency rate. The protocols and energy strategies can be analyzed with Castalia software. They might be suitable for precise energy consumption scenarios for designing the realistic models.

2.7 Mobile application in remote patient health monitoring

Tamilselvi et al.[56] developed a health monitoring system to record parameters of an individual, like heart rate, percentage of oxygen saturation, body temperature, eye movement and record the information in the cloud. Arduino microcontroller was used as a gateway in the system. The researcher has not precisely explained about accessing the recorded parameter by the medical experts. The benefits of creating a web based mobile phone application using a low-cost method have been presented by Melvyn Zhang et al.[57].

Kakri et al.[58] have described the benefits of getting the latest health care services to the patients. Honan et al.[59] have analyzed Digital Health (D-Health), which outlines two main sections, front end, and back end. Front end involves data gathering using IoT enabled sensors and incorporates a cloudlet that accomplishes accumulation and preprocessing. Backend comprises the cloud platform, which primarily provides the storage and processing for services that include visualization and analytics. Zhibo Pang et al.[60] have introduced a prototype that includes an iMedBox, a wearable ECG sensor node, a series of intelligent pharmaceutical packages, and a professional web interface. It is an intelligent medicine box that can effectively integrate in-home health care devices and services.

Amin et al.[61] have proposed a prototype using a Wireless Medical Sensor Network (WMSN) and then designed anonymity preserving mutual authentication protocol for the mobile users. Automated Validation of Internet Security Protocol and Application (AVISPA) tool and BAN logic have been used to simulate the proposed protocol. Security was achieved using an efficient login, robust mutual authentication, and user-friendly password change. Lee et al.[62] have developed a smart elderly health monitoring system. It consists of a accelerometer sensor of the smartphone. This device is utilized to detect the fall of the user. Since mobile sensor is used in developing the prototype the user should carry the mobile every time.

IoT- based heart disease monitoring systems have been designed by Chao Li et al.[63] for pervasive healthcare service. In this system physical signs such as blood pressure, ECG, SpO_2, as well as relevant environmental indicators are continuously monitored. This system is not enabled with pervasive healthcare services like an early warning and real- time knowledge support to the patients. Cloud assisted industrial Internet of Things enabled framework for health monitoring was developed for short time monitoring of only ECG signals [64]. The patient information are secured by adding noise to the ECG waveform. The main limitation of the system is single parameter monitoring, so the information processed is not possible to predict any decision about the status of the patient.

Firouzi et al.[65] proposed Internet of things and Big Data for smarter healthcare system. It utilized smart device to design the applications. But this system is still not deployed and its accuracy remains untested. Simko & Mattsson et al.[66] have analyzed that use of 5G frequencies can have a health impact. In this context, there is undoubtedly the need for clinical evaluation of most wearable devices, i.e. “a systematic and planned process to continuously generate, collect, analyse and assess the clinical data", pertaining to a device in order to verify the safety and performance.

2.8 IoT assisted personal healthcare devices

The survey conducted on the use of IoT based healthcare devices are summarized using the Table 2.1.

Table 2.1: IoT assisted healthcare devices

Sr.no	Healthcare device	Applications
1	Wearable Fitness Trackers	Heartbeat,calories burn,physical work carried out
2	Sleep Monitoring Band	Monitor sleep patterns posture and other sleep related parameter
3	Smart Contact Lens	Early detection of the tear glucose level also the early detection of the diabetes
4.	Blood Pressure (BP) Monitoring	Patient's oscillometric blood pressure
5.	Smart Bandages	Sensors that measure the wound's temperature and pH.
6.	Smart Pills	Stomach related information tracker.
7.	Intelligent Inhaler	Controlling the rates of asthma attacks.

Gupta et al.[67] have developed healthcare based on IoT using Raspberry pi. It helps to monitor the patient's health parameters on website, or by using GSM mobile communication. The said system will not able to predict the situation of a patient and doesn't log the details of the patient data for future prospects. The decision of health status depends on the type of sensor used. The system able to predict only on heart rate sensor.

The machine learning algorithm used in prediction of heart disease on Kaggle dataset was compared from various research papers. The accuracy rate of heart disease using various machine learning algorithms are summarized in Table 2.2. It indicates the type of algorithm used and the accuracy of the model for the test cases.

Table 2.2: Performance of heart disease prediction

Author	Algorithm	Accuracy
Gudadhe et al.[68]	MLP and SVM	80.14%
Kahramanli et al.[69]	Neuro fuzzy	87.4%
Olaniyi et al.[70]	ANN	88.89%
Kumar Dwivedi [71]	Logistic Regression	85%
Devansh et al.[72]	Random Forest	86.84%

After reviewing accuracy rate and performance analysis of the model for heart disease it was found that accuracy rate of the model can be improvised.

2.9 Research gaps and Challenges.

Taking into account previous literature, IoT health concerns and research gaps are presented. An attempts to investigate the scientific gap in the IoT healthcare sector and it also gives interesting directions for future research regarding the implementation of healthcare data. Most of the research papers have focused on healthcare services, and sensors for collecting and storing data about patients. This can contribute towards diagnosis of the disease. IoT and machine learning can help healthcare professionals to take quick decisions and start the early treatment, which is important for a healthy society.

Most of the devices used in the previous study illustrated single parameter monitoring without the analysis of data. Devices such as Lifeguard, Spot vital sign LXi, OLDES, My heart, and Chronic are the single parameter health monitoring devices in the market. They monitor ECG signals, respiration, activity, temperature, heart rate, SpO_2, and blood pressure. Such a system can send data to a computer via Bluetooth protocol. But the drawback of using Bluetooth are low bandwidth and less secure as compared to the Wi-Fi. They have limited data storage capability as well as short range of communication between the devices.

Data from multiple sources are required for the remote patient monitoring system. The cost of the devices available in the market is not easily affordable to the financially weaker community people. Smart watch/device are self monitored by the user, they will not able to get any assistance and analysis from the doctor. These data are not stored in a centralized place for exchanging information with doctors. Practically to understand the status of a patient multi parameter monitoring system is needed.

Through rigorous literature survey, it is observed that early disease prediction is the most required area of research in the healthcare sector. Heart disease (HD) and Diabetes have been considered one of the most complex and live deadliest human diseases in the world. Hence accurate and proper diagnosis of such disease in patients is necessary for reducing their associated risks of critical issues and improving the health. The invasive-based techniques for the diagnosis of heart disease are based on the analysis of the patient's medical history, physical examination report, and analysis symptoms by medical experts. All these techniques mostly cause imprecise diagnosis and often delay in the diagnosis results due to the human errors. Moreover, it is more expensive and computationally complex and takes more time to assess. The proposed model targets to achieve a good accuracy rate in the prediction of diabetes/heart disease. The machine learning model accuracy can be improved by avoiding overfitting and underfitting issues during the training period.

Feature selection in medical diagnosis helps to improve clinical decisions quickly. Proposed research work utilized dataset from Kaggle data repository [73] for heart disease and Mendeley data repository for diabetes [74].

IoT and machine learning can help healthcare professionals to incorporate the changes in the system, which is important for a healthy society by shifting from hospital centric to patient centric. Available mobile applications in healthcare are more focused on scheduling appointments, video calls, and medical prescription management. Features like report scanning, importing medical images, logging patient history, prediction analysis, real time monitoring of parameter for the health analysis is not available in the existing application. This will help to bridge the observed research gap. The main highlighted challenges considered in this work are as follows.

- A device with low cost multiple parameter monitoring and capable of communicating with the doctors through custom made mobile application is the requirement of smart healthcare. Hence the research attempts to take the challenge faced by most of the people in healthcare sector. It should strongly provide 24/7 service to track the vital sign of a patient. There by eliminating the patient's need for repeated clinical visits.

- The research aims to provide a solution to the challenges faced in traditional healthcare systems by saving time in diagnosis, cost involved in generating reports, and user friendly services. Proposed research contributes towards designing a generalized cost effective IoT assisted mobility based framework for health monitoring. The fundamental intention of this work is to provide modern technologies, protocols, and architectures in the design of hardware units.

- This research finds a method to develop of low cost mobility based IoT assisted healthcare framework with security feature and prediction model. Mobile applications and a prediction model in healthcare analysis assists the doctors. It helps in taking quick decision and monitor the patient virtually. This enables the doctor to give advice to the patient in a real time.

Chapter 3

Performance analysis of sensor nodes in healthcare system using simulation

3.1 Introduction

Understanding the behaviour of the sensor nodes in terms of throughput, latency rate, priority of packet transmission, placement of nodes, and protocol selection was performed using simulation tools. The analysis of sensor nodes was considered while designing a smart healthcare model. Proper selection of Media Access control (MAC) layer protocol helps in saving energy of the node thus increase the life time of the wearable sensor node. The simulation of wireless sensor nodes helps to analyze the consumption of energy. The requirement of suitable protocol for patient health monitoring system was studied under various configurations.

3.2 Performance analysis of wearable sensor nodes

There were two simulation tools used in the analysis of various parameters in healthcare monitoring model. The wireless sensor nodes are simulated using Cooja simulator. The nodes are configured using IPV6 address. The simulation of two available protocol contikimac and xmac are analyzed. The simulation was configured with six nodes. One node as coordinator and remaining five nodes configured as sender nodes. The random positioning of the nodes has been selected in the simulation. The proposed design of smart healthcare system is analyzed using Cooja and Castalia simulator. Initially Contiki operating system is installed to work under various conditions.

Simulator is used to analyze the position of sensor on wearable body area network (WBAN). The WBAN sensor nodes are selected to transfer body parameter such as temperature, pulse rate, blood pressure and, ECG. These parameters are used for an early detection of disease in a patient. Thus helps to alarm user to take preventive measures. To visualize the behaviour of the smart healthcare model, initially it was simulated by assigning priority to the packets. It is also necessary label the prioritization of the sensor data. In this analysis the sensor data is classified into normal and emergency data. Accordingly patient data are further categorized as, data is above normal (RP), or data below normal (OP), or critical packet (CP), or normal packet(NP). In the patient health monitoring as the data is normally heterogeneous the use of WBAN is more appropriate than WSN. The normal data should be given lowest priority and critical data should be treated as highest priority.

The sensor node stores the data into two different queue structure. Threshold values are defined as upper range and lower range limit. If the sensor data is below or above the threshold value it is termed as critical or emergency data, and it is saved in higher priority queue otherwise it is stored in normal queue. Under emergency situation data it is further classified into critical time dependent and independent. The critical time dependent should be given highest priority to transmit with low latency (fast rate of transmission). The data collection phase by the server node is categorized into four phases:

- Regular monitoring takes place at regular or at a scheduled time and recorded at the server.
- Emergency data monitoring in the sensor node are giving alarm due to the condition when the value is above or below the threshold limit. These data needs to be transmitted and medical assistance should be provided to the patients using suitable actuator units.

An algorithm which can handle data priority of the sensor node, through which wireless nodes achieve the maximum efficiency is proposed in this work. Low latency for critical data should be given an importance in the design of WBAN. This system should guarantees to obtain the solution in the shortest time with good reliability. The urgent data should not be delayed or denied due to dynamic availability of network resources.

The proposed algorithm for priority based MAC layer protocol is developed below.
Step 1: Start sending request to coordinator node.
Step 2: Testing whether the sensor data is urgent (above/below the set limit)?
Step 3: If data is urgent wait for a slot UIFS else wait for a slot interval NIFS.
Step 4: If data is normal send RTS (request to send) frame, wait for CTS (clear to send) from coordinator node. Then send the data frame.
Step 5. End.

The algorithm was implemented using Cooja simulation software. WBAN nodes are configured using two types of wireless sensor nodes: Sky node and Zolertia (Z1). Sky node is equipped with 8 MHz Texas Instruments, MSP430 low power microcontroller, 10 KB RAM and 48 KB flash memory. Zolertia node is equipped with 16MHz MSP430F2617 low power microcontroller, 8 KB RAM and 92 KB flash memory. It has 250 Kbps, 2.4 GHz, IEEE 802.15.4, CC2420 transceiver.

The existing MAC layer protocols are verified on the Sky and Zolertia node by configuring sensor nodes as client and server nodes. The results observed in the simulation window depicts the server node is turned on 100% and client nodes turned on only when data is ready for the transmission. Average power consumption of the each nodes are calculated. The existing protocol are not differentiating the priority of the data. It transmits the data to the server with same rate. This creates no differentiation between normal packet and emergency data packet. So priority to the data packets should be given importance in transmission of the sensor data is implemented using proposed algorithm.

Power consumption is a necessary requirement in Wireless Body Sensor Networks (WBSNs). The sensor nodes must function properly and independently for a longer duration without replacing or changing the battery. According to the early researchers in WBSN, major issues faced are :

1. Physical layer issues helps in the selection of frequency for data transmission, issues related to the fault tolerance and collision or interference.

2. MAC layer focus on the assigning channel slot for transmission, reliability, algorithm related to the scheduling.

3. Routing layer issues involve the varying data needs, resource constraints, mobility amongst other architecture.

4. Energy consumption and network life time improvement.

3.2.1 Analysis of path loss and transmission sequence of sensor nodes

Data transmission from the human body to the central server demands high energy consumption for information acquisition and transmission. Therefore the reduction in the consumption of energy is one of the most important aspects to be considered. An efficient MAC protocol aims at maximising network lifetime and minimising end to end delay in successful packet transmission. This helps to achieve the maximum throughput. This aim is being achieved by controlling the major sources of energy dissipation including re-transmission of data packets, control packet overhead, collision of packets, idle listening, state switching, frequent transceiver switching and overhearing.

The various MAC layer protocol are studied and the comparison are done based on the parameters; efficiency, total energy consumption, and latency recorded during transmission of data packets. The comparison of two protocol used in Wireless Body area network is performed using a simulator OMNET++ with Castalia framework. The results of the simulation for 3 different test cases are observed.
Test case 1: Varying path loss vs no loss, and fixed guaranteed slot vs contention slots. Results obtained in the figure 3.1 depicts the packets received per node under general and noTemporal condition. In general condition packet transmission is drastically small as compared to the noTemporal (no path loss) condition. The main difference between WSN and WBAN is path loss component. The signals transmitted in WBAN are heavily attenuated and shadowed by human body. So Baseline MAC (B-MAC) layer protocol is considered over Zigbee protocol in the implementation model. The path loss component is expressed in dB according to Friis formula.

$$PL(d) = PL(do) + 10 * \eta + log(d/do) + X_\sigma \tag{3.1}$$

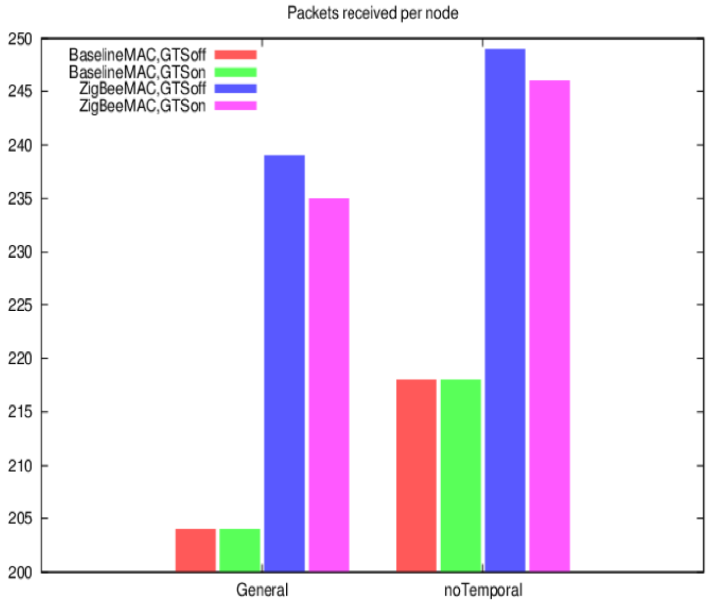

Figure 3.1: Analysis of communication protocol

where the PL(d) is the path loss at a distance d, PL(do) is the known path loss at a reference distance do, η is the path loss exponent, and Xσ is a gaussian zero-mean random variable with standard deviation σ.

Test case 2: Assuming there will be path loss during transmission of data and also considering if there is no path loss in the transmission. The figure 3.2 illustrates the throughput analysis of protocol with this condition. Data transmission during fixed

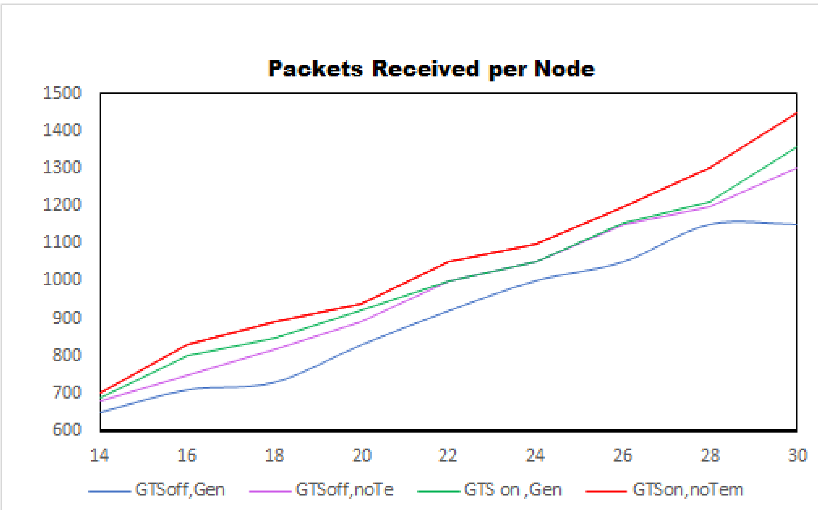

Figure 3.2: Throughput analysis of protocol

guaranteed slot is also compared with contention slot to measure the performance of MAC layer protocol.

The packets will get transmitted during the guaranteed interval with no collisions is GTSon and with collision is GTSoff. It is observed that under no collisions environment (GTSon,noTem) the packets received at the coordinator node is higher as compared to data transmitted under non guaranteed slot (GTSoff,noTem)).

Test case 3: Simulation is carried out to analyze the protocol by varying the power supply to the sensor nodes. The packets transfer rate is measured. The figure 3.3

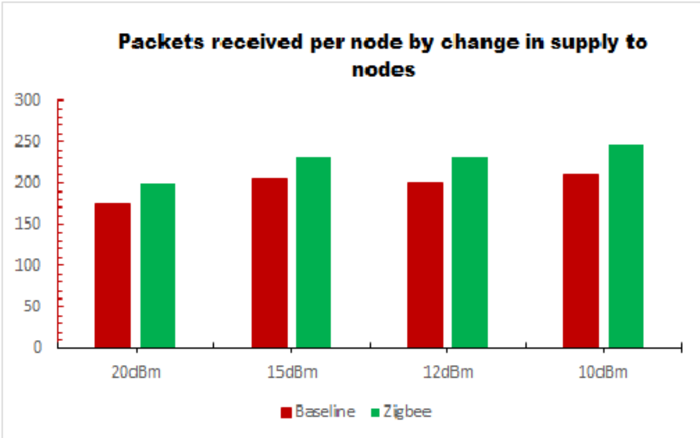

Figure 3.3: Energy consumption of sensor nodes

illustrates energy consumption of the node on x-axis and number of packets transferred on y-axis. The energy consumption of sensor nodes are set as 10dBm, 12dBm, 15dBm and 20dBm respectively. The packets collected by the coordinator node is verified graphically. The figure shows 10dBm energy consumption rate gives more throughput for both the protocol.

Further it is observed that both protocols perform best when 10dBm of power is supplied to the nodes. However, a remarkable improvement in the performance of B-MAC protocol is observed when number of scheduled slots for packet transmission are increased. Furthermore, Zigbee MAC protocol performs best when random channel access is permitted along with GTS, whereas efficient functioning of B-MAC protocol requires a proper combination of scheduled and random access slots to access the channel. Thus the model developed in this work utilizes 802.15.6 protocol in the transfer of data packets to the coordinator node.

Table 3.1: Simulation setting for Contki Cooja

Parameters	Specified values
Simulation area	40cm x 40cm
CCA threshold	45 dB
MAC protocol	802.15.6 CSMA/CA
Mote Type	Sky Mote
Slot Time	20 μs
CCA Time	15 μs
Channel Check Rate	128 Hz
Radio Channel	26
RTS/CTS	Off
Packet size	97 bytes

3.2.2 Analysis on the placement of sensor nodes

The proposed system uses non invasive methods for measuring vital parameters. The sensors are placed on the fingers and on the ear lobe. Most of the measuring techniques are depended on the optical mechanism. Through the literature study it is concluded that, they should be placed at an equidistant point from the gateway. Attenuation of the signals occurs if sensors are placed on the body of a patient.

The selection criteria for sensor node are taken atmost important to reduce the path loss. The main criteria for acquiring the data depends on the health status of the user. If the patient is healthy the sensor should be placed or carried along with them without affecting daily activity. The mobility of the user is taken care while placing the sensor on the body. The implanted sensor is placed inside the body tissue after surgical intervention. The direction of the antenna, the size of the antenna and power source of the sensor nodes is a challenge for a generic healthcare system. Hence this model implements on body sensor nodes instead of implant nodes.

Simulation of WBAN sensor nodes and their Optimal placement on the user is carried out using Cooja simulation software. Each sensor in IoT enabled WBAN is assigned a different priority value and a topology for the network is shown in the Table 3.1. The priority value is assigned which ranges from 0 (lowest) to 7 (highest). The sensor nodes and coordinator node is deployed within the simulation area of 40cm X

Table 3.2: Data transmission based on priority of packet

Priority of the nodes	Packets delivered
0	18
1	24
2	25
3	30
4	34
5	36
6	38
7	39

40cm. The simulation is carried out for 180 seconds. Size of each packet transmitted by the node is 97 bytes. It has been assumed that each sensor node has always a data packet in the buffer for the transmission. The network performance is measured using various protocols ContikiRPL for Network Layer, WBAN MAC for Data Link Layer, and ContikiMac (RDC) for the Physical Layer.

Performance of the nodes was analyzed using delay for transmitting the packets to the coordinator node. Table 3.2 shows the data transmission based on the priority of the packets transmitted to the coordinator node. It is observed that around 50% more packets of the highest priority nodes are delivered as compared to the percentage of packets delivered by the lowest priority nodes. In the same interval of time 39 highest priority packets and 18 lowest priority packets are delivered. By ensuring the priority estimated time for delivery of packet was reduced.

3.2.3 Analysis of latency rate of sensor

Various results obtained using simulation window concluded that the average delay taken to deliver a packet for the highest priority sensors is nearer to 450 milliseconds, which is about 14% less delay as compared to the lowest priority sensors. The nodes having different priority has different time delay and power consumption, where nodes having higher priority have least time delay (latency) and maximum power consumption. Thus higher priority node is getting more opportunity to send the packet via shared channel than the other nodes. As per our initial study, we concluded that our proposed solution can be considered in the design of efficient healthcare monitoring system.

3.2.4 Analysis of channel rate of the sensor

The behaviour of the two protocol are analyzed using the sensor nodes. Simulation window shows the energy consumption of two different protocol used in transmitting the sensor data, Sky node 1 is configured as coordinator (receiver) node and other sky nodes are set as sender nodes. By keeping the radio on continuously at the receiver to receive packets from rest of the sender nodes nodes. The parameter that defines the channel check rate is set to a power of 2 (2, 4, 8, 16, 32 Hz). It defines how many times the nodes will check the media in seconds. By varying the parameter to 8Hz, and 16Hz the energy analysis of MAC layer protocol was observed for a duration of 4 to 5 minutes. Figure 3.4 illustrates the various sensors transmitting the packet by using channel rate at 8 Hz. The average time of the sensor consuming power was measured

PowerTracker: 6 motes

Mote	Radio on (%)	Radio TX (%)	Radio RX (%)
Sky 1	99.79%	0.51%	2.42%
Sky 2	5.98%	0.48%	0.19%
Sky 3	5.80%	0.49%	0.14%
Sky 4	5.95%	0.47%	0.23%
Sky 5	5.96%	0.50%	0.15%
Sky 6	5.98%	0.49%	0.23%
AVERAGE	21.57%	0.49%	0.56%

Figure 3.4: Performance of channel rate 8 Hz

as 21.57% of the total power consumed for 4 minutes.

By changing the channel rate to 16 Hz simulation was further carried out to analyze the behaviour. The energy consumption is comparatively more if channel rate is assigned high. Experimental results in figure 3.5 shows the average energy consumption reduces if the nodes sleep time is more than the wakeup time. The results of the Cooja confirms that the energy saving is decided based on the selection of MAC layer protocol, RDC layer, and radio duty cycle period. The channel accessing mechanism and collision free delivery improves the throughput of the designed system.

PowerTracker: 6 motes

Mote	Radio on (%)	Radio TX (%)	Radio RX (%
Sky 1	100.00%	0.46%	2.12%
Sky 2	10.79%	0.43%	0.23%
Sky 3	10.69%	0.44%	0.26%
Sky 4	10.79%	0.42%	0.22%
Sky 5	10.66%	0.44%	0.20%
Sky 6	10.73%	0.43%	0.24%
AVERAGE	25.61%	0.44%	0.55%

Figure 3.5: Performance of channel rate 16 Hz

A two bit priority field was created in the packet header to classify the packets. The value 00 in the field indicates normal traffic, 11 indicates emergency traffic further 10 for critical time dependent and 01 for critical time independent traffic. The packet classes used in the proposed MAC layer are further classified as type 1 data with high priority, type 2 data with medium priority and type 3 data with low priority. This protocol is implemented using C programming on the Cooja environment. The conclusion gathered using various case study helped to select appropriate protocol while implementing in health monitoring application. The generated data should be transmitted to the cloud at a higher data transfer rate. The critical data recording at the cloud should able to provide quick services to the patient monitoring unit. This will help to treat the elderly patients, post operated patients at the early stage without the delay in delivering the packet.

3.3 Conclusion

Advancements in the field of Wearable Body Area Network have encouraged the development in medical applications. But the stringent energy requirements of WBAN have led to the optimisation of the MAC protocols. The objective of the work was to analyse the working of IEEE 802.15.4 (Zigbee MAC) and IEEE 802.15.6 Baseline (B-MAC) standards. Based on the evaluations, it is observed that Zigbee MAC performs better than Baseline MAC protocols in terms of throughput, latency when it is subjected to no path loss and guaranteed time slot (GTSon) of data transmission is fixed. Further it is observed that both protocols perform best when 10dBm of power is supplied to the nodes. However, a remarkable improvement in the performance of

B-MAC protocol is observed when number of scheduled slots for packet transmission are increased. Hence B-MAC protocol is implemented in the body area health monitoring model. The priority, latency, and energy consumption of the nodes are given consideration while implementing the real time monitoring system.

Chapter 4

Android based heaLth Enabled Remote Terminal (ALERT) system for preventive Smart Healthcare System

4.1 Introduction

An increase in the usage of wearable sensor nodes and advanced communication techniques helps to progress in the diagnostic methodology. This results in improving the quality of human life. Virtual monitoring of patients through wearable sensor nodes can extend the services of an expert doctors in the region where there is scarcity of healthcare infrastructure. Hence medical services in those areas can be enhanced and people may utilize the proposed prototype unit for the regular check-up of health parameters and receiving the advice from the physicians.

The financial burden on the global healthcare system is caused by the rapidly growing numbers of chronic diseases and illnesses. These are due to the lack of exercise, as well as the increasing aging population. Due to the enhancement in technology, we currently witnessing the emergence of what is often described as the 'digital health revolution'. This prompted a significant increase in the research and commercial developments of specific health care devices.Smart health care products can offer disease detection, monitoring, and management. Thereby empowering the user to lead a healthier lifestyle and make healthcare more effective.

The wearable health assistant could help people to fight diseases through a preventative lifestyle and early diagnosis. The user could take control of their health status and adopt a healthier lifestyle. This self-management of health makes people more independent, improves their quality of life, and at the same time reduces health care costs. The proposed health care model was developed using wearable sensor nodes. A Wireless Body Area Network (WBAN) is a short-range network that consists of a coordinator and a collection of low-power sensors that can be attached to the human body.

4.2 Android based heaLth Enabled Remote Terminal (ALERT) system

The designed system was named as “ALERT” i.e Android based heaLth Enabled Remote Terminal (ALERT) system. This unit was having a builtin low-power, small-sized and low-cost device. Architecture of this model permits contact less monitoring of vital parameters of a patient. The recorded parameters are displayed using android based mobile terminal.

In the mobility based remote monitoring system a patient can be equipped with a wireless body area network consisting of sensors that constantly measure specific biological functions, such as temperature, blood pressure, heart rate, electrocardiogram (ECG), respiration rate, and oxygen saturation level. ‘ALERT’ system collects the vital parameters from the patient/user body and transmits them to the storage unit. Further, the designed mobile application helps to get an early medical assistance to the patient from the doctor. This chapter gives a brief description about wearable sensor nodes used in measuring various body parameters, selection of sensor, gateway node, sensor data validation for anomaly detection, and storage of data in the cloud.

The design of an “ALERT” system that would allow ubiquitous monitoring of patient’s health continuously across the clock was proposed in this research work. This system thrives on advanced wireless communication technology with body sensor nodes as the main sensing component. These nodes are mounted on a patient’s body, sense physical stimulation, and subsequently transform the same into digital readings. Such wireless body sensor networks (WBANs) are capable of providing remote health monitoring in seamlessly. The flexibility and availability of such healthcare can be increased, if it can be provisioned as an on-demand service to the patient. Therefore, there is an envision to acquire and analyze data in real-time data from multiple WBANs integrated with a cloud framework.

The raw data concerning a patient's health are transmitted to a cloud of healthcare service providers through a middleware. Health data analytics are continuously executed on the raw data to detect any unusual health condition. Detection of irregularity, if any, is notified then it will send a notification to the concerned patient or caretaker. Smart health care products can offer various services to alert a patient in an early stage.

4.2.1 Design of IoT assisted healthcare system.

The proposed model consists of four blocks. They are:

- Acquire data: The data is captured using sensor nodes from the human body. Digital sensors are selected to reduce the time required for the transmission. Analog sensor have to convert the data into digital using ADC converter which results into delay. Temperature sensor, Heart rate sensor, oxygen saturation sensor and ECG sensor are selected in the proposed unit.

- Gateway node: Data collected from the sensor node are transmitted to the gateway or a microcontroller unit equipped with a communication module. Sensor anomaly detection algorithm was developed in this work. It helps to detect malfunctioning of any sensor unit. Only valid information from the sensor is transferred to the cloud. The microcontroller unit selected in this work is integrated with a Wi-Fi module to transfer the data to the chosen cloud unit.

- Cloud storage: The information from the sensor was transferred to the cloud storage. The sensor data from the cloud, further accessed remotely using a designed mobile application. The patient information was securely stored in the database.

- Prediction model with Mobile Application: Prediction model in early detection of the disease along with user friendly interface was developed to virtually monitor the health-related signals of a person.

This framework is the fusion of four main units, i.e sensors, a control unit or gateway, cloud storage and a prediction model with mobile application. The block diagram of the proposed model is represented in figure 4.1. The selection and configuration of each block are described in the following sections.

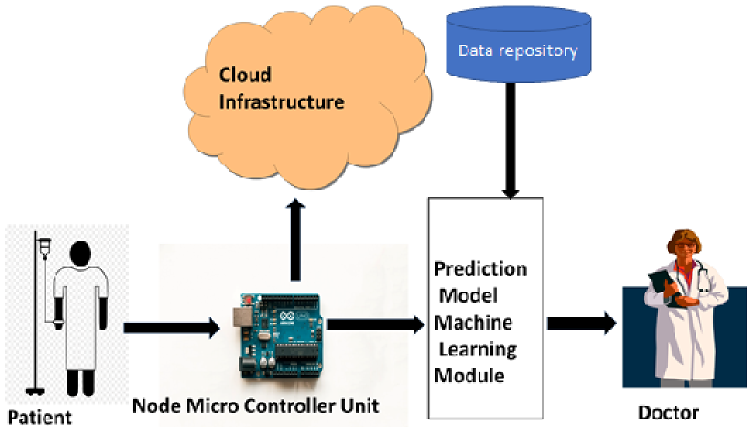

Figure 4.1: Proposed IoT assisted healthcare model

4.3 Selection of parameters in the proposed model

The system is composed of health monitoring unit and the information retrieval unit. The information retrieval unit informs the doctors and health professionals about the patient's health. The following factors were taken into consideration in the design of the prototype unit:

- Mobility: The proposed hardware unit should be easy to wear. It should allow the patient to wear and move without any restrictions. Potential problems such as network connectivity and battery duration or chargeable unit is taken into consideration. Weight and dimensions of the unit was also given importance while designing a prototype unit.

- Quality of service: It is very important to have near accurate measurements transmitted appropriately to the cloud. Parameters such as data accuracy, delay, network speed is given an importance while designing the prototype.

- Data sensitivity: The acquired medical data is sensitive and shall be available only to the patient itself and his/her supervising doctor. Therefore adequate network safety mechanisms shall be applied along with authorization module at the information retrieval system.

- Cost and user friendly: One of our main aim is to propose a system that has affordable cost so that it can be used by all kind of people with ease. User friendly features are Incorporated in the design.

Design of proposed system is also analyzed in terms of type of measurement. We have considered two different system in parameter monitoring, single parameter and multi parameter monitoring.

- Single parameter monitoring system: In this instance, a single parameter is monitored. Using this reading multiple values can be derived depending on the type of algorithm used. An ECG reading can give the heart rate and oxygen saturation value. Similarly sensor used for particle detection can be used for measuring body temperature, heart beats per minute (BPM), oxygen saturation level and detection of eye blinking for the physical presence or body movement.

- Multi-parameter monitoring system: This has multiple parameters being monitored at the same time. An example of such a system can be found in High Dependency Units (HDU), Intensive Care Units (ICU), during the surgery at a hospital theatre or post surgery recovery units in the hospitals. Several parameters that are monitored include the ECG, blood pressure, respiration rate, temperature, heart beat, oxygen saturation level and blood sugar.

This research aims at early detection of symptoms and assist the people in taking preventive measures. The proposed design concentrates in multi parameter monitoring. The sensors used in monitoring health parameters of a patient are decided based on the survey conducted through the google forms. The questionnaires were framed in a pilot survey involving two hundred and twenty three participating volunteers (50 medical personnel and 173 general public). Initially survey was conducted to understand the need of the customer and physician in terms of type of vital body parameter necessary to be monitored. The response received from 223 users were visualized using a chart

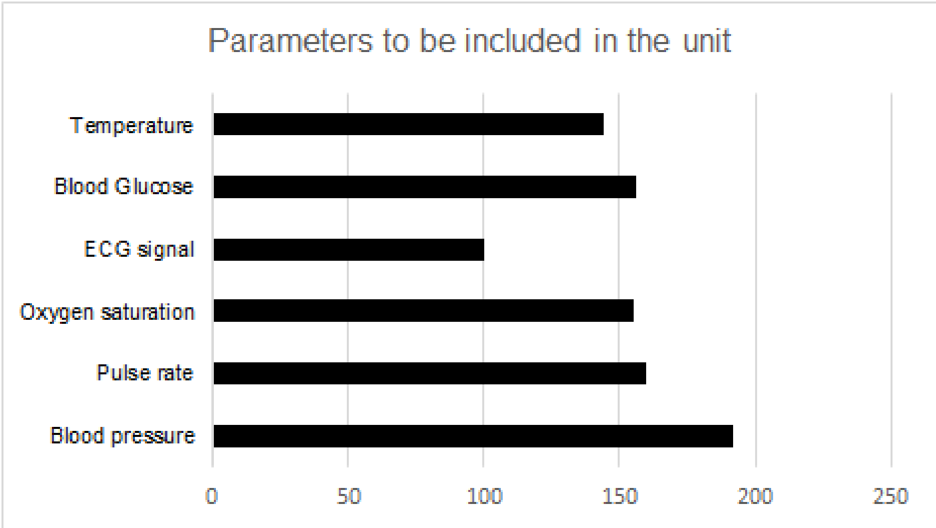

Figure 4.2: Collection of user's input

as shown in figure 4.2. According to the received input the most expected parameters suggested by the users were: blood pressure (86%), pulse rate sensor (72%), blood glucose sensor (70%) and temperature (65%). So they are considered in the design of the hardware unit. The hardware unit is composed of following sensors for health monitoring.

i. Body temperature (temperature sensor)

ii. Small Electrocardiography Device (3-9 ECG Electrodes for monitoring heart and heart pulses)

iii. Oxygen saturation sensor.

iv. Heart beat or pulse rate sensor.

4.4 Types of sensors used in "ALERT" system

The following parameters of an individual are measured at any instant of time using the proposed hardware unit and logged into the cloud using patient/user ID. The sensors selected for the "ALERT" model are as follows.

1. Body temperature: Variations in body temperature are highly informative during an illness. Abnormalities in body temperature are the key indicators for the prognosis of various illnesses. Body temperature is one of the most important vi-

tal signs for evaluating human health. The continuous monitoring should be done for the early identification of patients who are at a risk for poor prognosis. In the clinic normally the temperature is measured using glass mercury thermometers, electronic thermometers, infrared ear thermometers, and infrared forehead thermometers. In IoT based healthcare wearable devices are used to record temperature. Among the human body parts, the wrist is the most responsive body part for wearable devices that measure thermal sensation. Wearable temperature sensor IC's which provide clinical-grade accuracy combined with ultra-low power operation are selected for monitoring body temperature.

Various sensors used to monitor body temperature were reviewed and selected two different sensors for measurement purpose. Experimentation of an analog sensor and a digital sensor performance are compared in monitoring body temperature and accordingly a sensor is selected in the final proposed model. The values recorded using the sensor is interpreted as follows:

- Body temperature: below 95 degree Fahrenheit is termed as hypothermia.
- Body temperature: 97 - 98.6 degree Fahrenheit is refereed as normal.
- Body temperature: above 100.4 degree Fahrenheit is considered as fever.
- Body temperature: above 102 degree Fahrenheit is treated as critical.

Sensor1: LM35 is an analog sensor used in measurement of body temperature. It is a popular, less expensive temperature sensor, and it gives a voltage reading which are linear to the temperature readings in degree Celsius and, it provides an output voltage of 10.0 mV for each rise of temperature in degree centigrade. It is 3 pin IC, consists of Vcc, ground pin and analog output. The figure 4.3 representing the analog temperature sensor LM35. Sensor2: MAX30205 is a digital IC, used to measure human body temperature. MAX30205 digital thermometer temperature sensor is accurate to 0.1°C over the measurement range of 37°C to 39°C and the resolution is 16 bits (0.00390625° C). MAX30205 is contact-less sensor used to measure body temperature by placing the sensor on the wrist. Figure 4.4 represents MAX30205 sensor used in recording body temperature. I2C port was used to interface the sensor to the microcontroller. The readings obtained from the digital sensor are more precise in monitoring human body tem-

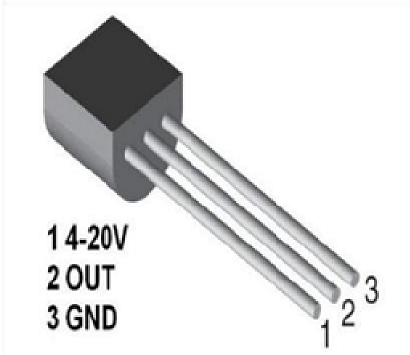

Figure 4.3: Analog temperature sensor LM35

Table 4.1: Comparison of analog and digital temperature sensor

Property	LM35	MAX30205
Accuracy	0.5	0.1
Operating voltage	4V-30V	2.7V -3.3V
Current drawn from supply	60 uA	600 uA
Heating problem	Occurs more	Occurs less

perature. Sensor readings are calibrated to obtain the actual value by comparing with standard equipment used for measuring. Thermometer readings are used as standard reference to obtain the correction factor. Correction factor (K) was maintained uniform for the remaining measurement of the temperature. Table

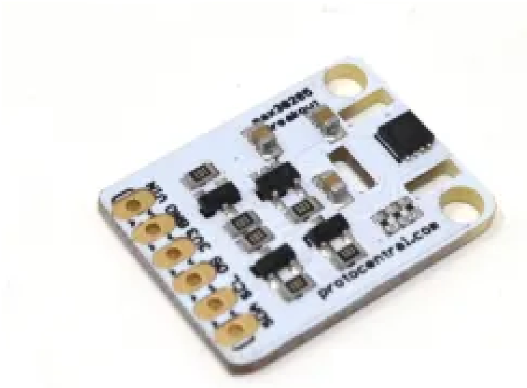

Figure 4.4: Digital temperature sensor MAX30205

4.1 compares the performance of the sensor with the digital sensor used for body temperature measurement. Digital sensor MAX30205 is selected in building the proposed prototype.

2. Measurement of pulse rate (heart rate): Heartbeat can be checked manually by checking one's pulses at two locations i.e wrist (the radial pulse) or neck (carotid pulse). The procedure is to place the two fingers (index and middle finger) on the wrist (or neck below the windpipe) and count the number of pulses for 30 seconds and then multiplying that number by 2 to get the heart beat rate. However, pressure should be applied minimum and also fingers should be moved up and down till the pulse is felt. Heart beat sensor is shown in figure 4.5 measures heart beat using optical method. It is a 3 pin IC, with Vcc, ground and digital output. They are used in interfacing with the gateway node. Heart beat can

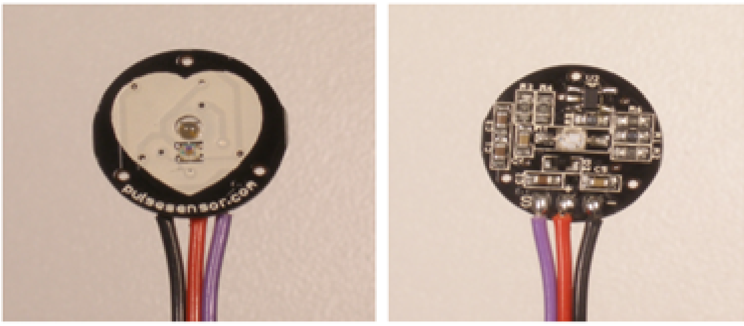

Figure 4.5: Heart beat sensor

be measured based on optical power variation. When the light is scattered or absorbed during its path through the blood as the heart beat changes. Sensor works on the principle of the photo plethysmography (PPG) which is a non-invasive method for measuring the variation in blood volume in tissues using a light source and detector. The following criteria was used to check the pulse rate observed using this sensor. Sensor was attached to finger and ear lobe to verify the test results. The following parameters was considered in understanding the pulse rate.

- Heart rate per seconds: 50- 60 low rate.
- Heart rate per seconds: 70- 80 normal.
- Heart rate per seconds: 80- 100 high.
- Heart rate per seconds: above 110 critical.

Hypertension can lead to the heart disease and stroke. So regular monitoring of heartbeat/ blood pressure helps the people to know about their health condition.

In this direction the measurement of pulse rate becomes more significant.

3. Measurement of Oxygen saturation level in the blood (SpO_2) sensor:

   The MAX30102/MAX30105 sensor is a flexible, powerful sensor enabling sensing of oxygen saturation in the blood, measures heart rate, and even the blinking of an eye (body movement). The MAX30105 has been equipped with three light emitting diodes (LED) as well as a very sensitive photo detector. It utilizes a red LED, green LED, and an Infrared (IR) LED for presence sensing. MAX30105 is designed to operate at 5V and can communicate with both 3.3V and 5V microcontrollers. The LEDS used in the pulse oximetry sensor are helps to determine the true hemoglobin oxygen saturation of arterial blood. The properties of red LED and infrared LED is utilized for determining the oxygen saturation level. Content of oxyhemoglobin (HbO_2) absorbs visible and IR light differently. The absorption capacity of deoxyhemoglobin (Hb) is different than that of (HbO_2). The color appears bright red as compared to the darker brown in deoxyhemoglobin. Absorption in the arterial blood is contains two components AC and DC. The AC signal getting superimposed on a DC signal. DC signal mainly representing absorption of blood by other substances like pigmentation in tissue, and bones. SpO_2 is calculated using equation 4.1 [75].

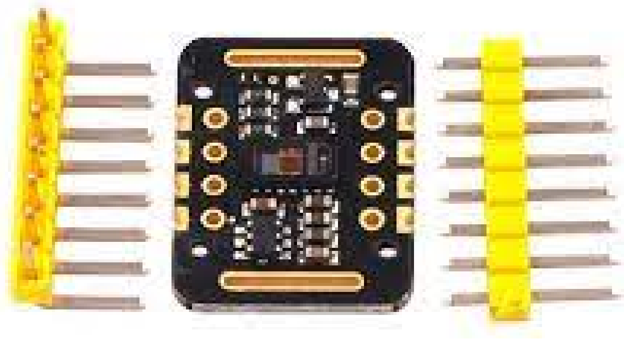

Figure 4.6: Pulse oximeter sensor

$$R = [[ACrmsofRed/DCofRed] \div [ACrmsofIR/DCofIR]] \tag{4.1}$$

A pulse oximeter uses two frequency of light to determine the percentage of hemoglobin in blood that is saturated with oxygen. The percentage is called blood oxygen saturation or SpO_2. Usually level of SpO_2 is ranging from 96 to

99% in healthy individuals. However, when patient has chronic diseases at time SpO_2 may decrease. SpO_2 lower than 90% is defined as respiratory failure. When SpO_2 drops by 3-4% from its usual level even if it is not less than 90%, as acute disease may be suspected.

- Oxygen saturation level: 95-100% normal
- Oxygen saturation level: below 90% low hypoxemia
- Oxygen saturation level: 80 to 85% low oxygen level, affects brain
- Oxygen saturation level: below 67% cyanosis

4. Blood pressure sensor: Sensor works on the principle of photo plethysmography (PPG) which is a non-invasive method for measuring the variation in blood volume in tissues using a light source and a detector. The TCRT1000 reflective optical sensor is used for photo plethysmography. The use of TCRT100 simplifies the build process of the sensor part as both the infrared light emitter diode and the detector are arranged side by side in a leaded package. Thus blocking the surrounding ambient light, which could otherwise affect the sensor performance. Output is a digital pulse which is synchronous with the heartbeat. The output pulse can be fed to either an ADC channel or a digital input pin of a microcontroller for further processing and retrieving the heart rate in beats per minute (BPM). It is observed that blood pressure rises with each heartbeat and falls when your heart relaxes between the beats.

5. Measurement of ECG signals: The measurement of electrical activity was measured using single lead electrocardiogram (ECG card. The electrical activity of the heart can be understood using the device AD8232. This research intends to build up a small-scale electrocardiogram monitoring device that will measure the heart activity. An ECG acquisition device was developed using a single-lead ECG sensor. The figure 4.7 represents the ECG sensor used in this prototype. The figure 4.8 represents standard one cycle ECG signal from a heart beat. One cycle consists of P wave, QRS wave until T wave. P wave provides information about the propagation time of the impulse to both atria. This is followed with a flat trend with the PR segment which is in consequence of propagation of the electric impulse from atria to ventricles. This will follow with QRS complex wave. Q, R,

Figure 4.7: ECG sensor

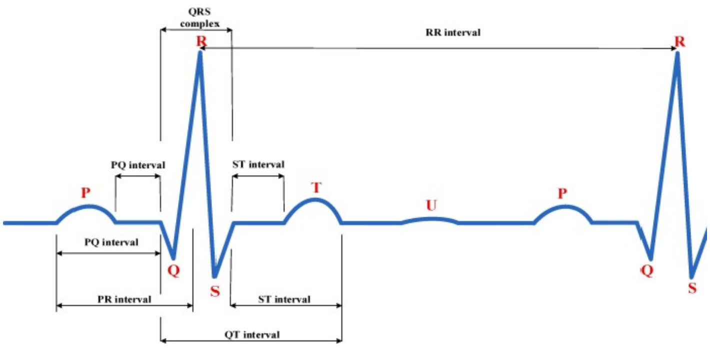

Figure 4.8: Standard ECG waveform

and S complex contains of three small wave i.e small Q wave, the high R wave and the small S wave.

The interval of ECG waveform is tabulated in Table 4.2.

The QRS complex give information about the ventricular systole in consequence of the impulse propagation to the ventricles (Q wave), whereas the transmission to the whole tissue is caused by the R and S wave. The QRS complex provides information about fibrillation and arrhythmias, it can be helpful to analyze heart attacks. ST interval is followed by the S wave and including with the T wave. It can point out the ischemia occurrences. It represents the period during which ventricles are contracting, which is the last stage of the heart cycle. The T wave permits one to have information about the cardiac hypertrophy, heart attacks, and ischemia. Moreover, others parameters, such as the QT interval allow specific further pathology to be characterized. Finally, the ECG signal ended with a small peak, U wave. The standard duration of the interval was refereed using Table

Table 4.2: Phase duration in ECG waveform

Waveform	Duration(s)
P Wave	0.06-0.11 less than 0.25
PR Interval	0.12 to 0.20
PR Segment	0.08
QRS Complex	less then 0.12 0.8-1.2
ST Segment	0.12
QT Interval	0.36-0.44
T Wave	0.16 less than 0.5

4.2 to know the abnormalities in the ECG signals.

4.5 Selection of gateway node in the proposed "ALERT" system

The gateway (coordinator) used in receiving data from all the sensor nodes. Gateway unit was selected based on the criteria of number of analog pins/digital pins, transmission capability, power consumption, size and inbuilt communication module. The most important factor considered for the selection of the microcontroller as a gateway node are as listed below.

- Security
- Cost
- Expansion Capability
- Power Consumption
- Dimension

The features of various microcontroller boards were compared while conducting set of experiments with a gateway node.

- Ardiuno Uno Atmega 328 is a 32 bit, 16 MHz processor, having 6 PWM pins, 14 digital I/O pins, 6 anlaog pins working with 5V D.C. It has 32 KB flash and 2

KB SRAM. Size of the board is 68.6mm x 53.3mm. Weight of the Board is about 25 grams. Sensors can be interfaced to analog pins and I2C ports available on the board.

- Node MCU works with 80 MHz, having one analog pin and six digital I/O, equipped with in built communication module, I2C Interface. Size of the board is 24mm x 16mm works with 3.3V to 5V D.C. It is very compact to use as a wearable unit.

- Texas MSP 430 requires a 25 MHz Clock, 16 bit RISC, 10 Bit ADC, 24 bit I/O capacitive touch panel. Flash memory of 128 KB, 48 GPIO pin.

- Intel Galileo is a 32-bit works with 400 MHz, size of the board is 80mm X 65mm works with 1.8V to 3.6V D.C. It is having 6 analog and 14 digital pins.

- Raspberry Pi works with high speed, 1.2 GHz Quad-Core ARM Cortex A53 (64Bit), 802.11b/g/n Wireless LAN and Bluetooth. Memory of 1 GB LPDDR2, onboard Bluetooth, and Wi-Fi. Size of the board is 85mm x 56mm x 17mm (length, width, breadth).

- Particle Photon board is having dimension of 36.58mm x 20.32mm, works with 120 MHz, ARM 32 bit Cortex M3 operating voltage of 3.3V to 5.0V D.C, having 18 digital and 5 analog pins, 1 MB flash memory, 128 KB RAM integrated Wi-Fi chip.

- BOLT is having dimension of 35mm x 35mm, works with 80 MHz working voltage is 5V D.C, 32 bit, 4 MB Flash memory ESP8266 with custom firmware, having 1 analog and 5 digital I/O port.

- ESP 32 working with operating voltage from 2.2V to 3.6V D.C, Xtensa dual-core 32-bit LX6 micro controller, operating at 160 or 240 MHz. Size of memory is 320 KB RAM, 520 KB SRAM, Wireless connectivity Wi-Fi 802.11 b/g/n HT40 Wi-Fi transreceiver. Size of the chip is 25.4mm x 48.26mm.

Table 4.3: Cloud storage for saving sensor data

Cloud platform	Salient features
Thing speak	Open source data platform for the Internet of Things.
Firebase	Cloud service designed to power real-time, mobile and web. Supports real time backend and API and accessible to mobile push messaging.
Ubidots	A cloud service to capture and make sense of sensor data. IBM blue mix
Microsoft Azure	Manage billions of IoT devices with Azure IoT Hub, a cloud platform that lets you easily connect, monitor, provision, and configure IoT devices.
AWS IoT	easily and securely connect devices to the cloud.

4.6 Selection of cloud storage

Measured data from various sensors are uploaded to the cloud storage. Various cloud structures were studied for performance and experimented to save the sensor results. The Table 4.3 highlights the important specifications and features of cloud used in this work. Cloud presents an efficient platform for archiving patient's medical data for long term storage as well as providing assistance to medical professionals for better diagnosis. Cloud provides data analytics that use sensor data in addition to e-health records for better diagnosis and prediction of health related disease. Cloud also offers data visualization that presents enormous amount of data from sensors in a digestible format for the medical experts. Data storage from the sensors are tested using two different cloud platform. Figure 4.9 illustrate the data flow sequence in the smart healthcare unit.

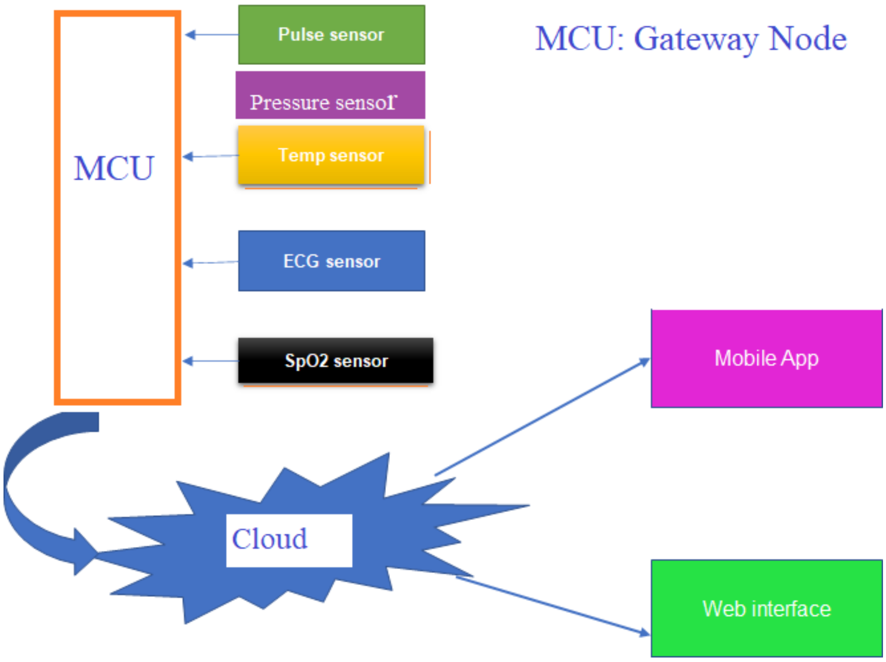

Figure 4.9: Data transfer from gateway to cloud

ThingSpeak is an open source IoT cloud platform for the development of IoT applications [76]. This is one of perfect solutions to compete with existing non-open source platform. As the ThingSpeak is an open database platform, it has integrated support from MathWorks. This helps in analyzing and visualizing data using MATLAB. ThingSpeak cloud is selected for storing the data collected from the sensors. Each patient will be identified using unique channel ID. Patient identity is saved using login id and password. The channel will create various fields to register the sensor parameter and recorded time with date. Channel ID utilizes the API key for reading and writing data. Dashboard on the ThingSpeak helps to visualize the sensor data graphically on the web interface. Data stored in the cloud can be public or private. The private data is protected with an API key that user can control. User can access the data by logging into ThingSpeak account. Further user can view the information and securely download the data. Saved data is in a comma separated variable (CSV) or java script object notation (JSON) format. It can be retrieved using REST API call.

The information collected from the hardware module was saved in the cloud is represented in the figure 4.9. Alternate cloud for storing patient record was performed using Firebase cloud storage. It has excellent feature in saving data and mobile push application as inbuilt feature. The dashboard utility of ThingSpeak outperform the Firebase cloud. Firebase creates a relational database with secret key which helps to keep the recorded data of patient securely without disclosing information to unknown user.

4.7 Sensor data validation algorithm for anomaly detection

Sensor data collected at the gateway node is tested for its validation. Data collected from the sensors is verified for its integrity, before sending to the central server. To provide sensor data validation by detecting any anomaly detection is considered in this research work. Sensor data validation algorithm is developed and tested during the data acquisition and data processing modules of the system. One of the major reason for the incorrect values of acquired data during the acquisition process is due to interference or noise. The data may still be incorrect due to the several factors. It is due to increase in temperature of the surrounding, internal/ external noise caused in the operating region, power fluctuations, and coordination problems. Data validation techniques are mainly performed using various statistical methods. The reliability of the system can be achieved by imposing data validation in the design of acquire system.

The sensor used in the proposed hardware may malfunction due to physical damage or environmental interference or blocked due to the shortage of power supply. The proposed algorithm 1 is implemented at the gateway node.

Algorithm 1 Processing sensor data

Input: Sensor input values

Output: Sensor data uploading to cloud storage

Result: Accept or rejection of data and generation of alert message

Start:

step 1: Read the sensor value from the configured port used for interfacing.

for each received data d_i for an interval T.

step 2: Compare the sensor reading d_i with the lookup table values stored as reference values according to vital parameters.

step 3: if d_i < threshold or d_i > K* threshold assume a chosen value of K > 1. reject the sensor reading and go to step 1.

else continue.

step 4: If reading d_i is greater than K*threshold ($0 < K < 1$) generate alarm signal.

step 5: Delay of t (5) seconds to obtain the stabilized reading, and then transfer the data to the cloud storage.

step 6: End.

4.8 Experimental results analysis

Experimentation was performed using various gateway nodes and cloud storage platform to understand and decide about the selection of sensors, gateway node and cloud storage for the final prototype used in implementation of 'ALERT' model .

- Experimentation-01: Experimentation was performed using Ardiuno Uno (gateway node), sensor for body temperature, heart beat sensor, oxygen saturation and ECG signals, ThingSpeak was used for cloud storage. The I2C port's SCL and SDA pins are used for connecting MAX30102 sensor and MAX30205 sensor. ECG signal was acquired by connecting analog pin Ao and digital pins 11, 12 to Lo+ and Lo- respectively. Sensor board are supplied with 3.3V D.C supply from the gateway. Communication module ESP 8266-01 was interfaced to Ardiuno Uno board. As Ardiuno Uno needs external chip to establish communication to the cloud service. The designed hardware unit needs more space and consume more power. Ardiuno Uno is having only one analog port for interfacing sensor.

In order to reduce the dimension, weight of the prototype unit and power consumption capacity of the unit, the design was modified. Next experimentation was carried out using Node MCU ESP 8266-01 as a gateway node.

- Experimentation-02: It was performed using Node MCU 8266-01 with the sensors, MAX30205, MAX30102, ECG AD8232 unit. Dimension of the prototype was reduced in terms of size and weight, as it was equipped with Wi-Fi module on chip, power consumption was reduced as compared to Ardiuno Uno. Firebase cloud service was used to store the sensor values. It provides additional features in terms of security and application programming interface (APIs) to store the patient data.

- Experimentation-03: This was performed by using a microcontroller WeMos D1 R1 with the same sensors and Firebase as a cloud. The number of analog ports available in the gateway node was observed was five as compared to one port in NODE MCU. On chip communication module was also available. Size and power consumption of the board was same as Ardiuno Uno.

- Experimentation-04: Prototype for experimentation 04 was built using ESP-32 microcontroller board with builtin battery unit. It was observed that size of final prototype board was compact, more powerful with all necessary ports for communication. The restriction observed in the previous experiments was evaded with the new proposed prototype.

Few sensors are used in this experiments for measuring blood sugar and blood pressure by commercially recommended device. Beat-o Glucometer sensor and Blood pressure sensor from Dr Morepen. Blood /blood sugar meter were used to collect the data and upload the image to the cloud. The parameter recorded using individual sensors and aggregation of all sensors to the gateway node was conducted. The latency time to upload the data to cloud was measured at individual instances. The latency time depends on the available network speed. It was observed that ThingSpeak cloud provides dashboards to represent the data for better visual appearance. The experimentation conducted using three different controller and three different cloud storage was illustrated in the next section.

4.9 Results of proposed “ALERT” system

Final results of the program used in collecting sensor data and storing in the cloud was performed. Three test cases are generated to verify the results.

- TEST CASE 01: NODE microcontroller board ESP 8266-01 with MAX30205 temperature sensor and ThingSpeak cloud.
- TEST CASE 02: WeMOs D1 R1 microcontroller with ECG sensor node and Ubidots cloud for storage.
- TEST CASE 03: ESP-32 microcontroller with heart beat and oxygen saturation sensor. Firebase cloud storage for storing the sensor information.

4.9.1 Measurement of body temperature using MAX30205 sensor

The figure 4.10 illustrates the measurement of body temperature using selected sensor. Sensor is interfaced to I2C bus of microcontroller.

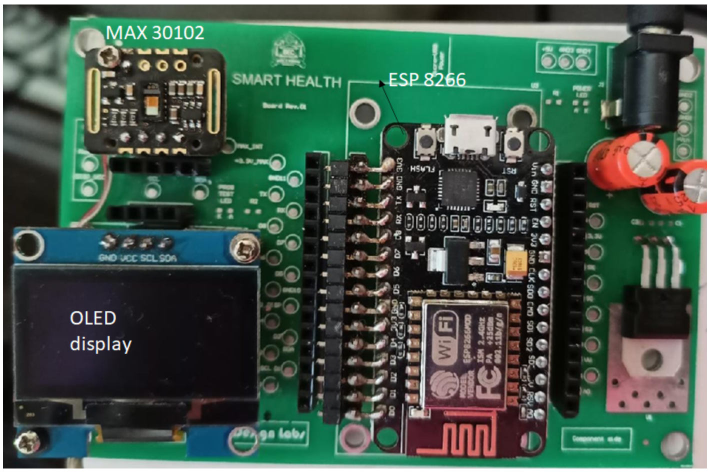

Figure 4.10: Sensor data displayed on gateway unit

The program developed was uploaded to the Node MCU. Temperature sensor reads temperature in degree centigrade, it was converted into degree Fahrenheit.

$$\deg F = 1.8 * \deg C + 32. \tag{4.2}$$

Correction factor K was calculated to get actual body temperature. Body temperature was measured by using standard analog thermometer. The difference in the reading between analog thermometer and MAX30205 sensor was found with a difference of -4 degree Fahrenheit. Correction factor was added to the final reading obtained form MAX30205 sensor. K was obtained as 4, and it was maintained same for the rest of the reading. Node MCU connects to Firebase cloud using valid user name and the password. This features enables to maintain secrecy in the patient data from unauthorised access. The gateway node uploads the current body temperature to the real time database maintained at the Firebase cloud. The structure of data stored from one of the sensor (temperature) was represented in figure 4.11.

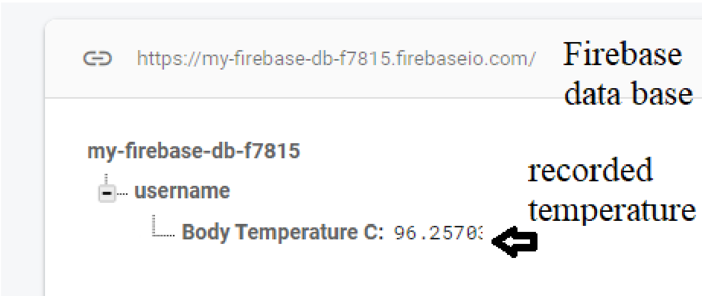

Figure 4.11: Sensor data uploaded Firebase cloud

Firebase security for uploading or downloading data was maintained using Firebase security key. Only registered user of the hardware device can able to send or view the data. Sending data to ThingSpeak cloud allows to view the data in the dashboard as indicated in figure 4.12. The visualization capability is more attractive in ThingSpeak platform as compared to Firebase. Thing speak generates a security API key for writing

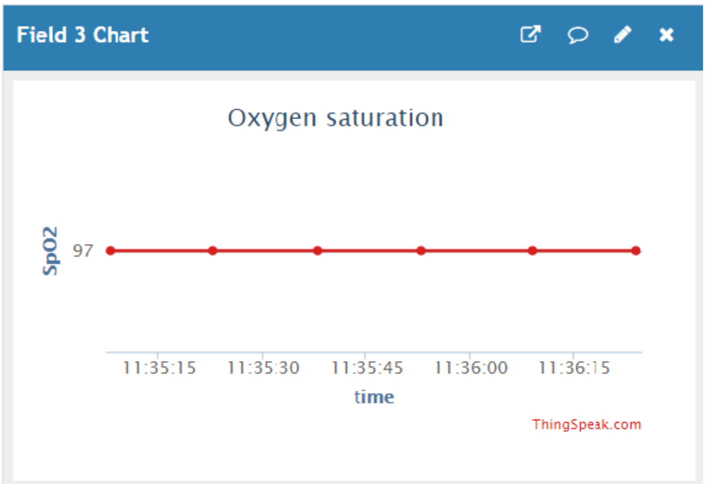

Figure 4.12: Sensor data uploaded to ThingSpeak cloud

and reading data onto the created channel. This channel ID and API key was used further for accessing the values on any remote terminal. Thingspeak and Firebase cloud services were tested to upload the patient data.

4.9.2 Measurement of ECG signal using AD8232

Analog port AO was used to measure ECG signal of a person, Sensor used was AD8232, it is connected to the microcontroller WeMos D1 R1, Lo+ and Lo- signal from the board was interfaced to digital pin 10, and 11 respectively. Single channel probes were connected to right, left arm of the patient/user, ground terminal to cancel noise if any. Sensor is interfaced to microcontroller WeMos D1 R1 as shown in figure 4.13. ECG waveform was further uploaded to the cloud Ubidots. AD8232 sensor provides high signal gain of 100. With D.C blocking capability and Common mode rejection ratio 80 dB (D.C to 60Hz). The AD8232 sensor was connected to various gateway node to observe the waveform received from human body, the waveform was observed using serial port. ECG measurement acquired is represented in figure 4.14.

4.9.3 Measurement of pulse rate and oxygen saturation

The experimentation was performed to receive combined value of heart beat, oxygen saturation and body temperature using MAX30102 sensor. The experiment was conducted using the microcontroller ESP-32. The results obtained using this microcontroller is represented in figure 4.15.

ESP-32 was used in the final proposed model. “ALERT” is equipped with display device and in built battery. Size of the unit is 54mm x 54mm, with a weight of 200 grams. Device can be inserted on hand/pocket and carried along with the user easily.

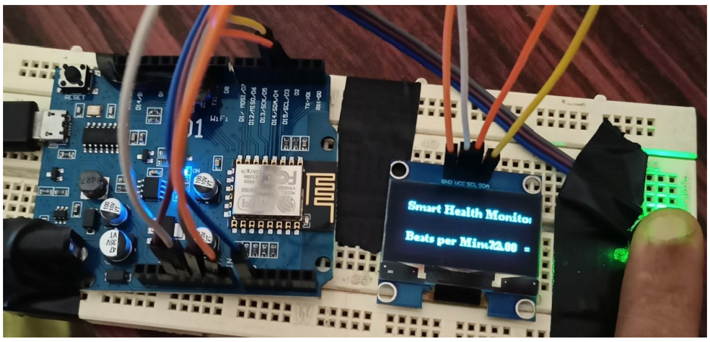

Figure 4.13: Sensor data using WeMos D1 R1

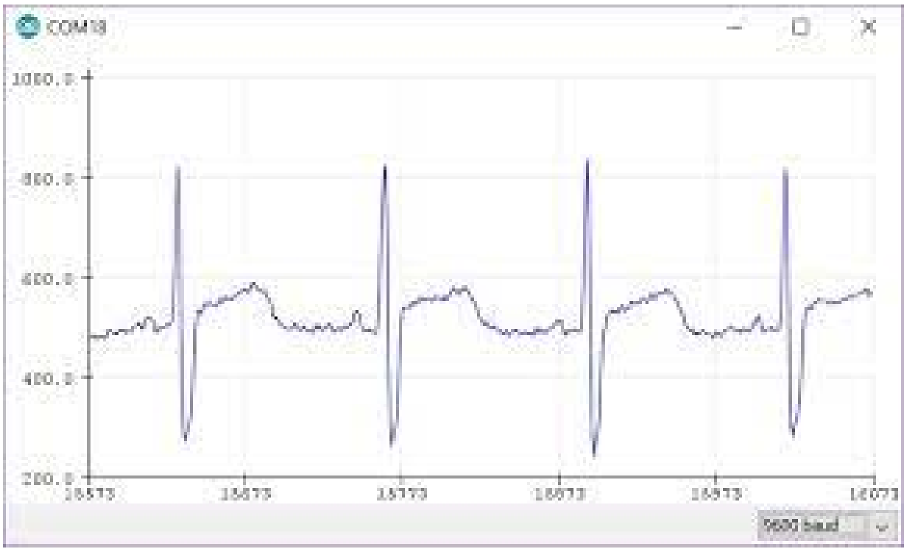

Figure 4.14: ECG information measured using AD8232

Sensors interfaced to his prototype are heart beat sensor MAX30102 and MAX30205 and ECG sensors. Sensor units are attached to the finger as shown in the arrangement. More number of sensor can be easily interfaced with the gateway for the expansion purpose. This prototype allows the device to collect various body parameter as per the requirement of the user. An algorithm is developed and coded in the gateway to determine heartbeat, oxygen saturation level and ECG parameters. Algorithm 1 is tested to find the anomaly in the sensor parameters. Values are getting displayed on the display unit after a delay of 5 sec interval to get a stabilized readings. The value recorded on the gateway is transferred to the cloud with respect to the assigned patient id (registration number). Figure 4.16 represents valid sensor data collection

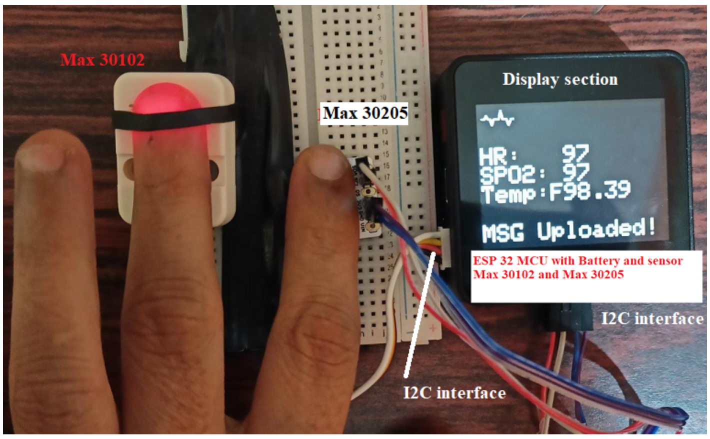

Figure 4.15: Sensor data recorded on prototype

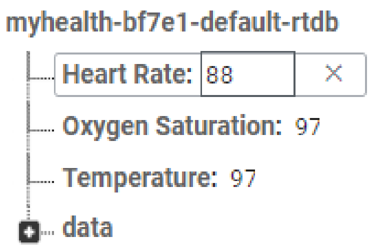

Figure 4.16: Firebase storage

at the gateway node. When a finger was placed on the sensor the PPG sensor helps to determine the heart beat in beats per minute using the program code written and uploaded on the MCU. Sensor data was displayed on the display unit was uploaded to the Firebase cloud. The data can be further accessed from Firebase real time database with proper authorization on any mobile or computer terminal. The sensor data was uploaded to the cloud for further analysis purpose. Figure 4.16 represents the real time database structure created in the Firebase. The name of Firebase host ID created was "myhealth-bfe1-default-rtdb". Each user had to register before using the hardware unit (ALERT). The privacy and authentication of the patient was considered while uploading the information to the publicly available cloud. Three parameters monitored using hardware unit were heart rate 88 (BPM), Oxygen saturation 97(%), and temperature in degree Fahrenheit 97. This information was uploaded to the cloud is represented in the figure 4.16. The field "data" in the figure 4.16 is holding the continuous data of ECG waveform.

4.10 Results of various parameters monitored using hardware unit

Final prototype unit for "ALERT" selected and assembled with the sensor is shown in figure 4.17. Attributes of the unit are battery of 110mAh,3.7V rechargeable unit, cost of the unit is Rs 3500 (single unit). The various interfaces equipped are SPIx1, I2C, Uartx2, LCD display, TFcard, Type C connector/UART. The unit is provided with 1 Watt speaker, and a 3D antenna. The speaker helps to alert the user under critical events and also during anomaly detection.

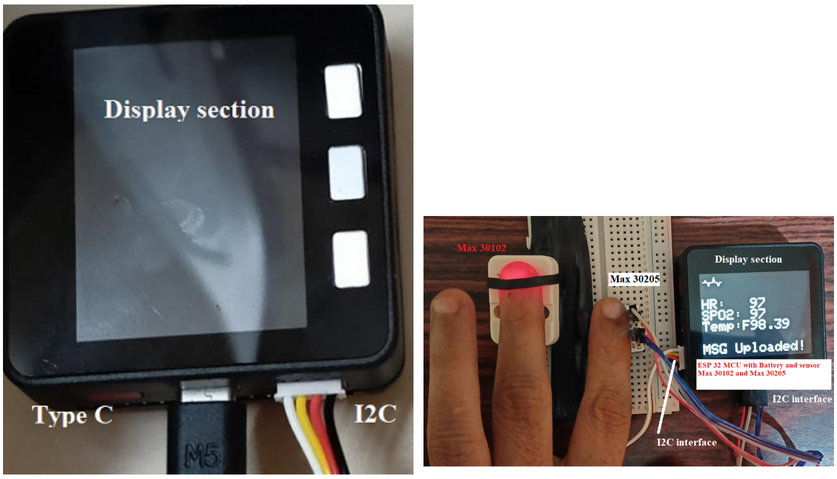

Figure 4.17: Hardware unit for vital parameter monitoring

4.11 Conclusion

Design of IoT enabled healthcare system "ALERT" was experimented using the final prototype selected as shown in figure 4.18. Various sensors are connected to the human body, and the sensor data is imported to the cloud storage. Each entity collected by the hardware unit was identified using user's name and registered email ID. The inputs provided by the physician through the google form was considered while selecting sensors. The healthcare unit was designed by considering low cost so that it can be easily affordable by the financially weaker section. This unit produced near accurate results with ±5% tolerance rate. Hardware unit contains a built in battery and all necessary

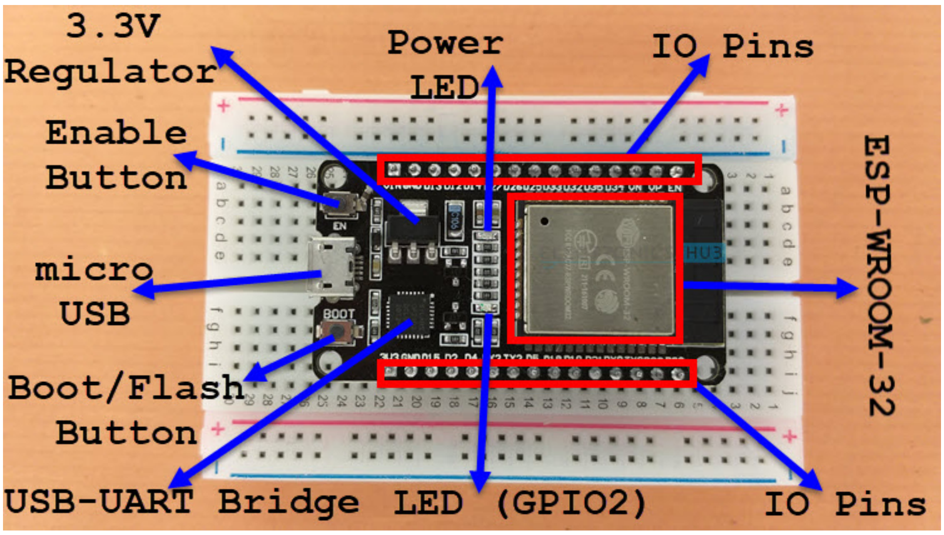

Figure 4.18: Gateway node in vital parameter monitoring

communication modules. It can be easily worn and can be used for continuous data monitoring purpose. The final prototype designed to measure and transmit the data to the cloud and mobile interface was successfully tested. Final hardware model used in real time health parameter monitoring is developed using ESP-32 MCU. Specification of the board are

1. Power supply unit: 5 Volts D.C, built in battery unit
2. Interface connector: USB, TYPE C, I2C, SPI.
3. Display unit: LCD panel.
4. Dimension: 55 x 55 x 17 (mm).
5. Weight: 200 grams.
6. Communication module : Blue tooth, Wi-Fi.
7. Speaker: 1 Watt

The LCD panel displays the various sensor parameter. The delay of 5 seconds is configured in the gateway node to obtain stabilized values of all the sensors. If the sensor values exceed the threshold value (based on patient health condition and previous history) an alarm will trigger at the hardware unit. This will also send a message to the caretaker. Under the normal conditions sensor data will be uploaded to the cloud storage, and an appropriate message gets displayed on the hardware unit. This ensures the user will understands the kind information is communicated to the cloud server for seeking further assistance.

The cost of the hardware unit used in measuring health parameters and sending alert messages is comparatively low with satisfactory accuracy. The single unit costs $50 and further if the unit is ordered for mass production it will reduce the cost of the unit. Each of the sensor costs used in developing the model is approximately calculated as $10 and gateway node ESP-32 with a waterproof case and port expansion feature to interface more sensors is calculated as $40. Developed prototype outperforms the performance with the existing units in terms of cost and functionality. The multi parameter monitoring with validation of sensor data and the services offered to log the data with security key for future use.

Chapter 5

Implementation of Prediction Model in Healthcare System

This chapter presents a healthcare recommendation system that provides effective prediction to heart/diabetes disease. The correctness and applicability of the proposed system are evaluated in comparison to the existing disease prediction models. A major challenge faced by the healthcare industry is the quality of service. Early detection against diabetics and heart disease will reduce complications hence lower down the mortality rate.

The proposed design of healthcare system is the integration of machine learning and IoT based sensors for monitoring the vital parameters. In this prediction framework, machine learning algorithms are used for the evaluation of heart disease, and diabetes. The knowledge of machine learning is used to detect the risk score and chances of having diabetes/heart disease. Proposed prediction model is based on standard risk factors, which could help to reduce the cost and time required for conducting the clinical/laboratory tests. Healthcare providers and clinicians can use this tool to see the risk of having cardiovascular and diabetes disease in advance. Web based and android mobile based graphical user interface was developed to access the patient's data and obtain the prediction results. This prediction results are utilized by medical expert for taking the decision quickly.

5.1 Proposed Prediction Model in Healthcare System

We introduced a novel and intelligent healthcare system that was based on modern technologies like Internet of things (IoT) and machine learning. This system is low-cost solution for the people of remote areas. They can use it to get advice from experts to find out whether they are suffering from any health issue.

The proposed framework consists of three parts: a lightweight and low cost IoT node, machine learning (ML) model for early diagnosis and smartphone application (app). The IoT node tracks health parameters, including body temperature, blood pressure, ECG signals, heart rate, and blood oxygen saturation. Machine learning algorithms are used to build the prediction model for early detection of the disease. Mobile/web interface application to track the health status of a patient. The flow chart of the prediction model proposed in this work is represented in the figure 5.1. The methodology used in building the model is classified into four stages.

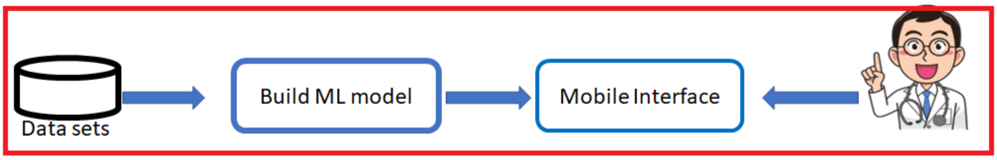

Figure 5.1: Proposed prediction model

1. Collection of datasets: Datasets for heart disease and diabetes prediction model are retrieved from the valid reference source. Data prepossessing methods are used to remove the noisy data. In this work dimensional reduction methods are considered to determine most important parameters from the dataset. Dimensional reduction was performed using various features selection method. These method helped to select most important features from the dataset.

2. Machine learning algorithms used in prediction: Comparison of various machine learning algorithms, was used to understand the behaviour of model in predicting the disease. Analyzing the performance parameters of machine learning algorithm helped to know the optimal algorithm to be selected in the model.

3. Building graphical user interface for the prediction model: Performance of prediction model was tested using designed web and mobile application.

4. Virtual patient monitoring application: To access the data from the patient and analyze the parameter using the proposed prediction model, a dedicated mobile application was designed. This application assists the doctor to take quick decision based on the results of prediction model along with his/her wisdom.

5.1.1 Collection of datasets and its description

There are various datasets are publicly available in the data repository. Selection of appropriate dataset also plays a major role before designing a predictive model. The dataset selected should contain more quantitative parameter as compared to the qualitative parameter. Thus dataset is collected from the UCI Cleveland Clinic Foundation.

It consists of 303 records; there are 165 records showing target output as one (heart disease) and 138 number of records with no heart disease. The input parameters of the dataset are 13 in number and output are 01. Target or output value 1 represents chances of having heart disease and 0 represents the healthy condition. Table 5.1 represents the range of all attributes used in the dataset. The attributes are expressed in nominal range. Although the UCI Cleveland dataset has 76 attributes, the dataset provided in the repository furnishes information for a subset of only 14 attributes. There are 13 input attributes, only one output attribute. This dataset is merged with a database provided from Stat log [77] which has the same number of attributes as that of UCI Cleveland database. This increases the sample size of the data used in training the machine learning algorithm. The Stat log dataset has a 270 instances of which 150 instances with no heart disease and 120 instances with the heart disease. The Stat log dataset is used mainly for testing the prediction model. UCI dataset records are used for training purpose of the model.

This work was carried out by using python program to build custom made algorithms in the prediction of heart disease. The data mining tools were used to visualize the performance parameters of each machine learning algorithm. But it was not able to tune the parameters of the learning algorithm to improvising performance of the model. Thus proposed algorithm designed using custom made programs helped to achieve good accuracy in the prediction of the heart disease. Two experiment scenarios

Table 5.1: Attributes of heart disease data set

UCI Dataset	Stat log Dataset
age	age ;Age in Years
sex	sex ;('M(0)' or 'F(1)')
cp	cp ;(chest pain) expressed as 0,1,2
restbp	bp ;(blood pressure) systolic blood pressure
fbs	bsugar ;(blood sugar) fasting blood sugar
restecg	recg ;(rest ECG) ECG waveform
thalach	hr ;(maximum heart rate) heart rate
exang	eang ;(angina pain) pain due to exercise
oldpeak	st ;(ECG information) slope of ST segment
slope	pst ;(ECG information)
ca	ve ;(coloured by flouroscopy)
thal	thal ;(thalassemia) stress information
target	target ;presense ('1) absence('0')

were created to find the most important parameters to be selected in the design of prediction model.

5.1.2 Feature selection methods

Features selection method reduces the number of attributes and improves the machine learning training time and avoids under/over fitting issues. This methodology is used in reducing the dimension of the dataset. The block diagram shown in the figure 5.2 represents

The block diagram contains three blocks. Block I selects the dataset D (Heart Disease or Diabetes disease). Block II is the chooses the feature selection method. Block III is the selection of a machine learning algorithm. Results of the given block diagram are in terms of confusion matrix and performance parameters. Dataset with all features are used to calculate the performance and it is compared with dataset with reduced features. Reduced features are obtained using appropriate selection method.

The proposed framework is to select highly discriminative features of the dataset.

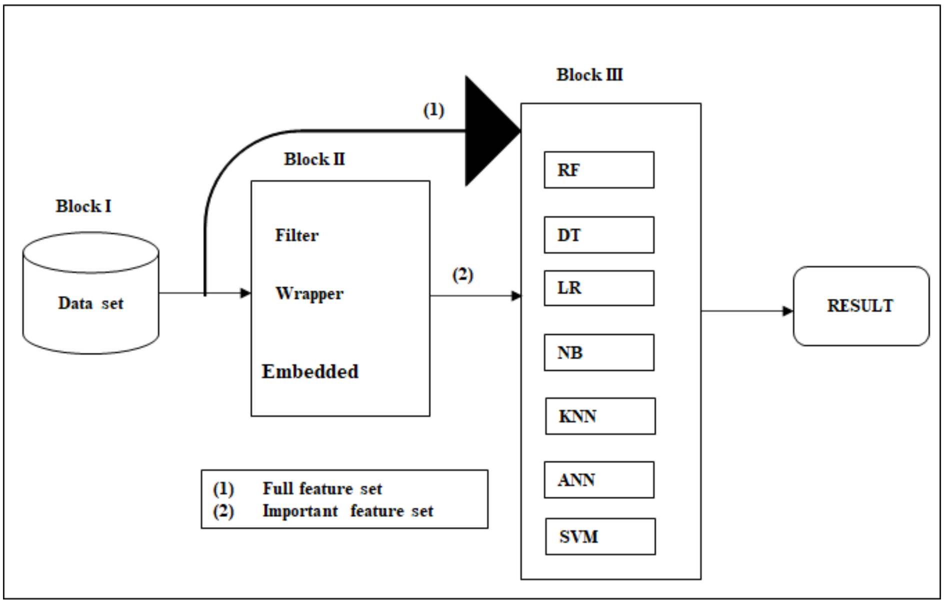

Figure 5.2: Dimension reduction methodology

The various algorithm available in dimension reduction of the datasets were studied and applied to the model. Feature selection procedure helped to select most appropriate parameters responsible in deciding target variable. Usually three types feature selection methods were used [78]. The filter method, wrapper method and combination of both (embedded) method. As data volume keeps increasing, analyzing it and deriving conclusion from them becomes more complex. The healthcare records collected from the data repository for predicting the chances of heart/diabetes disease was having large number of records (high dimension in space). These dataset are converted into to low dimension space. Reducing size of the dataset helps to reduce the training time, improvise the accuracy and eliminate the overfitting issues. Dimension reduction involves the feature selection process, generation of best features, assessment of accuracy using selected subset, stopping method, and validation of the model. List of feature selection methods applied in thedimension reduction process are:

- Filter method: The attributes from the dataset are selected based on the score obtained using statistical methods. These set of features are tested for their association with output variable. The results obtained will give the correct subset from the input dataset. In the Filter method there are three different analysis. They are Chi-square method, Linear discriminate analysis (LDA) method and Pearson's correlation method.

Chi-square test: This method utilises python library to select K-Best class of attributes. The library facilitates a group of statistical tests to obtain a specified number of attributes. Chi-squared (chi) statistical test was performed on the given dataset to get eight best attributes. The results obtained is represented in the figure 5.3. The selected parameters from the dataset 01 are thalach, oldpeak, ca, cp, exang, chol, age and trestbps whose Chi-square score was high among the 13 input parameters(dataset 01).

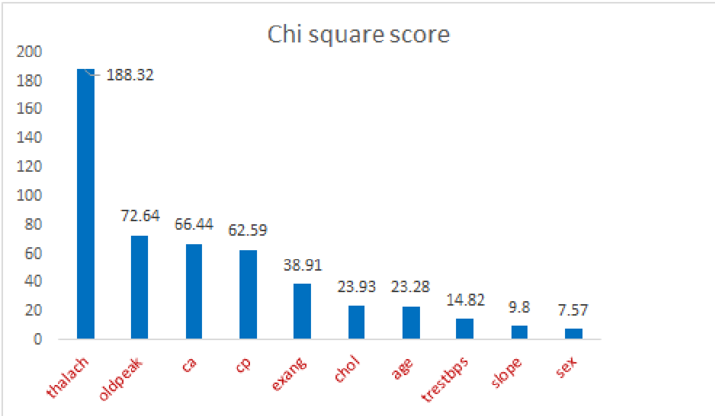

Figure 5.3: Chi-square score of the heart disease parameters

Pearson's coefficient: The selection of best input attributes from the given dataset is carried out by calculating linear correlation between the input attribute to the output attribute. Correlation value can rage between positive correlation (+1) to negative correlation (-1), If it is zero then there is no correlation between input and output. Pearson's correlation heatmap illustrates the selection of feature subset. Coefficient is calculated using covariance of the input attribute, and output attribute it is divided by the product of standard deviation of the both. The figure 5.4 represents the coefficient obtained using this method. The high coefficient parameters are considered in the selection.

- Wrapper Method: This methods generates best features from the given dataset for training the prediction model. The accuracy of the model is calculated by selecting subset of attributes. Selection of attributes can be performed using adding feature or removing feature on at a time. The prediction accuracy is measured for every instance of addition or elimination of attributes. They can be classified as forward feature selection, backward feature elimination, and recursive feature

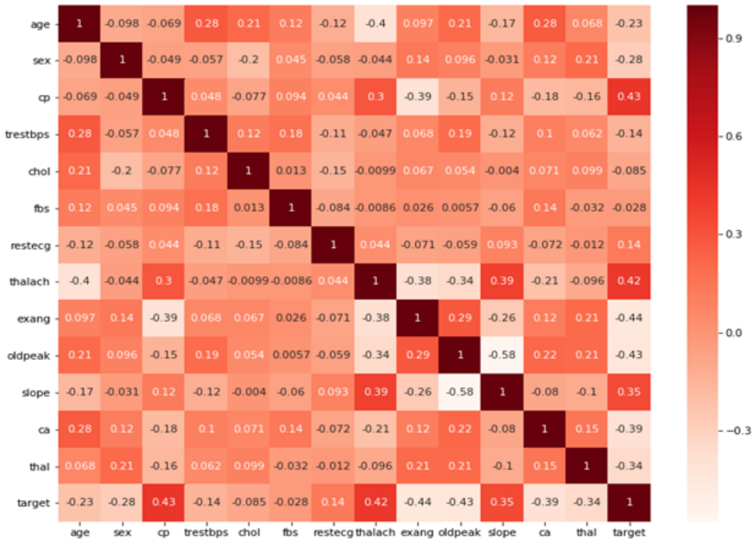

Figure 5.4: Pearson's coefficient of the heart disease parameters

elimination.

Backward feature elimination: In this method worst features are eliminated from the dataset iteratively one after other till the overall accuracy of the prediction model gives the satisfactory results. Recursive Elimination method (RFE): Initially all the attributes of the dataset are considered to determine accuracy of the model. The significance of each feature is calculated using either the coefficient or score. By setting the appropriate value, to the selection of input attributes, least significant features are recursively trimmed. The figure 5.5 representing score of the various attributes obtained from the dataset 01. The high score parameters are retained in the feature selection.

- Embedded Method: This is an aggregation of filter and wrapper methods. This kind of hybrid method provides more accuracy. Most common embedded method include random forest and extra tree algorithm. This can be implemented using Least absolute shrinkage and selection operator regularization (LASSO), Ridge regularization, and accumulation of both regularization.

  LASSO feature selection is performed on the dataset. If the selected feature is minimum significance on the output variable, LASSO assigns zero to it's coefficient. The zero coefficient attributes are removed and remaining subset are considered.

  Figure 5.6 shows the most important parameters selected using the LASSO

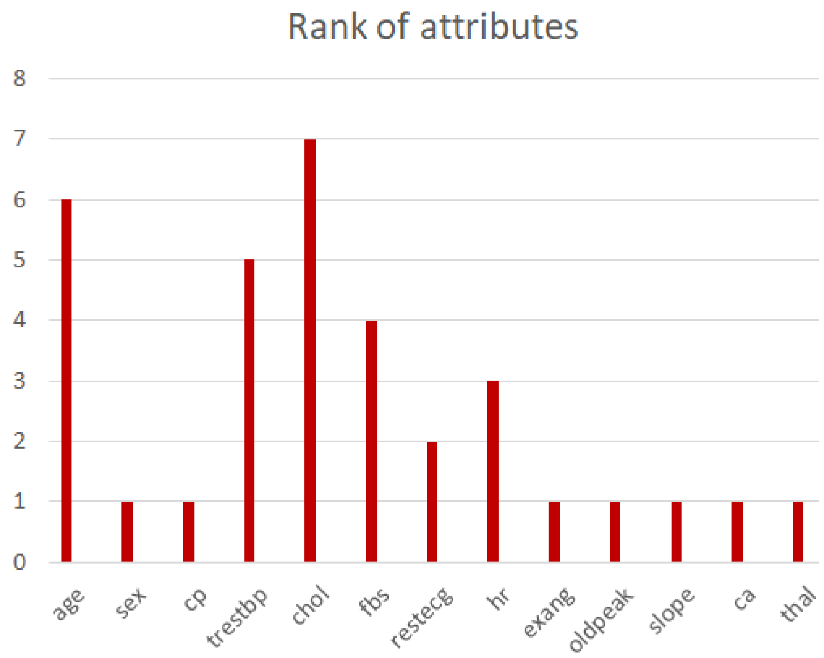

Figure 5.5: Recursive elimination attributes of the heart disease parameters

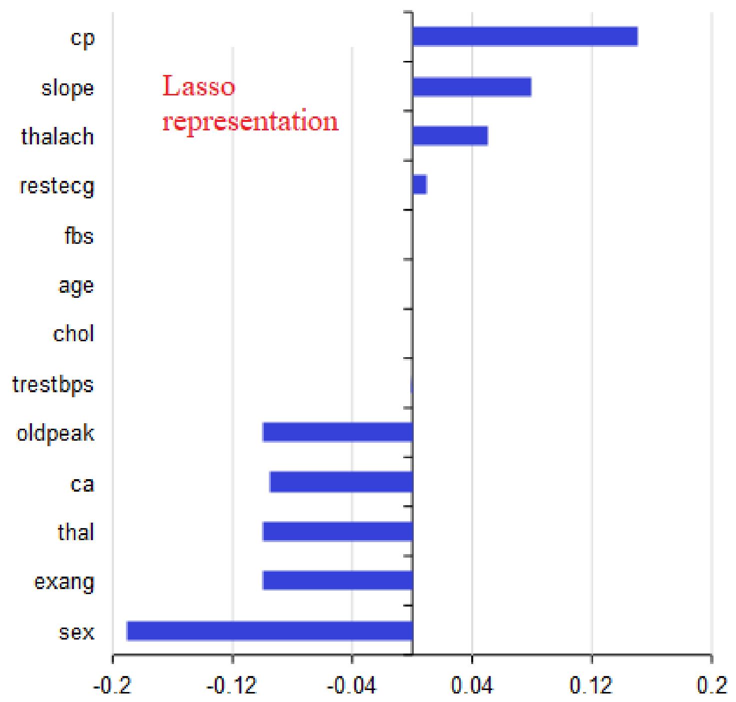

Figure 5.6: LASSO attributes of the heart disease parameters

method.

The dimension reduction methodology used in the reduction of the number of attributes in the prediction model is tabulated in the Table 5.2. Using the various attributes obtained with the help of different feature selection method a machine learning algorithm performance of the heart disease prediction was measured. The feature selection using LASSO regularization was considered in building the prediction model. Feature selected using dimension reduction methods can be also acquired through the hardware unit. ECG waveform recorded through the sensor can able to calculate the slope and old peak values ST segment. Similarly the SpO_2 sensor is used for measuring maximum heart rate, thalassemia (thal). Hence real time data can be captured and provided to the prediction model. The more significant attributes chosen from feature selection method is listed in Table 5.2 was further used to train the five selected machine learning algorithms.

Table 5.2: Features selected using dimension reduction of heart disease dataset 01

Feature selection methods	Attributes
Chi-square method	thalach, oldpeak, ca, cp, exang, chol, age, trestbps
Pearson‘s coefficient	cp, thalch, exang, oldpeak, slope ca,thal
Feature importance	cp, ca, thalach, oldpeak, thal, age, chol, trestbps
Backward elimination	sex, cp, ca, thal, oldpeak, exang, thalach, trestbps
RFE	sex, cp, restecg, exang, oldpeak, slope, ca, thal
LASSO	sex, exang, thal, ca, oldpeak, thalach, cp, slope

5.1.3 Machine learning algorithms used in the prediction model

Five different machine learning algorithm were chosen to study the performance in determining heart disease prediction.

1. Logistic Regression is a supervised learning technique. Regression can be classified into two types; they are linear regression and logistic regression. Logistic regression is used to implement the classification of low dimensional data exhibiting nonlinear boundaries. Logistic regression models the probability of the output class and also calculating the probability of success.

2. Naive Bayes classifiers are the working on the principle’s of Bayes’s algorithm. It deals with uncertainty using probabilistic methods. They works on predicting

based on the conditional probability. The assumption of conditional independence is termed as “naive”. Although it is unrealistic (all input variables are independent from one another). It works good on large dataset in recommending system and forecasting application.

3. Support Vector Machine (SVM) is supervised learning method. SVM algorithm is used to create decision boundary that can segregate n-dimensional space into distinguished classes. This best decision boundary is called a hyperplane. Kernel used in SVM are linear, polylinear and radial basis function.

4. K’s Nearest Neighbours (KNN) is a memory based learning algorithm. It stores all the available cases in memory map and classifies the new test data based on a similarity measure. Similarity is calculated using cosine index or euclidean distance It classify or adds the new test data to the sample similar to the neighbour points. K value denotes the number of nearest neighbourâĂŹs of the new point which needed to be predicted

5. Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both classification and regression problems. Random forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The hybrid machine learning algorithm proposed in building prediction model is represented as Algorithm 2.

Algorithm 2 Proposed hybrid algorithm

Input: Dataset D [R x C] with R no of rows, C no of columns (rows represent patient records and column represents attributes (features).

Output: Confusion matrix of machine learning algorithm.

Result: Prediction output in terms of Yes or No.

Step 1: Initialize KFold for cross validation,number of trees, depth of the tree, kernel function for the selected machine learning algorithm.

Step 2: Apply any one (LASSO Regularization) feature selection to select most important feature from the dataset.

Step 3: Save the reduced dataset as D1 with extracted features and the original dataset as D.

Step 4: Train the proposed algorithm to predict outcome using dataset D and D1.

Step 5: Test the same algorithm with new dataset.

Step 6: Go back to Step 2 and perform step 3-5, with another feature selection, and machine learning algorithm.

Step 7: Stop.

The figure 5.7 explains the flow chart used in training/ testing machine learning algorithm. The performance of selected machine learning helps in building the prediction framework.

Dataset 01 was partitioned into 80% as training vectors to train the algorithm and 20% is used as test vectors for testing the predictive framework. Cross validation techniques were applied while selecting training vectors.

The machine learning algorithm performance parameters are measured. Simulation was carried out using python programming. Scientific Python Development Environment (Spyder) is included in Anaconda navigator. Anaconda navigator offers the utility to perform Python and machine learning on a single machine. The performance parameters of various machine learning algorithm are calculated using confusion matrix. Confusion matrix illustrates the number of records predicted as true positive, true neg-

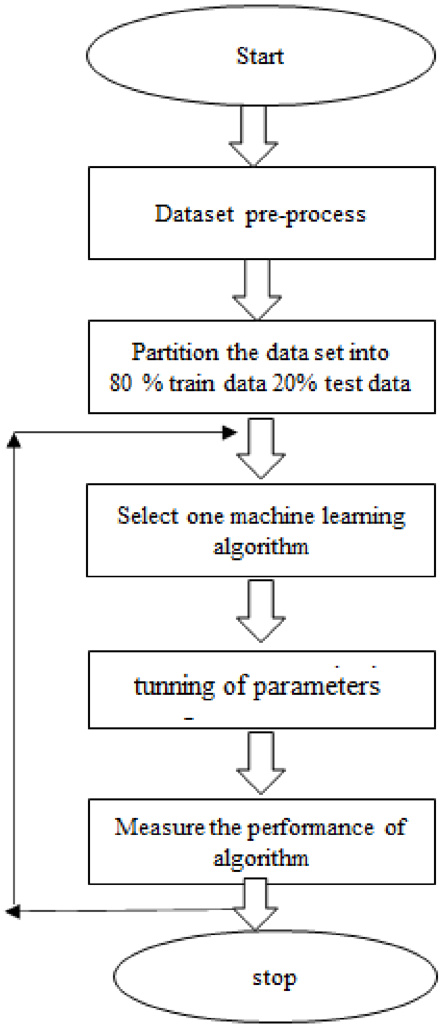

Figure 5.7: Flow chart to evaluate prediction framework.

ative, false positive, and false negative. True positive instances are unhealthy (sick) and diagnosed accurately. Similarly true negative instances are healthy (no disease) and diagnosed accurately. Confusion matrix is used to find the accuracy, precision, recall and Specificity. The following conventions are used in defining the confusion matrix.

- TRUE NEGATIVE (TrueN) is the number of correct predictions that an output obtained is negative.
- FALSE POSITIVE (FalseP) is the number of incorrect predictions that an output is positive.
- FALSE NEGATIVE (FalseN) is the number of incorrect of predictions that an is output negative.

- TRUE POSITIVE (TrueP) is the number of correct instances that an output is positive.

Table 5.3 represents the information present within a confusion matrix. This matrix is used in determining performance of the machine learning algorithm. The performance of machine learning algorithm was measured using accuracy (Acc), precision (Pre), recall (Rec) and specificity (Spec).

Table 5.3: Confusion matrix

	Negative (0)	**Positive (1)**
Negative (0)	TrueN	FalseP
Positive (1)	FalseN	TrueP

Accuracy = (TrueP + TrueN)/(TrueP + TrueN + FalseP + FalseN)

Recall = TrueP/(TrueP + FalseN)

Precision = TrueP/(TrueP + FalseP)

Specificity=TrueN/(TrueN+FalseP)

The Table 5.4 indicates parameter settings used in testing the algorithm. It indicates number of iterations used, types of Kernel in SVM, number of nodes included so as to obtain good accurate results.

Table 5.4: Tuning parameters used in machine learning algorithm

Algorithm	Tuning parameters
Random Forest	rounds 2000
Support Vector machine	kernel linear
K's nearest neighbour	number of neigh 05

5.2 Results of Machine Learning Algorithm

The prediction model used in the detection of having heart disease was tested for various criteria. The comparison of Random Forest with other four machine learning algorithms considered in this work.

The performance of the Random Forest improvement was considered by the hyper tuning of parameters. Random Forest offers a very flexible framework with a lot of freedom for designing task specific objective functions, different classes of splitting functions or posterior models. The two most important degrees of freedom are, number of trees and tree depth. The algorithm is trained by using 80% train vector and 20% test vector patterns. The cross validation is used in training the machine learning algorithm. Kfold is made equal to five, the value of random state is set equal to 168 to achieve significant performance. The figure 5.8 illustrates that the prediction error curve decreases with the tree depth until it reaches a minimum and then increases again. Correspondingly increase in number of trees reduce the prediction error. Table

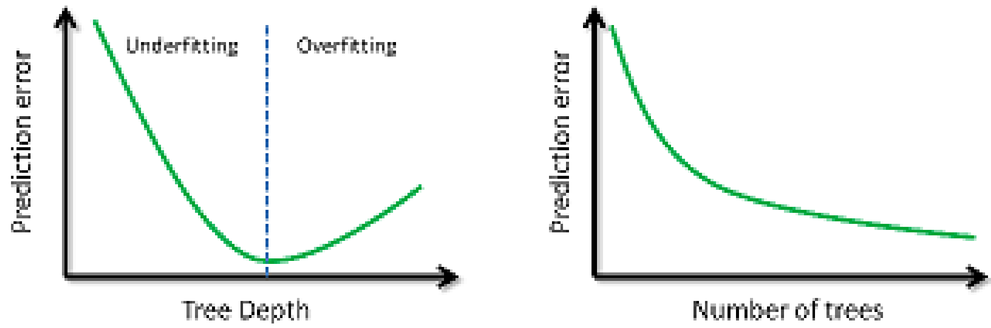

Figure 5.8: Tuning parameter performance in Random Forest

5.5 and 5.6 represents the accuracy score by tuning the number of trees and depth of tree. The optimal accuracy is observed for tree size equal to 100 and tree depth of 20.

Table 5.5: Performance by varying no of estimators

No.of Estimators	Accuracy	Prediction Error
10	86.89%	13.11%
50	86.89%	13.11%
100	90.16%	09.84%
200	88.52%	11.48%

The results of the five machine learning algorithm with reduced feature selection set (i.e performed using LASSO Regularization method) is tabulated in Table 5.7.

Selecting the samples randomly from the dataset is carried out in training and testing the model. Random sampling with cross validation and grid search method was carried out. This methods prevents memorizing the pattern and producing the

Table 5.6: Performance by varying depth of trees

Depth of tree	Accuracy	Prediction error
5	85.25%	14.75%
10	88.52%	11.47%
15	90.16%	09.83%
20	90.16%	09.83%
25	90.16%	09.83%

Table 5.7: Performance of machine learning

Algorithm	Accuracy	Recall	Precision	Specificity
RF	90.16%	91%	91%	88.88%
LR	85.25%	83.78%	91.77%	77.77%
NB	83.61%	83.33%	88.23%	77.77%
SVM	85.25%	83.78%	91.17%	77.77%
KNN	78.69%	78.37%	85.29%	70.37%

output. Training the model in generalized method provides more efficient prediction model. The processed dataset was applied to machine learning algorithm. The training of algorithm was carried out using five algorithm listed. The results obtained using Random Forest algorithm was evaluated for new records from the dataset (test dataset). The performance parameters of each algorithm are verified.

The results of Random Forest algorithm with hyper tuning of parameter in comparison with other algorithms were tabulated using figure 5.9. It represents the four expected parameters to know the performance of each machine learning algorithm. Accuracy, Recall, Precision and Specificity was compared to select most optimal algorithm for prediction of heart disease.

The performance of Random Forest algorithm gave the best score for precision (91%), recall (91%), specificity (88%) and accuracy score(90%). Hence it was considered in the prediction model.

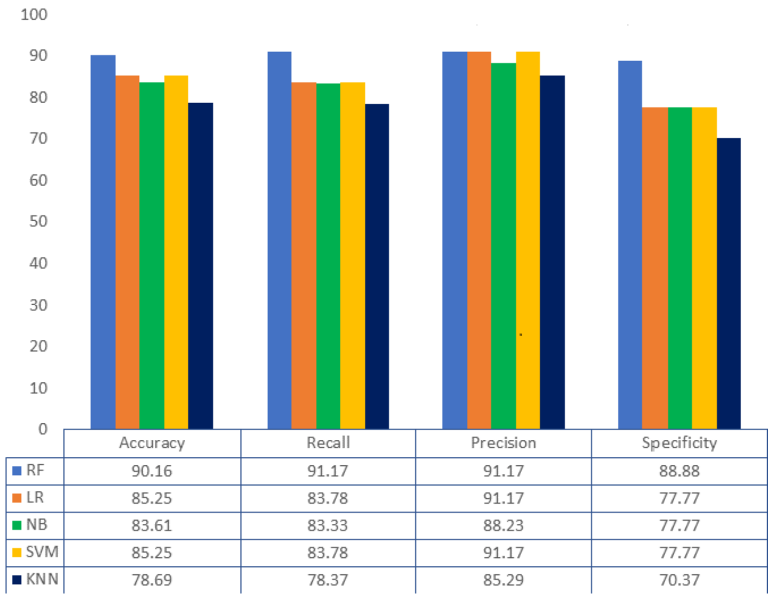

Figure 5.9: Performance of five machine learning algorithms

5.3 Prediction model for Diabetes detection using machine learning

The prediction model for detection of having chances of diabetes was carried out in the similar manner to the heart disease model. The two datasets were considered in the design of the prediction model. The dataset 02 used for training/testing was retrieved from "Pima Indians Diabetes" [79] dataset. Dataset 02 is having 768 observations with 8 input variables and 1 output/target variable. The variable names are as follows: Pregnancies, Glucose, Blood pressure, Skin thickness, Insulin, BMI, Pedigreefunction Age, and Outcome. There were 268 of 768 are showing output variable as 1 (means diabetic), the other output response was showing 0 (non diabetic). Dataset 03 was collected from the Mendeley repository. Modern medical procedures for diagnosing diabetes includes a urine test and the Glycated Haemoglobin A1c (HbA1c) test. Dataset 03 consists of a total of 1000 samples of patient data which includes type 2 diabetes disease and related attributes along with a predicted target column as a output variable. Out of the 1000 samples, 897 patients reports are diagnosed with diabetes disease, and others 103 are diagnosed with no diabetes. The Table 5.8 represents the dataset 03 with 13 attributes present along with their descriptions.

Table 5.8: Dataset 03 attributes of Diabetes

Attributes	Description
Gender	male or female
Age	age in years range(18-79)
Urea	urea nitrogen in blood
Cr	creatinine level
HbA1C	haemoglobin A1c
Chol	cholesterol
TG	triglyceride
HDL	high density lipoprotein cholesterol
LDL	low density lipoprotein cholesterol
VLDL	Very low density lipoprotein
BMI	Body mass index
CLASS	output variable

5.3.1 Feature selection for Diabetes

In order to reduce the dimensional size of the problem i.e the number of input attributes into the system, a popular feature selection technique using LASSO regularization method was employed. The technique excludes variables that have low correlation to the target variable, keeping only a user specified number of values. Number of features was set to 5 for this selection. The feature selection was performed to extract the most important parameters which influence on the outcomes.

The figure 5.10 illustrates the feature extraction obtained on the dataset 02 using LASSO. The parameter like Glucose, BMI, age, Diabetes Pedigree, Insulin, and Blood pressure influences more as compared to other parameters.

The feature selection was carried out using dataset 03. The figure 5.11 shows the feature extraction obtained on the dataset 03. It is observed that HBA1c, BMI, Age, Cholesterol and TG (triglyceride) influence more as compared to other parameters. These selected features are applied for the further analysis of the prediction model.

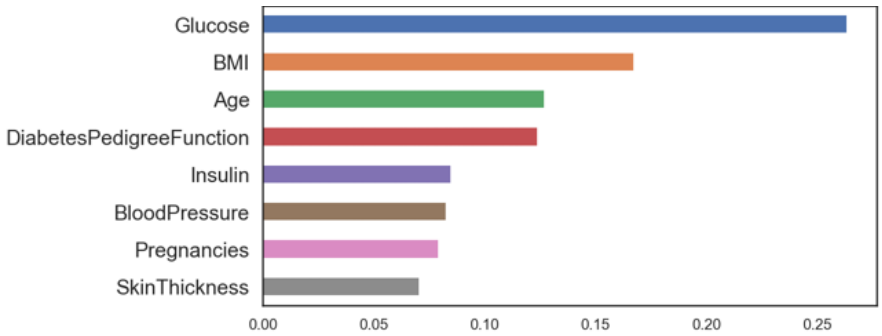

Figure 5.10: Feature selection from Diabetes dataset 02

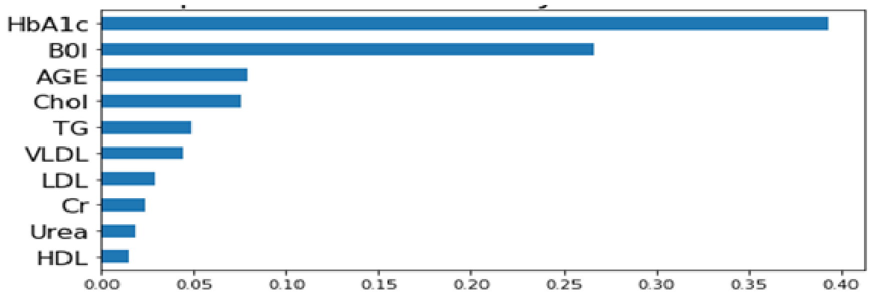

Figure 5.11: Feature selection from Diabetes dataset 03

5.3.2 Performance analysis of the Diabetic prediction model

The various machine learning algorithms were trained to predict the chances of having diabetic. The Table 5.9 represents the results obtained from Random Forest algorithm for the given two datasets. The dataset 03 was considered for the implementation of the final prediction model. Dataset 02 was more specific to the female patient. Hence to determine the prediction of diabetic to general patient dataset 03 was considered. Dataset 03 for diabetes disease gave the accuracy rate of 95.83% as represented in the table.

Table 5.9: Machine learning algorithms for diabetic prediction

Data source	Algorithm	Accuracy	Recall	Precision	Specificity.
Dataset 02 Diabetes	Random Forest	77%	78%	77%	76%
Dataset 03 Diabetes	Random Forest	95.83%	98%	97%	96%

5.4 Mobile application for smart healthcare application

As the usage of smartphones, tablets, and other smart devices and its application is ubiquitous. Thereby communication between patients and their doctors has been made much easier and flexible through the available mobile applications (app).

Mobile apps are convenient in clinical diagnosis and evaluation. It helps in providing timely advice, medicine prescription, virtual patient monitoring. The patient can able to share the medical information about his/her health condition securely through the developed mobile application. By this means travelling a long distance and visiting the doctor for a regular check-up may be evaded. Thus it stretches a thorough description of a mobile app developed for the virtual patient monitoring system.

A novel solution is proposed to monitor the most important health parameters of a patient using wearable sensors and images obtained using medical equipment. The mobile app supports receiving vital parameters such as body temperature, pulse rate, and oxygen saturation level from the wearable sensor node placed in the vicinity of a patient. So the developed application assists the doctor in the early prediction of the disease. It can able to analyze a patient's health status by comparing it with their previous history. Further, the application helps to send an alert notifications or short messaging services (SMS) to the patient for emergency physical examination.

An elderly patient finds difficulty in visiting clinics for a regular check-up and also finds difficulty in staying in hospital for a longer duration. Thus proposed and developed mobile application makes it convenient to monitor health status for any patient who are staying with limited access to the medical facility.

Mobile application in healthcare serves two major advantages, one is early diagnosis of any disease by sharing vital body parameters, thereby obtaining advice from medical professionals to avoid complications. Secondly, it saves time and cost in travelling to the clinic. The figure 5.12 depicts the various benefits of smart healthcare applications.

Initially inputs required for the easy use of mobile applications have gathered from users/physician. The google form was created to obtain the customer views. The customer/physician feedback was analyzed to understand the requirements for the design

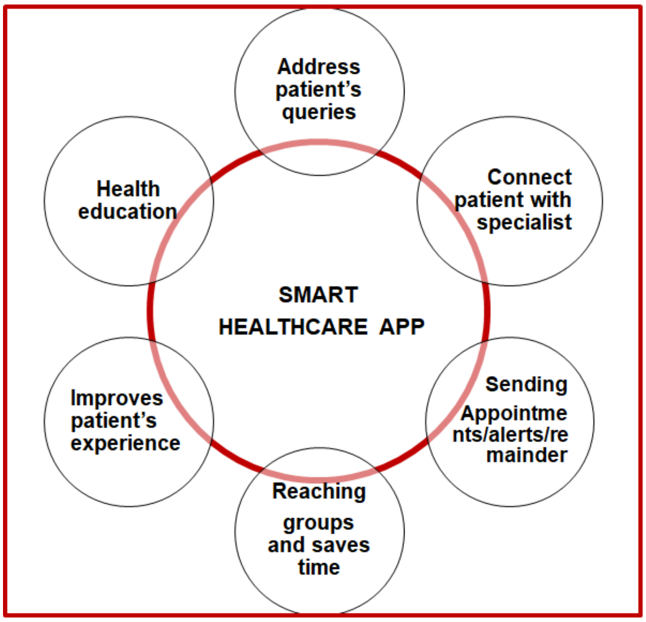

Figure 5.12: Applications of smart healthcare applications

of mobile application. Following factors are considered while designing the application. The feedback was generated by a total 500 customers which includes pharmacist, doctor, elderly patients and others. The following salients features are obtained from the users. They are:

1. Features to be incorporated in the application: The mobile application used in the healthcare services to remotely monitor the patient health should give near accurate results. It should be user friendly and can able to handle by any person with ease. It should be language independent, safe guard against personal information from unauthorized access. Application requires proper authorization and a log need to be maintained to understand the user's behaviour.

2. Expected Parameters to be monitored: Most of the users expressed to include the body temperature, heart rate, oxygen saturation, blood pressure to be monitored virtually and reported to the Doctor.

3. Interactive features between Doctor and Patient: Reporting an alert messages or send notification through email, short messaging service or chat to the registered user was the requirement expressed by 90% users. Uploading laboratory report using camera scanner, voice messages, audio, images of reading collected by an available instrument (BP meter, Blood sugar, ECG etc) was included in the

feedback.

According to the need of users, framework for designing mobile application is formulated.

The framework is categorized into two subsections. They are:

1. Virtual patient health monitoring and alert system using smart phone.

2. Mobile application to assist the doctor in analyzing patient's health parameters using the prediction model.

5.5 Proposed layout of developed mobile application

The virtual patient monitoring application is proposed for regularly monitoring the patient without physical interaction with doctors. The most important utilities included in this applications are, recording the parameters through wearable sensors, transferring laboratory reports, sharing the health parameters recorded using available medical gadgets, sharing the symptoms of the sickness using audio and video format. The medical professional can view and analyze the reports for obtaining the decision about early detection of the disease. They can notify the patient for an emergency condition. They can able to share prescription details, any other specific guidelines to be followed by the patient through a short messaging service (SMS). It also has online chat option with registered patients.

The proposed and developed virtual patient monitoring application's features are represented in the figure 5.13. The layout for virtual patient monitoring application is having two distinct features. The doctor's lounge and patient's lounge are the two sections with diverse features.

The algorithm used in implementing the mobile application is illustrated using Algorithm 3.

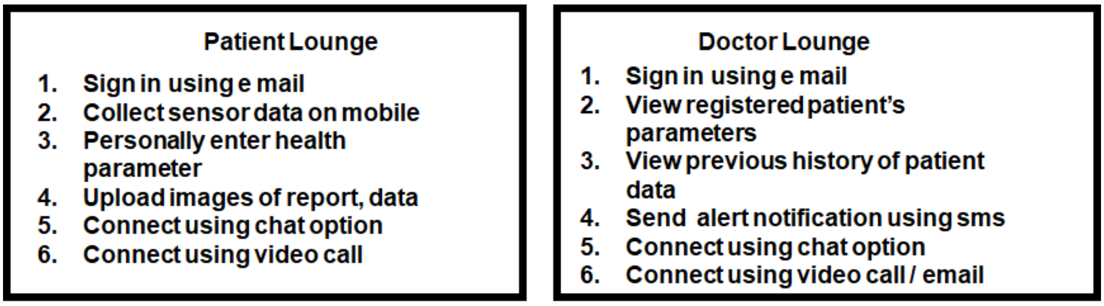

Figure 5.13: Proposed layout of mobile application in virtual patient monitoring

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Algorithm 3 Virtual patient monitoring application

Result: Virtual patient monitoring features

Step 1 Start the registration process.

Step 2 Classify the user as a patient or doctor.

Step 3 If the user is a patient Upload the wearable sensor information to cloud storage.

Step 4 View the information uploaded. Upload laboratory reports and readings using the image upload option. User can also add the health parameters manually. Connect the registered available doctor using email or mobile number. Go to step 8. else if a user is a doctor go to step 5.

Step 5 Find patient information from cloud storage or view real time data from the wearable sensor unit

Step 6: If present data > Reference value
generate an ALERT notification to the patient using SMS, chat, or email

Step 7: Communicate to patient using chat room facility to advice or alert.

Step 8 End.

Algorithm 3 explains the procedure used in developing the mobile application. The threshold values used in monitoring and alerting the patients are listed below.

Body temperature: 97 - 98.6 degrees Fahrenheit is referred to as normal.

Heart rate beats per second: 70 - 80 BPM as normal range.

Oxygen saturation level: 95 - 100 % normal value.

The Android app was developed using Thunkable application. Firebase was used as cloud storage in the backend for storing user's health and authenticated information. The mobile application's main features include login, view data, save data, sending short messaging service (SMS), communicating using Chat room/email, and viewing the history of the patient.

- Login screen: Mobile applications were authorized to use only by the registered user. All the users (Patient/Doctor) should sign-in using a valid email id in the application. Acknowledgment to the registered users will be communicated using email. Figure 5.14 shows the login screen used to register the application. It

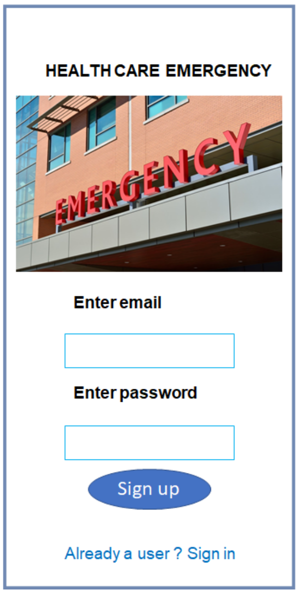

Figure 5.14: Login screen to register

  illustrates the sign-in option and option for the user to confirm as a patient or a doctor. Confirm option allows the doctor to use the available services designed for this application. The cancel option directs towards the facility created for the patient to use the application efficiently.

- Patient screen: The various features incorporated for the patient under this application are shown in figure 5.15. A patient can acquire the data using a hardware unit attached to the person. Wearable sensors can collect the current information and upload them to the cloud. This information can be accessed using the mobile application.

A patient can also enter the parameters manually with the option available in the application. Laboratory reports, images from commercial instruments (Blood pressure meter, Blood sugar meter) can be captured using the designed app and can be stored in the cloud.

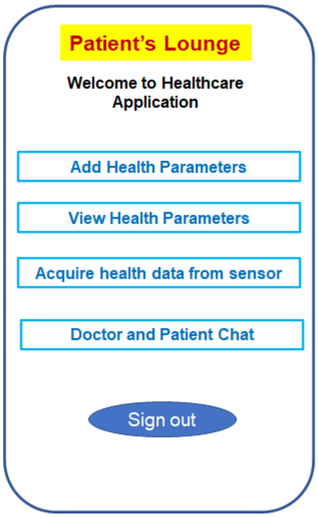

Figure 5.15: Patient's Lounge

The figure 5.16 shows sensor information gathered from the hardware unit and displayed on the designed app.

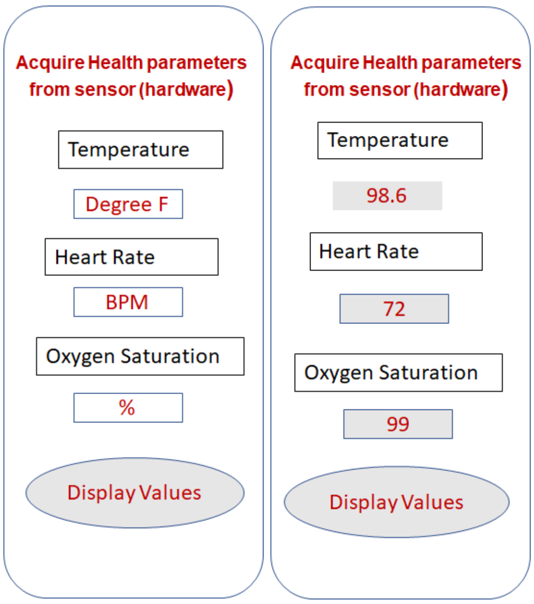

Figure 5.16: Mobile app for collecting sensor data

The display option on the mobile screen helps the users to obtain the sensor values by clicking the "Display value" button.

- Doctor/Physician Screen: The application facilitates the doctor's lounge to view patient's current information, history, email, send messages to the patient, and connect with the chat room facility. A doctor can communicate to the patient using online or offline mode. Figure 5.17 represents the doctor's lounge indicating the features included for the doctor in assessing patient data.

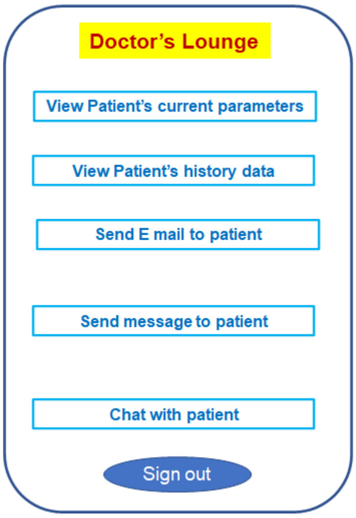

Figure 5.17: Doctor's Lounge

  Patient/Doctor can chat or connect using chat/email/short messaging services. The patient and doctor communication details and personal information are maintained secretly by considering security and safety. This ensures to send an alert messages and advice to the patient at an early stage thereby reducing the complications.

Mobile application designed has a capability to upload images of the report, images of recording, and readings of a patient collected by an instrument. Certain parameters like blood pressure, blood sugar, laboratory report, X-ray, and images of the report are uploaded using this application. Figure 5.18 below represents the pictures captured using available instruments before uploading the image into the cloud.

5.5.1 Mobile application in the prediction of heart disease and diabetes

Prediction model designed using machine learning algorithm was made user friendly. Mobile application designed helps to obtain the decision with the help of artificial

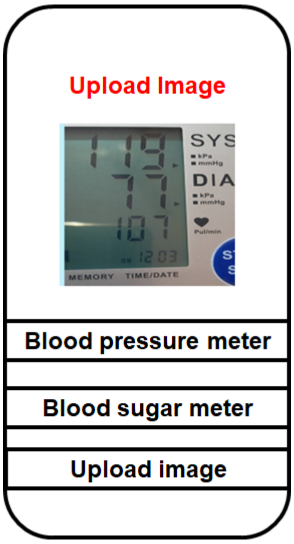

Figure 5.18: Uploading recordings of the meter

intelligence or due to the smartness incorporated by the use of prediction model. The output of the prediction model helps to determine whether the patient is having chances of heart/diabetes disease or not.

Proposed Random Forest algorithm used in the prediction model is worked as a backend tool for obtaining the decision. It helps to predict the chances of heart disease prediction based on the input values received from the user on the GUI screen shown in figure 5.19.

The parameters used in predicting chances of heart disease are represented on the screen. Predict option on the screen helped to determine the chances of a patient having heart disease or not. The user interface was developed to work on both Windows and Android based systems. This application assists the medical professional to make decisions about the patient's health condition quickly. Web based application represented on the desktop computer to analyze the health records. The web application was designed using Python with Tkinter. It is the fastest and easiest way to create GUI applications. The desktop interface accepts the user inputs and gives decisions regarding the occurrence of heart disease.

Prediction model designed for analyzing chances of heart disease was further extended to predict chances of diabetes. The design was adopted from the heart disease model. The input parameters used in determining the chances of diabetes was obtained from the reduced dataset 03. This application is helpful to the doctors in predetermining the risk of having disease and advice the patient to take precautionary measures.

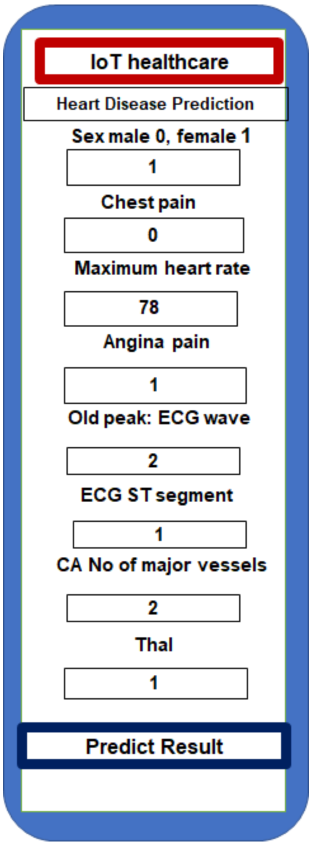

Figure 5.19: Mobile healthcare application for predicting results

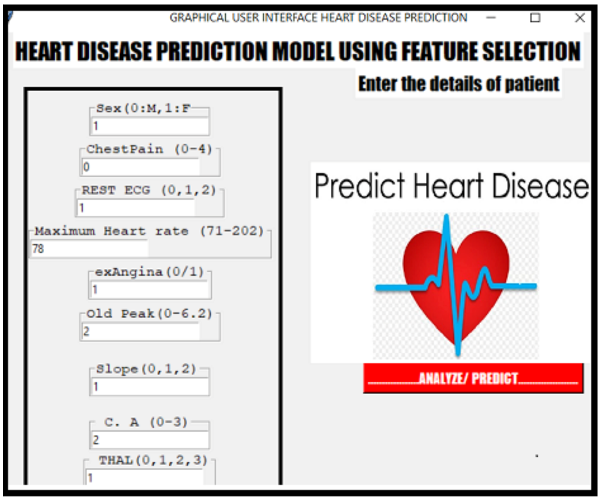

Figure 5.20: Web interface in prediction based healthcare application

The proposed layout of application is performed in stages. Patient's information history was logged using available services offered by the google sheet. This helps the doctor to correlate the factor uploaded by the patient. There is not a unique threshhold limit for a particular patient. The threshhold value differs from person to person.

The developed prototype was demonstrated to the Doctors. The usability aspects and features of the unit was illustrated practically. The response from the doctors are obtained about the prototype. The feedback was analyzed to know the strengths and further improvement of the developed unit. The figure 5.21 represents the responses collected from the team of 55 doctors. The response received from the doctors represented that 89.1% have expressed the of the device in patient monitoring is essential. The component such as artificial intelligence in disease diagnosis, mobile application, security features are important. Green bar in the figure 5.21 depicts response collected from the doctors in “YES” and Red colour represents response in “NO”.

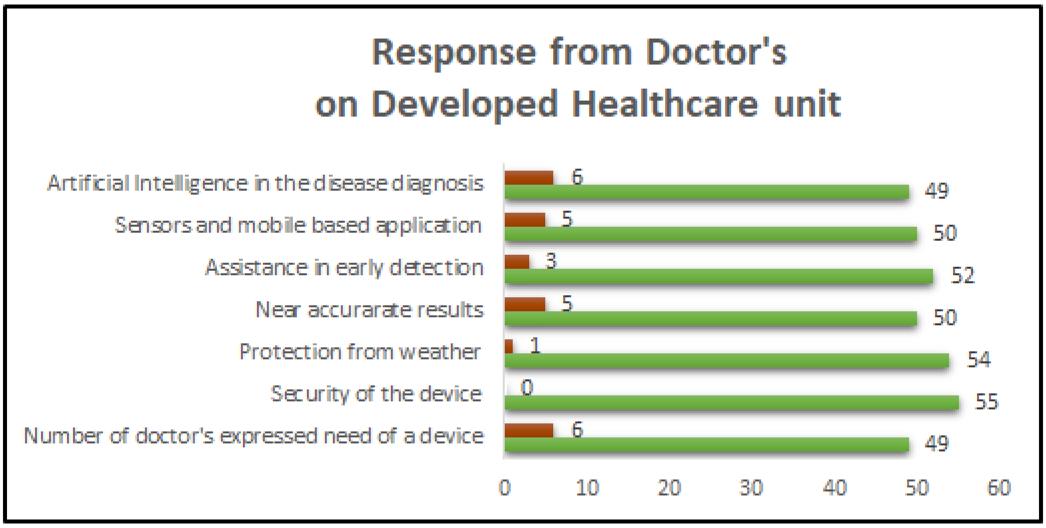

Figure 5.21: Responses of Doctors on developed prototype

5.6 Conclusion

The prediction model was built using the Random Forest algorithm. Training of the algorithm was carried out by tuning the parameter using a grid search approach. An accuracy score of 90.16% is obtained. Thirteen input parameters in the heart disease are reduced to eight utmost important parameters. Similarly eleven parameters from diabetes dataset was reduced to five most important parameters. Designed prediction model can be efficiently utilized by the experts to analyze the parameter in a short interval of time.

The designed application was communicated to the panel of doctor to obtain their feedback. Responses received from the various doctors are summarized as follows.

89.1% people have expressed that mobile app will be helpful to monitor the body parameters. They suggested that an early advice and notification helps in reducing the complications. They have expressed that rural India people can use this device for reporting to the doctor and seek early assistance from the physician.

The suggestion/advice for further modification of such remote monitoring healthcare device was received with following remarks: The results can be near accurate, hardware unit should be weather proof. Security of the patient data should be taken more concern. Considering all the review remarks the application was successfully build and tested.

This application finds very useful for the rural people to take assistance from expert doctor for early detection of the disease. People could utilize this application during ongoing pandemic situation. It has been uniquely designed to obtain wearable sensor data directly or patient can send the data by manually entering the parameters. Sufficient measures were taken to establish communication between the doctor and patient using secure communication. Doctor can able to refer back earlier history of the patient using the designed application. More features can be upgraded to the current application according to the end user/physician demands.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

The potential of IoT is summarized as a growing area of research in the field of healthcare. These developments provide a great opportunity for healthcare systems to proactively predict the health issues. They provide ample scope to diagnose, treat, and monitor patients both in and out of the hospital.

The proposed system is a dedicated solution for managing patient-related data. Data is stored on the cloud using patient ID and password by maintaining it's privacy. Hardware unit developed in this work is compact and can be easily carried with the person. It has a chargeable battery unit and enough number of ports for the expansion of sensor nodes.

Designed hardware unit allows a direct communication of the sensor nodes with the cloud application. The major features of the proposed architecture are its scalability, interoperability and lightweight access. It is scalable due to the fact that it relies on a cloud infrastructure that provides resources based on utilization and demand. Many users, sensors and other data sources can be added without affecting the functionality of the system. Thereby maintenance and expansion of the services are coherent. The IoT service ensure the maximum interoperability with the external applications.

The prediction model in healthcare will predict a patient's disease at an early stage. This model assists the doctor in the diagnosis of the disease. It helps to maximize the medical services and provide a better outcome in healthcare industry. The aim of this research helped to improve patient's experience in knowing the health conditions. The new healthcare system is a bright spot, as it makes the easy interaction between the doctor and the patient by providing virtual access.

The feedback received from the doctors indicates that the mobile application and hardware model is very helpful in patient monitoring system. The performance and benefits of the proposed mobile application are compared with the presently available mobile applications. They are:

- Wearable Fitness Trackers measures heartbeat, calories used, they help in educating people, whereas the proposed model consists of multiple features in alerting and warning the patient if any parameters exceeds the critical value.
- Health Assistant keeps a record of health parameters like weight, blood pressure, body temperature, and other physical activities. This information is privately accessible by the individual. Whereas in the proposed solution it shares the information securely with healthcare specialists and seeking the right advise.
- Freeletics, Sworkit, Nike Training Club, Daily Burn application using sensors, are available for fitness tracking they automatically track walking, running, and cycling activities. They help to educate the people in taking care about the health but not providing any advice from doctors.
- Sleep monitoring band is monitoring sleep patterns posture helps to track only specific patterns in the diagnosis of disease. The developed model is including multiple features in the diagnosis of various disease.
- Smart contact lenses used in early detection of diabetes. The cost of the device is expensive. The proposed unit is at low cost, so it is affordable and configurable to accommodate more sensors and can predict early detection of diabetes.
- Smart bandages that measure the wound's temperature and pH value are limited to specific diseases and have minimum assistance from the physician as compared to the proposed work.
- Smart Pills stomach-related information tracker requires careful attention from the physician. The designed unit equipped with wearable sensor are easy to use as compared to the ingestible sensor units.

Prediction model designed using machine learning depicts a 90.16% accuracy rate with only eight important parameters from the dataset. Thirteen input parameters from the UCI dataset are reduced to eight utmost important parameters. Similarly, prediction of diabetes is with five important parameters from the set of eleven parameters with an accuracy rate of 95.83% is achieved. The existing prediction model used in the heart and diabetes disease dataset is improvised with the proposed method.

The mobile application developed in the virtual patient monitoring system is incorporated with a vast number of features as compared to the existing application like Teledoc, Doctor on demand, ZocDoc, Practo, and Video chat using the Whatsapp application. The application helps to observe real time monitoring of patient. Hardware unit attached to the patient able to connect with the doctor using the mobile application. Most of the application existing are based on video conferences and video chat. The patient information (history) is securely stored for further use in the designed application.

6.2 Future Scope

The research has a scope in order to improve on the efficiency by implementation of block chain storage compared with centralized cloud-based storage. The prediction model can be enhanced to obtain the results of various other chronic diseases. Scope for exploration of new diseases using prediction model should be included. Many diseases that were either neglected or got inadequate consideration in the past can be added to the diversity of the IoT enabled health applications. The collection of data can be obtained from the hospital in addition to the dataset collected from the data repository.

Currently, researchers worldwide are trying to design healthcare devices that can generate power for themselves. One such potential solution may be the integration of the IoT system with solar energy. Alternatively thermal energy in the form of waste heat or metabolic heat is a promising source for reliably supplying power to the electronic devices. These systems can help in alleviating the global energy crisis to a certain extent. Mobile application designed can include local language and audio inputs. They can be easily used by the large community.

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List of Publications

1. Raykar, Suneeta S., and Vinayak N. Shet, "Design of healthcare system using IoT enabled application." Materials Today: Proceedings 23 (2020): 62-67.

2. Suneeta Raykar, and Vinayak Shet, "Comparative Analysis of Feature Selection Based Machine Learning Methods for Heart Disease Prediction." *International Journal of Information Technology and Electrical Engineering"*, Vol. 10, No. 1, February 2021.ISSN:-2306-708X

3. S Raykar, Vinayak N Shet, "Design of healthcare system using IOT enabled Application." *International Conference on Advanced Materials for Clean Energy and Health Applications*, AMCEHA University of Jaffna Srilanka. 8-Feb 2019.

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6. Raykar, Suneeta, and Vinayak Shet. "Mobile Healthcare Application for Virtual Patient Monitoring System." In Artificial Intelligence on Medical Data, pp. 317-330. Springer, Singapore, 2023.