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Healthcare IoT System and Network Design

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by

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Dedication

To my family.

Acknowledgments

First and foremost, I am extremely grateful to my supervisor Prof. Kwang-Cheng Chen for his advice, support, and patience during my master thesis study.

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Abstract

The developing IoT concept offers many opportunities to service providers in the medical field. However, the functionality of the developed systems is increasing day by day, and it brings many different problems. One of the most important problems is the transmission of biomedical data of real-time monitoring systems to the medical server with the least delay. Network architectures are changing to meet the changing needs of densely connected devices, and “computing at the edge” is the new architectural approach emerging in IoT networks. This architecture is more dynamic than computation in the cloud because it enables data processing at each layer of the network. In this way, it solves two problems created by computing in the cloud: increase in data traffic and latency in the services provided.

In this thesis, an IoT-based medical e-health system design has been proposed. It aims to transmit the vital data obtained in the proposed system to the medical server by sending it directly to the smartphone. The obtained data is transferred to the smartphone via BLE 5.0 and the BLE data channels used are specialized. The proposed smart health system is performed data analysis and data traffic performed on the smartphone. According to the analyzed health status, the intelligent data traffic structure of the system decides how often the data will be sent to the cloud dynamically. It is aimed to design in such a way that the use of bandwidth is optimal.

Chapter 1: Introduction

1.1 Overview of Internet of Things

The Internet of Things (IoT) can be defined as a technology that enables physical things/objects to communicate with each other or to connect larger-scale systems and exchange data to provide better services to users and make their lives more accessible [1]. The IoT offers each object a unique identity and internet access, allowing physical objects to think and perform different tasks [2]. The IoT architecture, shown in Figure 1.1, basically consists of the perception or sensor layer, network layer, and application layer. Moreover, it is also used to offer new solutions in many different areas such as transportation, health, home automation, environment, agriculture, personal and social.

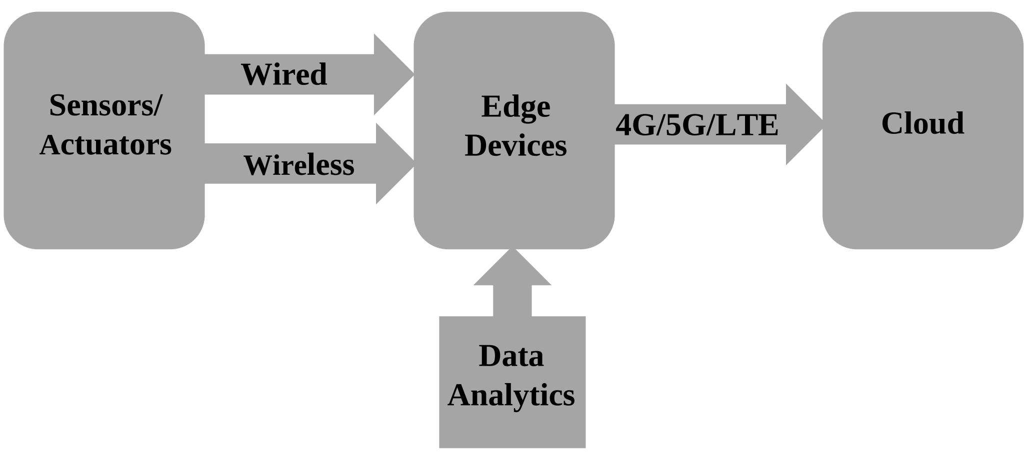

Figure 1.1 IoT Architecture

In today's world, where sensor technology is developing more and more each day, systems have emerged that enable the provision of advanced services to people by integrating physical objects into information networks. It has become an indispensable part of life with the expansion of internet usage, the move of almost all physical media to virtual environments, and cloud systems development. Many organizations in various industries use IoT technology to work more efficiently and provide better services, improve decision making, and increase the business's value and a better understanding of customers. Healthcare is one of the areas where the use of IoT-based systems is widespread, and the latest smart healthcare solutions offered have been so crucial for physicians and patients [3].

1.2 The Role of Smart Healthcare

The measurement and evaluation of physiological signs in the human body play a critical role for doctors to diagnose and treat diseases and have a good understanding of the patient's health status. Physiological vital data such as electroencephalograms (EEG), electrocardiogram (ECG), heart rate (HR), blood pressure (BP), respiratory rate (RR), oxygen saturation (SPO2), glucose level are signals that are observed intensely in the diagnosis and treatment of diseases [4]. However, there are specific difficulties in practice, although it seems possible that these physiological data can be monitored continuously and evaluated instantaneously. In particular, doctors cannot continuously assess the data of many patients simultaneously, making it difficult to evaluate the given size. At this point, smart health systems not only allow doctors to observe their patients for a more extended time but also facilitate the evaluation of these data.

Recent developments in the healthcare industry help make it easier to design IoT-based healthcare systems that allow the collection of patients' biometric signals, analyze these data, and send them to physicians over secure wireless networks [5]. An IoT-based healthcare system can help physicians in treatments and predict a symptom before starting the diagnosis. By using IoT-based technologies, the medical industry improves the ability of the healthcare system to minimize human error, simplify the treatment process, and enhance the quality of life for caregivers as well as patients [6]. For this reason, the development and use of smart health systems have now become a part and necessity of daily life.

1.3 IoT-Based Healthcare System

With the shrinking of electronic devices and increasing processing power, small and portable devices that can communicate around the human body are being developed. Some of these devices can be worn, while others can be placed on the human body during medical operations. These devices need to be able to transfer the human body signals they collect to another remote device so that the biological signals in the human body can be examined. Sensors and other components are integrated to form a new technology named wireless body area network (WBAN) and this is essential for IoT-based healthcare design [7].

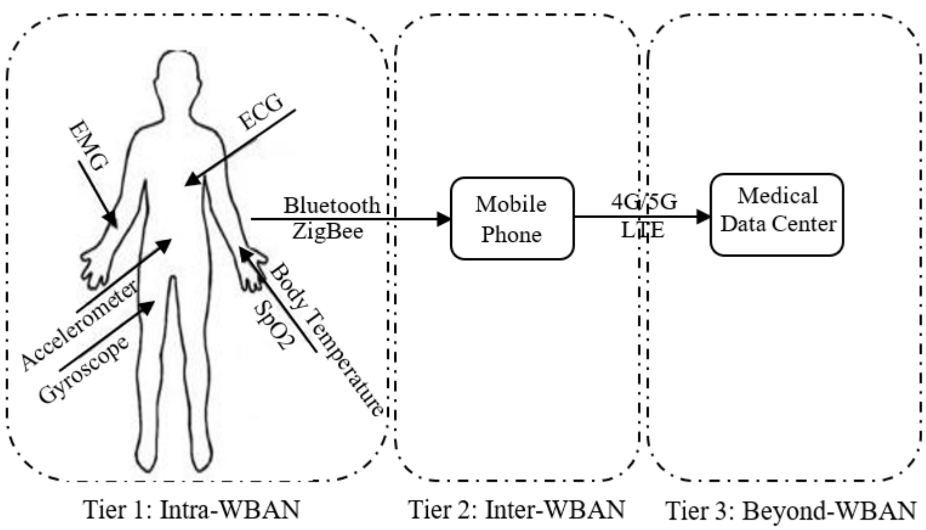

Figure 1.2 Conceptual System Architecture of Wireless Body Area Network (WBAN)

IoT-based smart healthcare systems are combined with various protocol types and heterogeneous networks using different technologies. The main purpose of setting up this system is to monitor a patient remotely by collecting as much up-to-date body condition information as possible using sensors. In addition, these systems are designed in such a way that patients should not feel uncomfortable, and those sensor devices should not disrupt their daily lives [8]. This multivariate system of multiple smart sensors collects raw biomedical data and creates valuable services by processing, analyzing, and spreading it. The system architecture of the wireless body area network in Figure 1.2 fundamentally consists of 3 tiers: Intra-WBAN, Inter-WBAN, and Beyond-WBAN communications.

Intra-WBAN is responsible for collecting vital data and securely sending them to the PDA using wireless communication protocols like Bluetooth, ZigBee, or Wi-Fi. Inter-WBAN, also called PDA, sends data from Intra-WBAN to the medical data center after necessary pre-processing such as compression, filtering, and extraction. The wireless protocols that can be used in designed IoT-based healthcare systems need to meet the requirements such as low power consumption, easy configuration for network connection, lightweight integrated chipset, and the ability of real-time data communication [9].

The widespread use of smartphones in our daily lives plays a vital role in developing designed systems and reducing the problems encountered in the system design process. The large amount of biomedical signal data obtained causes data processing difficulties and bandwidth and overload problems in wireless communication systems, as well as reliability and robustness problems. Moreover, these features not only increase the complexity of IoT devices, but also seriously affect the stability of optimization parameters such as delay, efficiency, accuracy, efficiency, mean residual error, latency, and more energy consumption [10, 11]. Therefore, real-time computing requirements and the increase in computing power of edge devices such as routers, switches, and access points lead to the emergence of the edge computing paradigm [11].

Edge computing is a model that shifts computing resources from central data centers or public clouds closer to devices, that is, embedded at the edge of service provider networks. The main purpose of this approach is to process data with lower latency necessary for many new applications and to save network costs [12]. Unlike cloud-based IoT systems, edge-based systems bring data processing closer to the network edge, resulting in faster response times and higher energy efficiency. In cloud-based systems, sending information to the cloud frequently for computing results in even higher power consumption and associated costs due to the massive amount of data produced by the sensors [13]. The comparison between edge and cloud-based IoT systems is shown in Table 1.1. These edge computing features have led to the recommendation of remote health monitoring architectures based on artificial intelligence and other technologies. These proposed systems allow for collecting vital data, increasing the accuracy of disease diagnoses and providing a faster response in a possible emergency [14].

Table 1.1 Comparison between edge and cloud computing

Technical Aspect	**Edge Computing**	**Cloud Computing**
Deployment	Distributed	Centralized
Distance to the UE	Close	Distant
Bandwidth usage	Low	High
Latency	Low	High
Jitter	Low	High
Data Processing Speed	Fast	Slow
Energy Consumption	Low	High
User experience	High	Low

1.4 Motivation and Objectives

Cardiovascular disease is one of the most crucial public health problems affecting millions of people and is directly associated with significant mortality and healthcare expenditure worldwide. With the advancement of wearable biomedical technologies and big data analytics, it is possible to create effective CVD management and monitoring system that benefits CVD patients and those at high cardiovascular risk. Wireless Body Area Networks enable remote monitoring of vital biomedical data and play an essential role in developing numerous medical applications. With the increasing popularity of smartphones, it has become the focus of newly developed wireless medical systems. When integrated with Body Area Networks (BANs), it helps collect desired health data and early diagnosis of abnormal health conditions that may occur without limiting patients' daily activities.

Edge or smartphone-based smart healthcare systems bring data processing closer to the network edge, resulting in faster response times and higher energy efficiency. Therefore, it facilitates the data processing process and accelerates the transfer of critical biomedical data.

In this thesis, an IoT-based smart e-health system design has been proposed. It aims to transmit the vital data obtained in the proposed system to the medical server by sending it directly to the smartphone. The obtained data is transferred to the smartphone via BLE 5.0 and the BLE data channels used are specialized. The proposed smart health system is performed data analysis and data traffic performed on the smartphone. According to the analyzed health status, the intelligent data traffic structure of the system decides how often the data will be sent to the cloud dynamically. It is aimed to design in such a way that the use of bandwidth is optimal.

Chapter 2: E-Health System Design and Requirements

This section will be shown the system design using the Android smartphone as the edge device and give detailed information about the proposed IoT e-healthcare system design and requirements.

Considering that IoT-based smart healthcare systems are a scorching research area that is growing day by day, there have been many studies that we can relate to and examine. The e-health systems used in this field make it possible for patients to take preventive measures before emergencies occur. Not only do prototypes made in these studies offer systems where patients can continue their lives without reducing their quality of life, but they also provide convenience in the doctor-patient relationships without limitations such as spatial and time [15, 16, 17, 18].

Based on current medical research, these systems can warn both the relatives of the person and the nearest medical center if the vital data falls below or exceeds a certain level. Telemedicine is a system designed for the care of patients with chronic conditions such as heart disease, diabetes, hypertension, hyperthermia and hypothermia, and for communicating with their doctors in emergencies. The most prominent among the recent developed systems is the real-time monitoring of chronic diseases such as cardiopulmonary disease, diabet and heart failure in patients far from medical care facilities via wireless monitoring systems [19, 20, 21, 22]. Nowadays, studies in this field focuses on systems that allow patients to access multiple vital signal data in real time. It has been shown that systems using multiple vital data instead of a single data increase the classification performance and accuracy of different machine learning models such as support vector machines, decision trees, artificial neural networks, and deep learning used for early diagnosis and anomaly detection. [23, 24, 25, 26].

Smartphones have become the center of new generation IoT-based system designs since they are an integral part of our daily lives, their complex designs, and ubiquitous use. Furthermore, smartphones' portable and high processing power allows easy processing of the obtained data and relieves patients from many restrictions [27]. Smartphones used as edge devices are any piece of hardware that controls data flow at the boundary between two networks. Moreover, they are utilized not only to demonstrate information but also to process and transmit data to the cloud via the internet [18, 28, 29]. The fact that smart phones enable data exchange via bluetooth has made it easier to design BLE-based systems that provide low power consumption. Figure 2.1 shows the general idea of general smartphone-based system architecture.

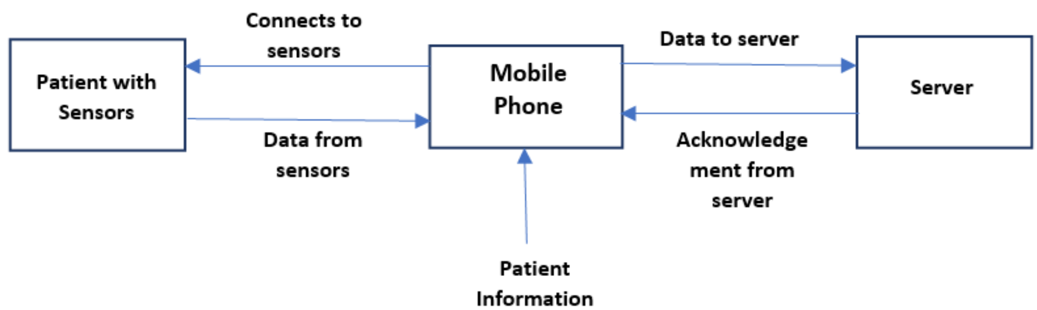

Figure 2.1 General Smartphone Based System Architecture

The general smartphone-based system generally can be divided into 3 parts. Data acquisition constitutes the first part, and this part is responsible for obtaining biomedical data and sending it to the smartphone via wireless communication protocols like Bluetooth, and ZigBee. The second part is the smartphone, and in the data acquisition part, the incoming data is processed. Data compression is performed by analyzing data and the resulting compressed data is sent to the cloud server using 4G, 5G, and LTE. Finally, the obtained data is kept on the server, and the doctor has access to this data.

The proposed e-health system conceptual diagram is shown in Figure 2.2. This proposed system aims to design an IoT e-health system that provides remote monitoring of vital signs to be used to check the condition of patients. First of all, modules are created to receive vital signals that are ECG, accelerometer, SpO2, and body temperature, each of which connects to a smartphone in real-time using a Bluetooth connection.

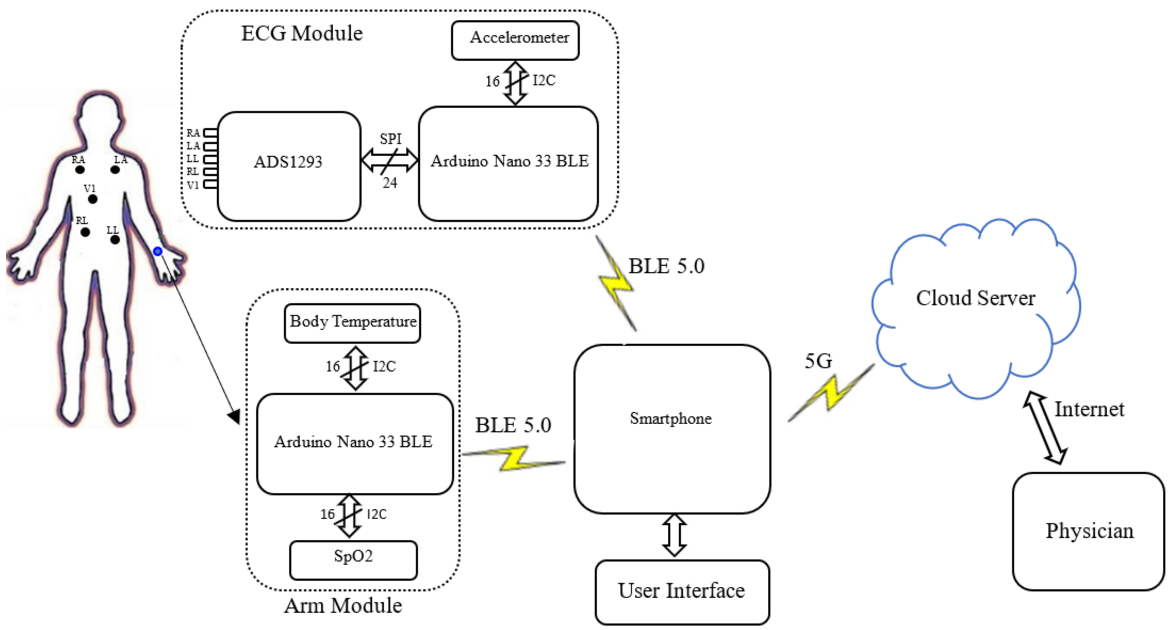

Figure 2.2 Proposed System Conceptual Diagram

After the data received from the modules are processed on the smartphone, certain features are extracted and the patient's condition is checked according to the values of these parameters, and the data is then sent to the cloud.

2.1 Biomedical Data and Acquisition

Biomedical sensors are electronic components that are specially designed to easily measure physiological signals and convert these measured signals into electrical signals. These sensors are the most critical part of all designed health systems and differ according to the characteristics of the desired signal. Therefore, the selection of biomedical sensors is essential for acquiring reliable and accurate information, the performance and functionality of the system to be designed [30].

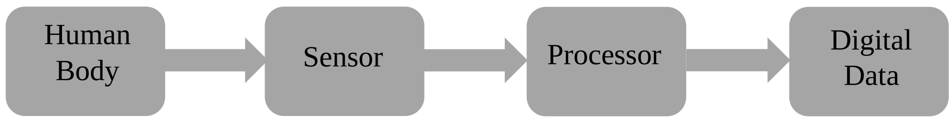

Figure 2.3 Basic Biomedical Data Acquisition Architecture

Human physiology has a very complex structure in which biomedical signals are transferred from one place to another. These signals, which are used to realize the physiological mechanisms underlying a specific biological system or event, are transmitted continuously and contain information about the state of the human body [31]. The main biomedical signals are electrocardiogram (ECG), body temperature, respiratory rate, and blood oxygen level.

Biomedical data acquisition is basically as shown in Figure 2.3. First, the sensors begin to collect analog raw biological signals by the requirements of the designed system. During data acquisition, it is essential that the obtained signal is preserved in accordance with the original structure of the biological signal. Since these signals are used to assist doctors in diagnosis and treatment, excessive distortions in the obtained signal can cause severe problems [32]. In this study, ECG, body temperature, and blood oxygen level signals were focused, and the basic properties of these signals were analyzed, and sensors were selected for these signals.

2.1.1 Electrocardiogram (ECG)

ECG has become a part of the main examinations in diagnosing mental and psychological diseases, especially heart diseases, and even routine health checks. Many heart problems can be diagnosed with ECG thanks to the electrical changes in each heart muscle movement and have tiny units and the differences shown by these changes. With the electrical activities obtained and observed with ECG, heartbeat, heart rhythm, and heart health, which is the sum of all these, become interpretable [33].

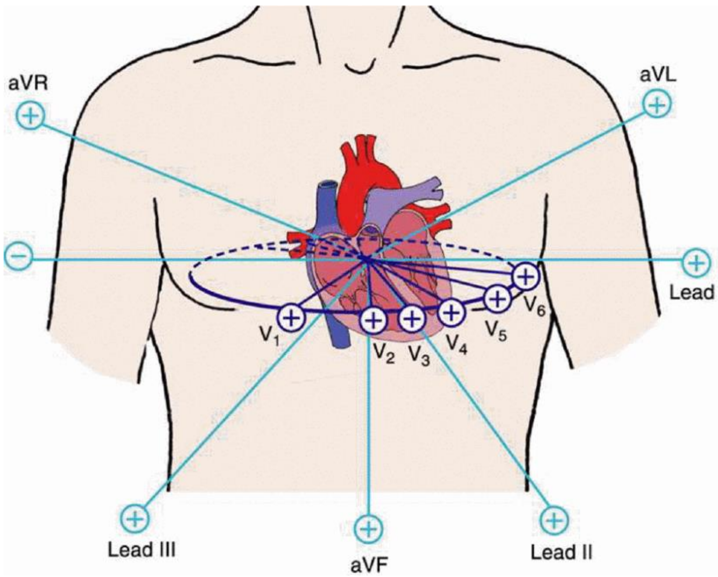

Figure 2.4 Heart Electrical Activity Projection Axes. From "Wearable wireless ECG sensor," by V. Pleskachev, 2017, Electromagnetics Research Symposium, p. 1727. Reprinted with permission.

The idea of an electrocardiography axis is defined as measuring the total electrical activity and the separated axis diagram in the space is shown in Figure 2.4. Each of the vectors showing the electrical activity of the heart and the direction of this activity is called a lead. There are a total of 12 leads: three limb leads I-III, three augmented limb leads αVR, αVL, αVF and six precordial leads V1−V6.

The feature points of normal ECG are shown in Figure 2.5. The components of a typical ECG wave are P wave, QRS complex, and T wave. Each wave-particle that makes up the ECG consists of electrical activity through the heart. Depolarization, which occurs with the stimulation in the atria, causes the P wave to occur.

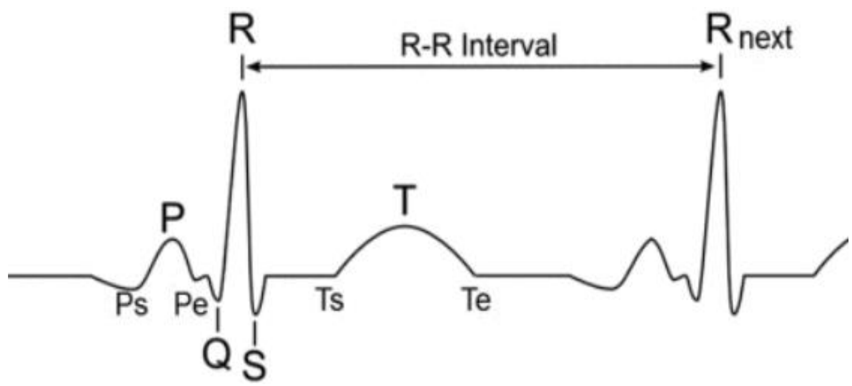

Figure 2.5 The Feature Points of Normal ECG. From “Multiple ECG Fiducial Points-Based Random Binary Sequence Generation for Securing Wireless Body Area Networks” by G. Zheng et al., 2017, IEEE Journal of Biomedical and Health Informatics, p. 655-663. Reprinted with permission.

The P wave period and the QRS complex represent the time it takes for the atria to contract fully before depolarization of the cardiac ventricles. The QRS complex represents the depolarization in the heart's ventricular area and usually creates the most substantial waves in the ECG. The T waveforms the final waveform in a period and represents the repolarization of the heart ventricle regions [34].

2.1.2 Blood Oxygen Saturation

The SpO2, or pulse oximeter, is a non-invasive method usually placed on the fingertip and used to measure the oxygen saturation in a person's blood. For a healthy person, the oxygen level is generally considered to be 95% or higher, however, if there are chronic health problems that are lung disease or sleep apnea, it may have normal levels of around 90%. It is considered risky if the oxygen level in the blood is below 90% [35].

Pulse oximeters work by analyzing color according to whether the hemoglobin in red blood cells holds oxygen or not. Since the color of blood cells changes according to the amount of hemoglobin carried, the absorption of red and infrared rays transmitted by the sensors helps us to get wise about the oxygen concentration in the blood. Oxygenated hemoglobin is bright red and shows the ability to absorb more actinic light waves while allowing the red-light wave to be tolerated. In contrast, deoxygenated hemoglobin absorbs red light waves more and tolerates actinic light waves [36].

2.1.3 Body Temperature

Body temperature is one of the most basic biomedical indicators used in e-health systems and provides essential information about the health status of patients. The average temperature of a normal person is considered to be 98.6°F (37°C), Although body temperature can vary due to many factors. Abnormal increases and decreases in body temperature are significant for detecting some health problems of the patient. [37].

2.2 Microcontroller

The conceptual diagram of the proposed system is shown in Figure 2.2, and one of the fundamental hardware elements of the system is the microcontroller.

Figure 2.6 Arduino Nano BLE 33 Sense.

Microcontrollers have an essential task as a hardware element that efficiently transmits the data from the sensors to the edge device. Therefore, Arduino Nano 33 BLE Sense was chosen as a BLE sense microcontroller in this study. The Arduino Nano 33 BLE Sense is an improved version of the classical Arduino and has a more powerful processor, the nRF52840 from Nordic Semiconductors, a 32-bit ARM® Cortex®-M4 CPU running at 64 MHz. The main processor includes other amazing features like Bluetooth® pairing via NFC and ultra-low power consumption modes [38].

2.3 Communication Protocols

2.3.1 Bluetooth Low Energy

Bluetooth Low Energy (BLE) introduced by the Bluetooth Special Interest Group in 2010 is a short-range wireless technology used for device-to-device data transmission. With the widespread use of IoT-based systems in our daily lives, the use of Bluetooth Low Energy (BLE) has increased as well, allowing the development of more different systems. It is especially suitable for new-generation systems that require low power consumption, low bandwidth, and long battery life [39, 43]. BLE protocol stack is shown in Figure 2.7.

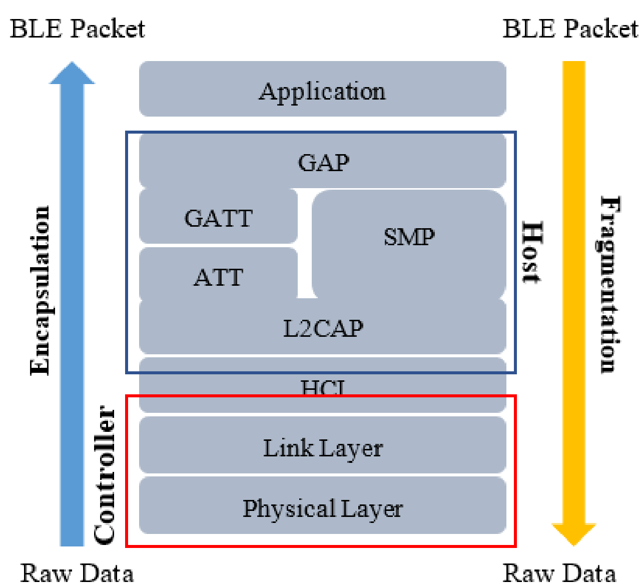

Figure 2.7 BLE Protocol Stack. From "Performance Evaluation of Bluetooth Low Energy: A Systematic Review" by J. Tosi, et. al, 2017, Sensors, p. 2898. Reprinted with permission.

BLE uses the unlicensed 2.4-GHz Industrial, Scientific, and Medical (ISM) radio band and is divided into 40 channels whose center frequencies are far away 2-MHz from each other. BLE data channels are shown in Figure 2.8. Three channels that are 37, 38, and 39 are called advertising channels and these are utilized to discover devices. The other 37 channels, called data channels, allow devices to perform data transfer in connection state. Adaptive frequency hopping is used when sending data over BLE data channels and generally allows data to be sent by excluding potential conflicts with Wi-Fi channels or channels with high packet loss. For this reason, it is important to avoid using the same frequency bands used by Wi-Fi traffic and to choose more suitable BLE channels for efficient data transmission [39, 40].

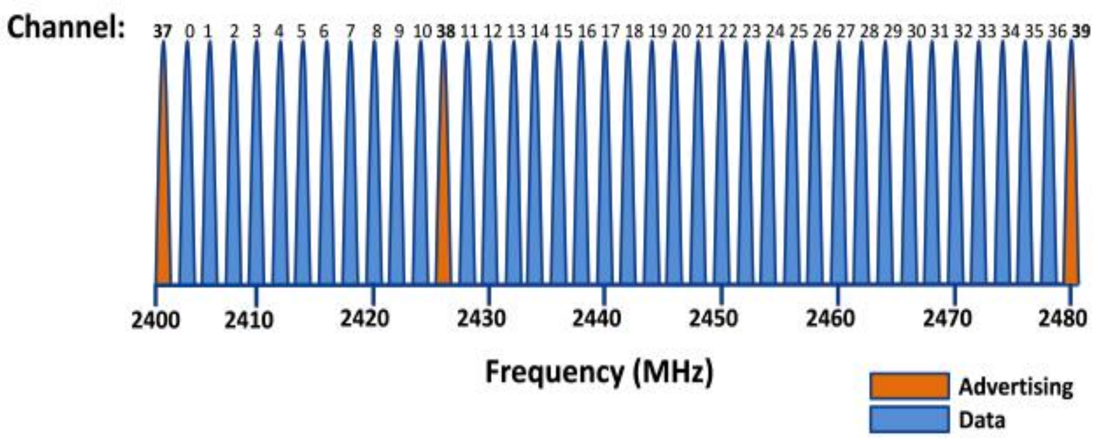

Figure 2.8 BLE Data Channels. From "Performance Evaluation of Bluetooth Low Energy: A Systematic Review" by J. Tosi, et. al, 2017, Sensors, p. 2898. Reprinted with permission.

For the sensors to transfer the obtained vital data, a connection with the smartphone must first be established. Figure 2.9 illustrates a basic established connection via BLE. Firstly, before the connection is established, the biomedical sensor sends advertising packages, and the smartphone discovers to receive the advertisements. After receiving advertising packets, the smartphone sends a connection request, the sensor responds, and the connection between sensor and smartphone is established [52].

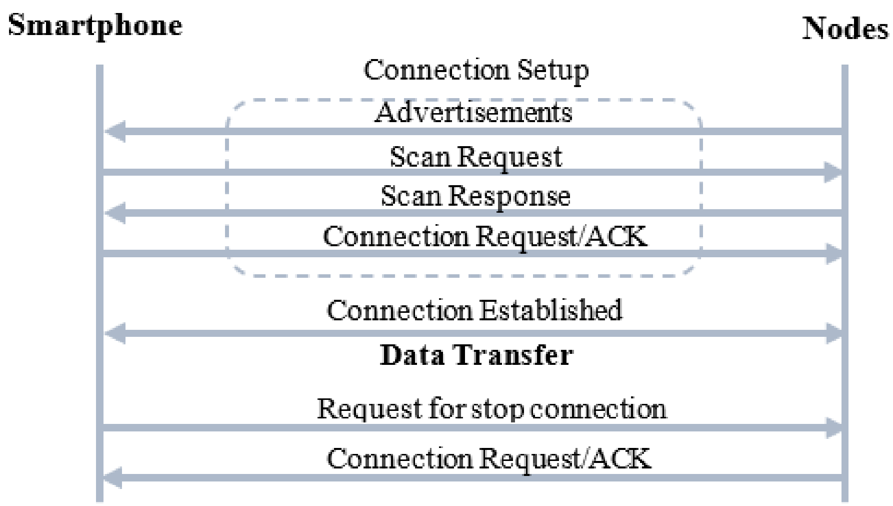

Figure 2.9 Bluetooth Low Energy (BLE) Connection.

Bluetooth has a single packet format for both advertising and data transmissions. Bluetooth Low Energy (BLE) packet format is shown in Figure 2.10. This packet format consists of a preamble, access address, Protocol Data Unit (PDU), and Cyclic Redundancy Check. The preamble size is defined as 1 byte for LE 1M and 2 bytes for LE 2M in BLE 5.0 [39, 40]. The access address is 4 bytes and this is an identifier value for the connection between nodes and the smartphone. The PDU segment has 2-bytes LL Header and the payload whose size changes from 0 to 255 bytes. In BLE 4.0 and 4.1 versions, the maximum ATT Payload is 20 bytes, however, in the 4.2 and above versions, the ATT Payload provides to hold up to 244 bytes of data [51].

2.3.2 5G

5G technology is a long-distance wireless communication protocol that offers high-speed data transfer as well as large capacity, large data transmission, low cost, powerful battery, and reliable mobile communication.

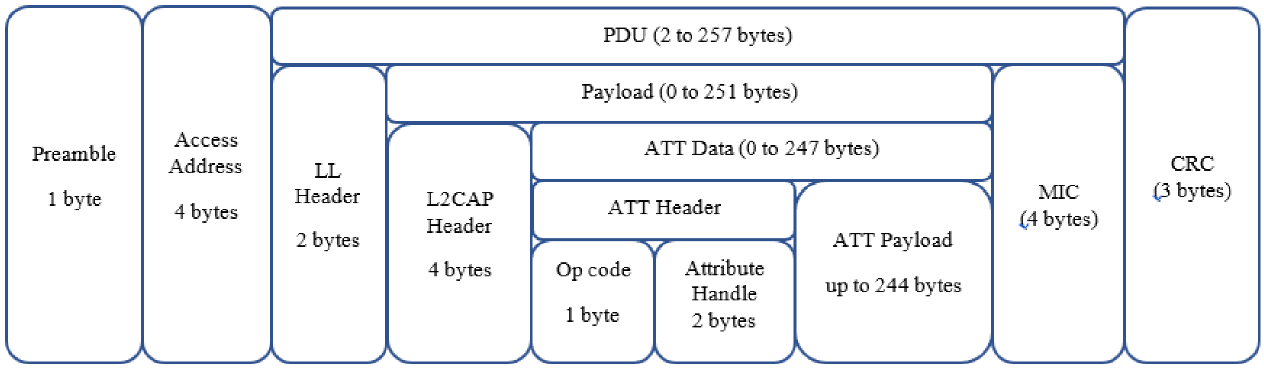

Figure 2.10 Bluetooth Low Energy (BLE) Data Packet Format. From "Analysis and Performance Evaluation of Bluetooth Low Energy Piconet Network" by Z.K. Farej, A.M. Saeed, 2020, Open Access Library Journal, p. 1-11. Reprinted with permission.

In addition, 5G networks have extensive coverage, presenting a perfect match for supporting IoT communications that will revolutionize the way of many everyday life activities [41]. Table 2.1 shows different kinds of long-range communication protocols and their characteristics.

Table 2.1 Long range communication

Technology	**Frequency**	**Data Rate**	**Distance**	**Power**
LoraWan	Various	0.3-50 kbps	2-5km (Urban) 15 km (Sub-urban) 45 km (rural)	Low
Sigfox	868/915MHz	300bps	50km	Low
4G	800, 1800, 2600MHz	12Mbps	10km	High
5G	Higher Bands	10Gbps	10km	High

5G and IoT will improve the service quality and experience of users in various industries that are in the fields of transportation, manufacturing, and healthcare, with a fundamental impact on people's lives. In this thesis, IoT solutions are presented, with a focus on applications to industrial healthcare [41].

2.4 Cloud Server

A cloud server is a powerful physical or virtual infrastructure that performs application and computing storage. Cloud servers are created using virtualization software to split a physical or bare metal server into several virtual servers. Healthcare informatics assists medical staff, doctors, and nurses with fast, on-demand access to patient records. In addition, medical cloud hosting allows for the secure storage of health records.

Chapter 3: Proposed E-Health System Model

In this chapter, detailed information will be given about the components used to fulfill the requirements of the proposed e-health system, and the necessary throughput calculations for the Bluetooth packet structure will be made.

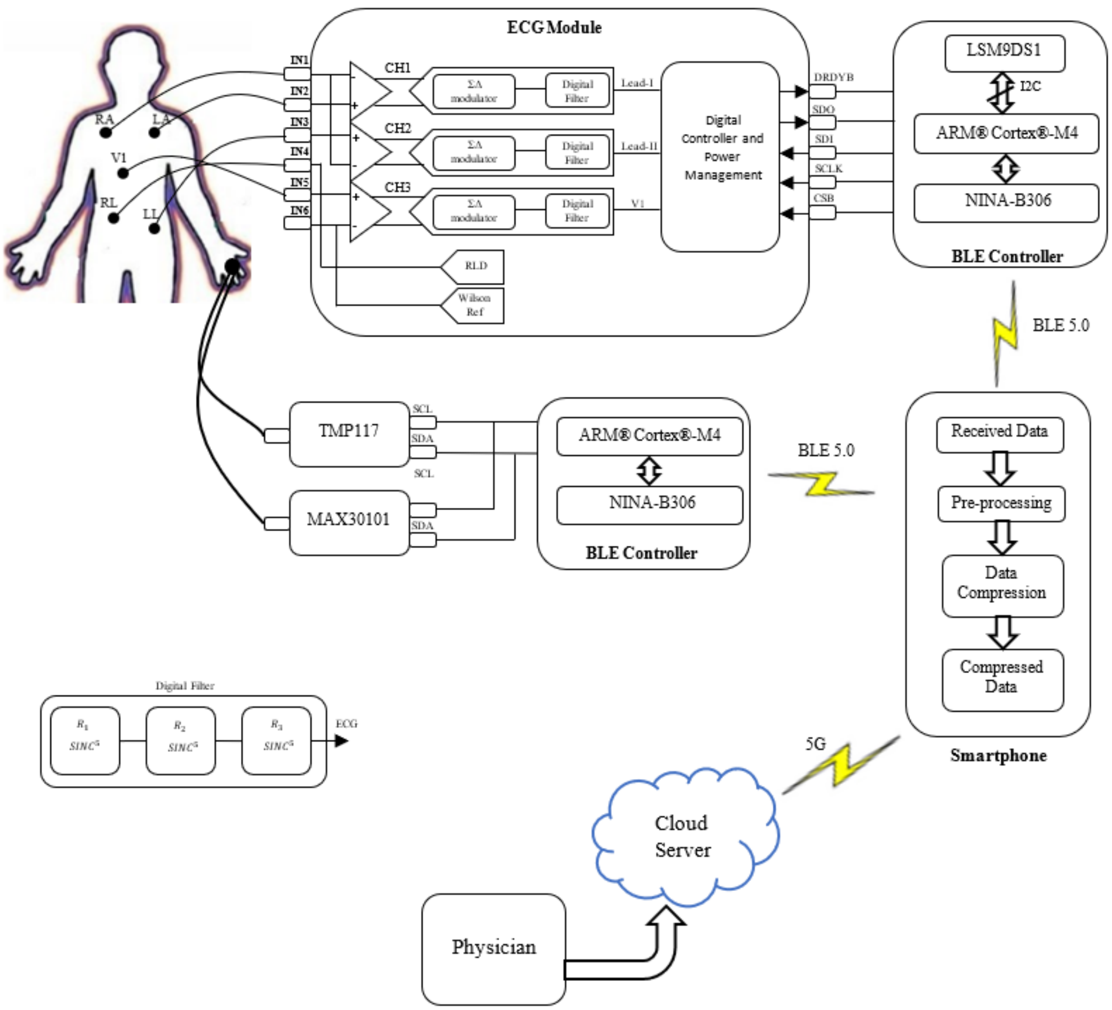

Figure 3.1 Proposed E-Health System Circuit Diagram

3.1 System Components

3.1.1 ADS1293

The proposed m-health system circuit diagram is shown in Figure 3.1. In this system, we use the ADS1293 sensor for collecting ECG data. The ADS1293 IC is a widely used biomedical sensor in portable, low-power ECG applications [42]. This study used it to convert the analog signals coming from the electrodes through 3 channels and 5-leads. The converted analog signals are sent to the BLE controller via SPI and sent to the smartphone via BLE 5.0.

Analog signals are converted to digital signals with the help of a sigma-delta modulator and digital filter, and these converted signals are transmitted to the BLE controller via SPI. The output of each digital filter is 24-bit, and a resulting sample consists of 9 bytes. The digital filter consists of fifth-order three programmable SINC filters, and the decimation rates of these filters are automatically adjusted by selecting the appropriate values. In this thesis, R_1, R_2, and R_3 are selected 4, 4, 32, respectively. The output data rate is calculated at 200 samples per second. When the DRDYB pin is low, an interrupt signal is created, and digital data is ready to read by the BLE controller.

3.1.2 LSM9DS1

A 3-axis accelerometer is a device designed to measure acceleration along three axes in space. The LSM9DS1 module on the Arduino Nano 33 BLE Sense gives a chance to detect the relative position of the board. Each axis contains 2 bytes of data and each sample for sensor has 6 bytes. Its output data rate was set 104 sps, and total data for a second is 4.992 kbps [53].

3.1.3 MAX30101

The MAX30101 is a widely used sensor for the measurement of pulse oxygen levels. In this study, the MAX30101-based Pulse Oximeter produced by SparkFun was used. This breakout board has 2 chips and the obtained data is transmitted to the BLE controller via the I2C communication protocol. It is placed on the fingertip to receive signals. The output data rate is 60 sps and the total sensor data for each second is 800 bps [46].

3.1.4 TMP117

The TMP117 is a widely used digital temperature sensor with high sensitivity. Since the low power consumption feature of this sensor reduces the heating problem, it ensures that the errors that may occur during the measurement are minimized. The body temperature data of the receiver is transmitted to the BLE Controller via the I2C communication protocol. It also provides multiple device support. The output data rate is 50 sps and the total sensor data for each second is 320 bps [55].

3.1.5 NINA-B306 Bluetooth Module

The NINA-B306 series module provides low power BLE 5.0 support used by Arduino Nano 33 BLE Sense. The stand-alone BLE 5.0 module provides some features that are high data rate and long range, Superior security functionality, and multiple antenna [44].

This module has an nRF52840 chip. Arm® Cortex®-M4 is used and it has 1 MB flash and 256 KB RAM, providing a very good capacity for different applications. It also supports four different BLE data rates, unencoded 1 Mbps, 2 Mbps, and encoded 500 kbps, 125 kbps. [44]. These features of the module make this module suitable for IoT-based designs.

3.2 System Setups

We proposed the IoT e-health system based on the Android smartphone that communicates with the sensors with BLE 5.0. The proposed e-health system flow chart is shown in Figure 3.2. The smartphone begins to scan and display the BLE controller device and successfully establishes a GATT connection. After installing the GATT connection, the smartphone receives vital biomedical data. The transmitted vital data are obtained, processed, extracted features, and calculated heartbeats.

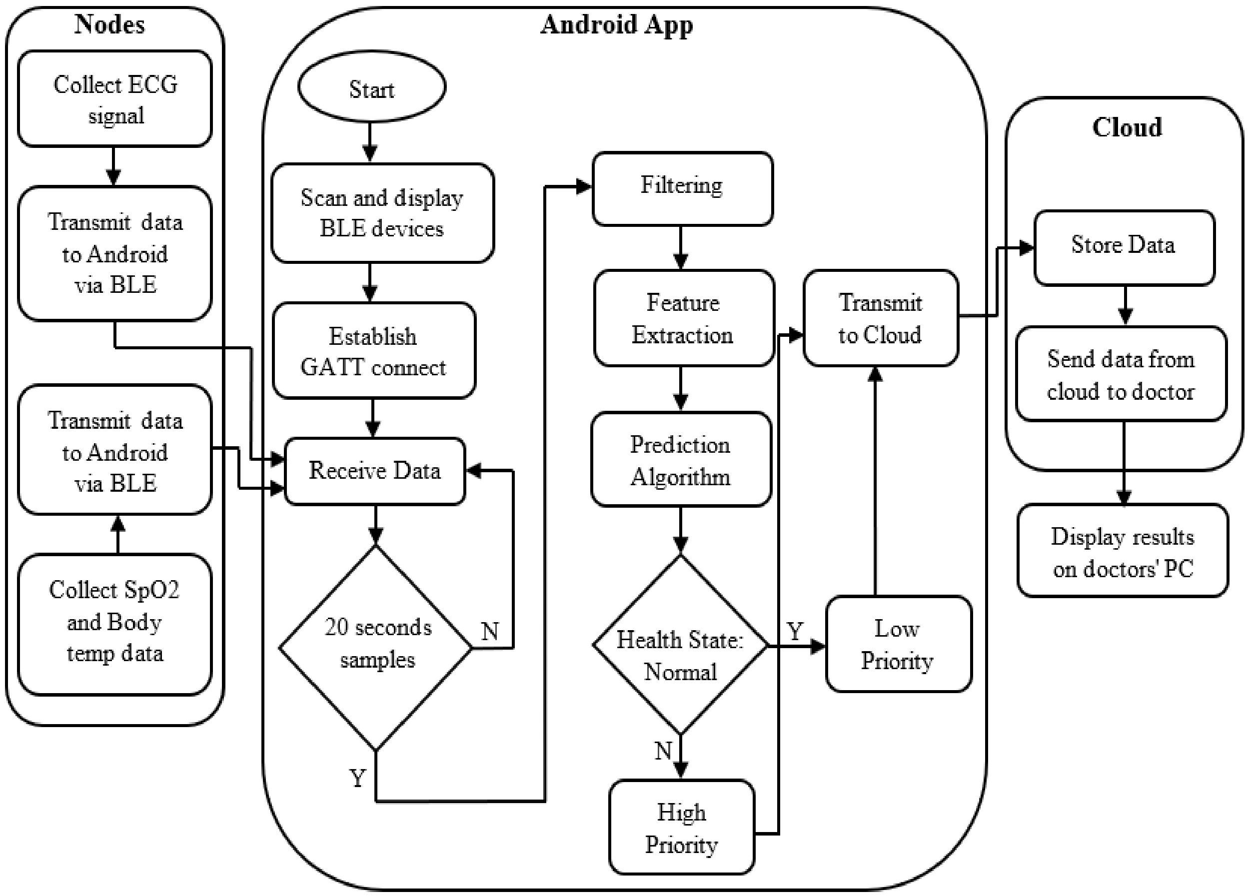

Figure 3.2 Proposed E-Health System Flow Chart

Figure 3.3 shows the connection setup and data traffic between the smartphone and modules for the proposed system. After starting the system, the smartphone sets the Initiating State and receives the ECG and arm modules' advertising packets. Then, the smartphone responds to the package by sending the initiating packet with the indicated Connection Interval = 20 ms to ECG Module and creates the connection with the sensor. After the first connection is made, the smartphone divides the specified connection interval into sub-intervals of 5ms.

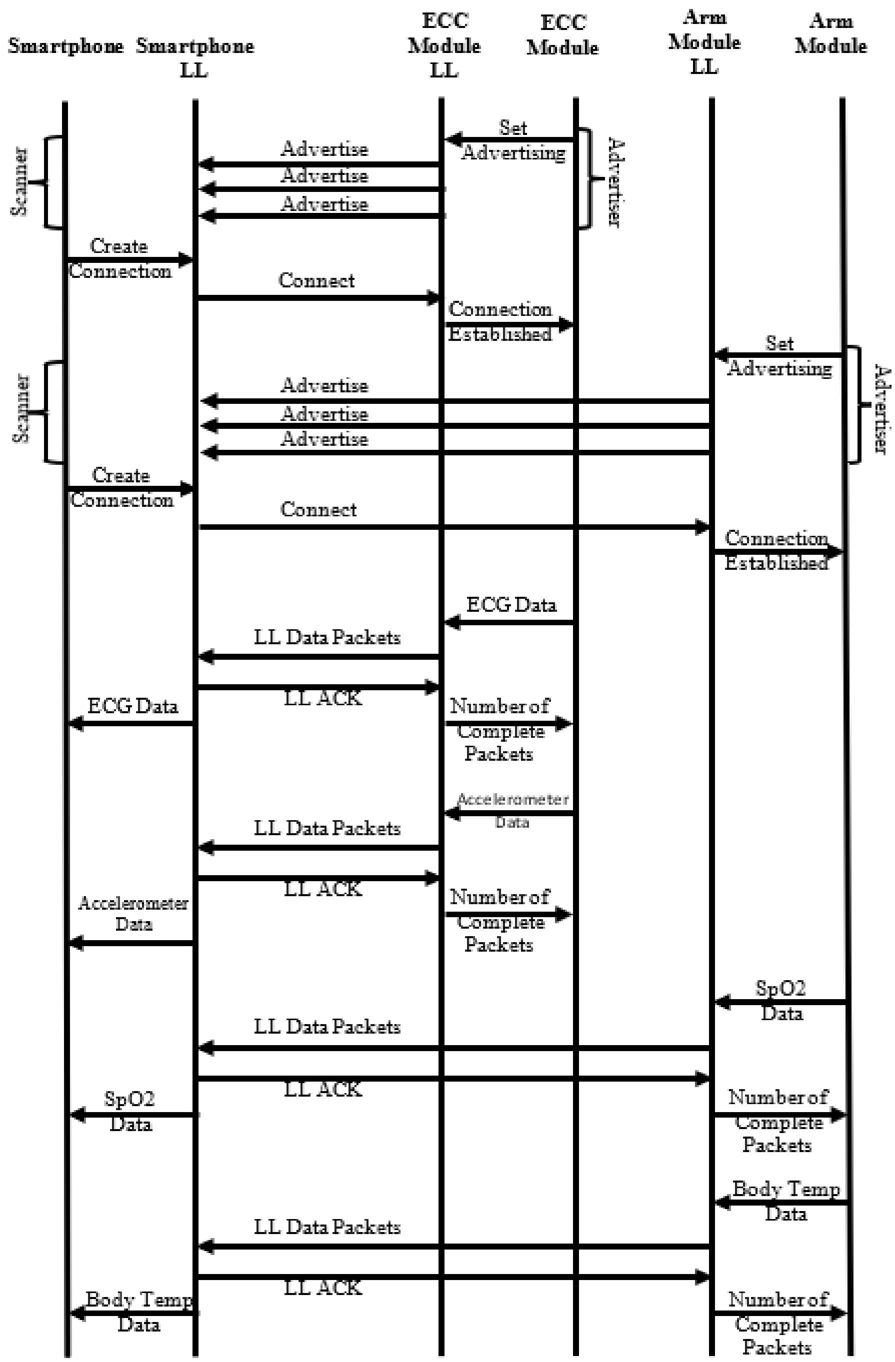

Figure 3.3 Connection and Data Traffic between Smartphone and Modules

After the established connection with modules, the smartphone starts receiving data. First and foremost, every module transmits data to the module Link Layer. These transmitted data are sent in packets to the Link layer of the smartphone. The smartphone Link Layer also sends ACK packets to Link Layers of modules. Lastly, received data packets are transmitted to the smartphone. The round-trip communication is completed.

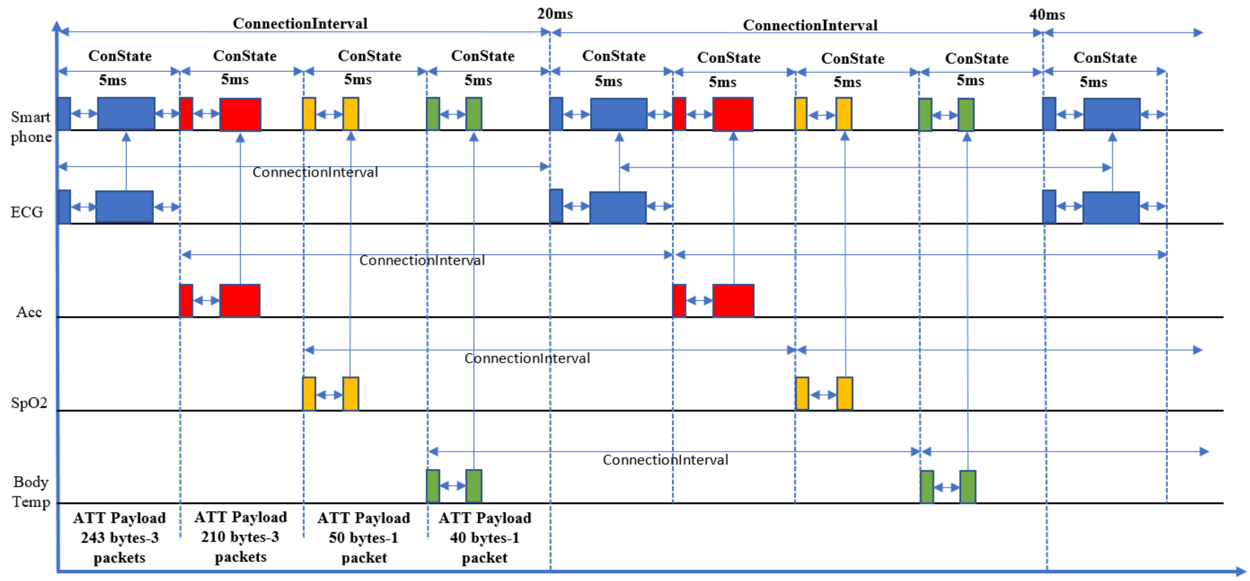

Figure 3.4 Proposed System Data Timing Diagram

The data timing diagram for the proposed system shows in Figure 3.4. In every Connection State, ECG and Accelerometer send three packets that have 243 bytes and 210 bytes of data, respectively. In addition, SpO2 and Body Temperature send one package that has 50 bytes and 40 bytes of data, respectively.

3.2.1 BLE 5.0 Throughput

The throughput of the proposed system is related to the data exchange scenario. The most common scenario used in calculating throughput is when the client transmits LL packets with zero payload length, while the server transmits notification packets. It is shown in Figure 3.5.

An empty packet size consists of Preamble, Access Address, LL Header, and CRC, and its size is 88 bytes for 2M PHY.

$$\text{Empty Packet Transmission} = \frac{\text{Empty packet size}}{\text{R}} \tag{3.1}$$

where R is PHY rate. Tranmission time of empty packet is 44µs.

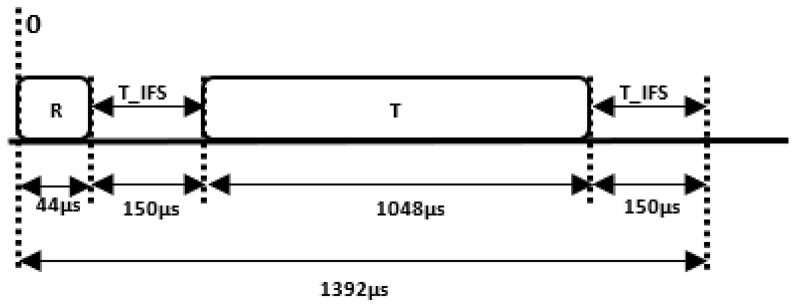

Figure 3.5 Packet Transmission

A L2CAP data packet size is 251 bytes and Link Layer overheads are 11 bytes for 2M PHY. Data packet time is calculated 1048µs, and total transmission time for every packet is 1392µs. According to this calculation, three ECG and Accelerometer data packets send 4.176ms and SpO2 and Body Temperature data packet transmission time is 1.392ms.

$$\text{Data Packet Transmission} = \frac{(\text{L2CAP} + \text{LL overhead}) \times 8}{\text{R}} \tag{3.2}$$

An upper bound for the GATT throughput can be calculated easily. To obtain throughput, it should be known the maximum number of data packets per connection interval. This value is equal to $CI/Data\ Packet\ Transmission$. Throughput calculation formula is

$$\frac{\text{Total data per CI}}{\text{CI}} = \frac{Max\ number\ of\ packets\ x\ LL\ Payload\ x\ 8\ bits}{CI} \tag{3.3}$$

For 20ms CI, this channel throughput is 1442.5 kbps. This system is designed to send eight data packets to the smartphone at each connection interval and contains 1449 bytes of data. Table 3.1 shows the number of packages and the sending data for each sensor. Considering the data transmission values and the obtained maximum throughput, it can be said that obtained vital data can be transmitted to the smartphone using the BLE 5.0 channel.

3.3 Data Analysis

The primary purpose of data analysis on the smartphone is to extract features and observe patients' status. Moreover, processing data in this way will prevent data overloads that may occur when sending it to the cloud. However, whenever data is transmitted from analog sensors over the Bluetooth communication channel, there is a noise that is added to the transmitted signals. Therefore, data enhancement techniques must be used to analyze data properly.

Table 3.1 E-health system data transmission value

		BLE 5.0 Data Transmission					
		20ms		100ms		1000 ms	
	Payload	Number of Packet	Sending Data	Number of Packet	Sending Data	Number of Packet	Sending Data
ECG	243 bytes	3 packets	729 bytes	15 packets	3645 bytes	150 packets	36,450 bytes
Accelerometer	210 bytes	3 packets	630 bytes	15 packets	3150 bytes	150 packets	31,150 bytes
SpO2	50 bytes	1 packet	50 bytes	5 packets	250 bytes	50 packets	2,500 bytes
Body Temp.	40 bytes	1 packet	40 bytes	5 packets	200 bytes	50 packets	2,000 bytes
						Total: 576.8 kbits	

The flow diagram of the proposed system is shown in Figure 3.2. The first thing to do before extracting the features is noise filtering. Two main problems: the baseline wander, and the high-frequency noises can affect vital signals.

Baseline wander is a low-frequency artifact in the ECG that arises from breathing, electrically charged electrodes, or subject movement and can hinder the detection of these ST changes because of the varying electrical isoline [45]. It can be caused by the movement of patients or the ECG sensor or breathing, which causes the received ECG signals to appear wavy. Figure 3.6 shows an ECG signal with a baseline wandering effect. The most common solution to filter out this effect is applying a high-pass filter of 0.5 to 0.6 Hz cut-off frequency to the ECG signal.

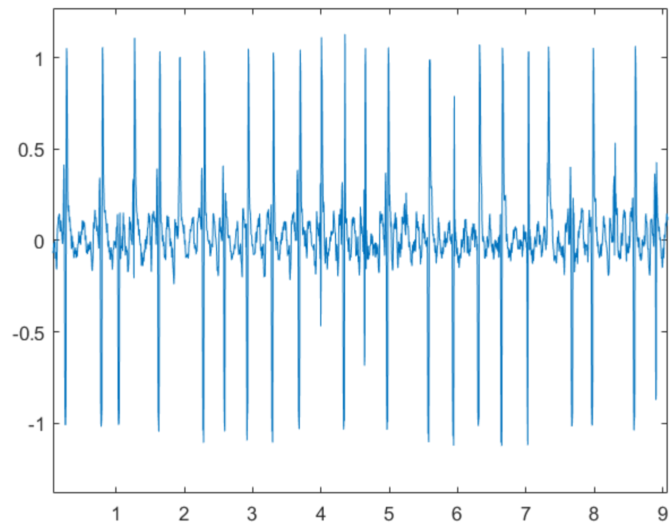

Figure 3.6 ECG Signal. (This figure is plotted using https://www.mathworks.com/matlabcentral/fileexchange/66565-heart-rate-detection-using-arduino-and-matlab-demo-files)

The high-frequency noise is other another primary reason that caused distortion in ECG signals. It mainly contains the powerline interference (50–60 Hz). A low-pass filter is needed to solve this problem. After the baseline wanders and high-frequency noise effects are eliminated, the features required for the system to make a decision should be extracted. From the ECG signal, heart rate, and RR intervals are extracted.

Wavelet and Fast Fourier transform (FFT) are common solutions to extract critical features from the ECG signal and give very accurate results. The Fast Fourier transform (FFT) algorithm can be applied to the ECG data sent to the Android smartphone, and it is helpful to obtain essential features in this way since Java-based Android FFT libraries allow to implementation of the FFT. The critical values of the extracted features and SpO2 and body temperature data and the problems they cause are given in the Table 3.2.

Table 3.2 Algorithm decision values

Normal	$60 \leq HR \leq 100, Temp = 36.5 - 37.5\ °C, SpO2 = 95\% - 100\%$
Bradcardia	$HR \leq 60$
Tachycardia	$HR \geq 100$
Concenrning SpO2	$91\% \leq SpO2 \leq 95\%$
Low SpO2	$SpO2 \leq 90\%$
Fewer	$Temp \geq 37.8\ °C$
Hypothrmia	$Temp \leq 35°C$

The data analysis process diagram is shown in Figure 3.7. Transmitted data from modules in 100ms consists of 3645 bytes of ECG data, 250 bytes of SpO2 data, and 200 bytes of Body Temperature data. Firstly, baseline wanders, and high-frequency noise is removed. Then, heart rate and RR-interval are extracted from the ECG signal using FFT.

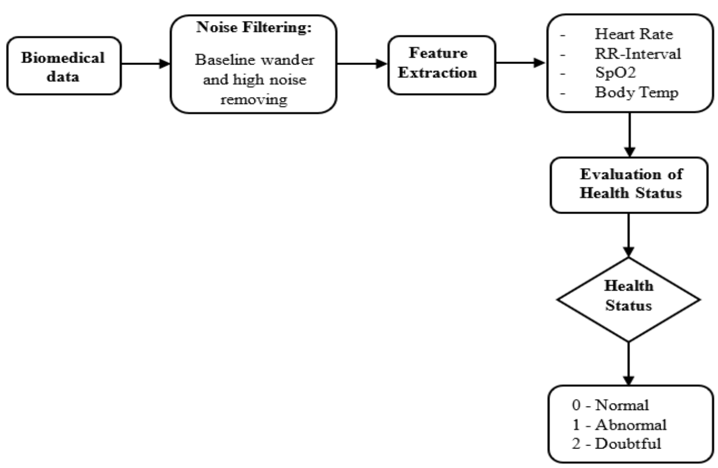

Figure 3.7 Data Analysis Process Algorithm

Finally, all features are sent to the prediction algorithm, and it decides whether the patients' status is normal or not according to a threshold value in Table 3.2. If patients' status is normal, transmitted data to the cloud should be decreased; otherwise, the system must remain to analyze data and transfer data to the cloud.

3.4 Smart Data Traffic

The most important part of the proposed smart health system is data analysis and data traffic performed on the smartphone. According to the updated patient status data, data transmission not only prevents the network from being overloaded, but it is easier to determine at what time intervals there are changes in the patient's condition. The intelligent data traffic structure of the system is shown in Figure 3.8.

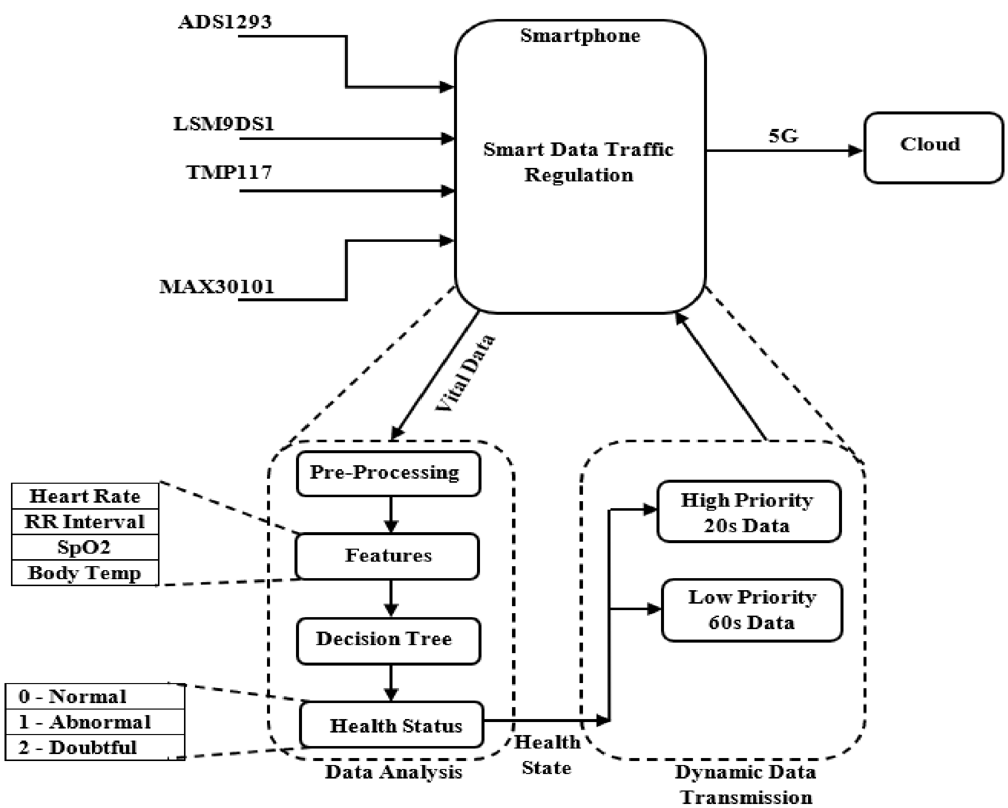

Figure 3.8 Smart Data Traffic Regulation

The system consists of two structures: data analysis and dynamic data transmission. After the smartphone receives the vital data, the noise components are extracted from the data, and the essential features are extracted. By sending these extracted features to the estimation algorithm, it is classified and normal, unhealth, and doubtful status are represented with 0,1 and 2, respectively.

The algorithm performs a real-time assessment of health status by utilizing the features. The smart data transmission process is shown in Figure 3.9.

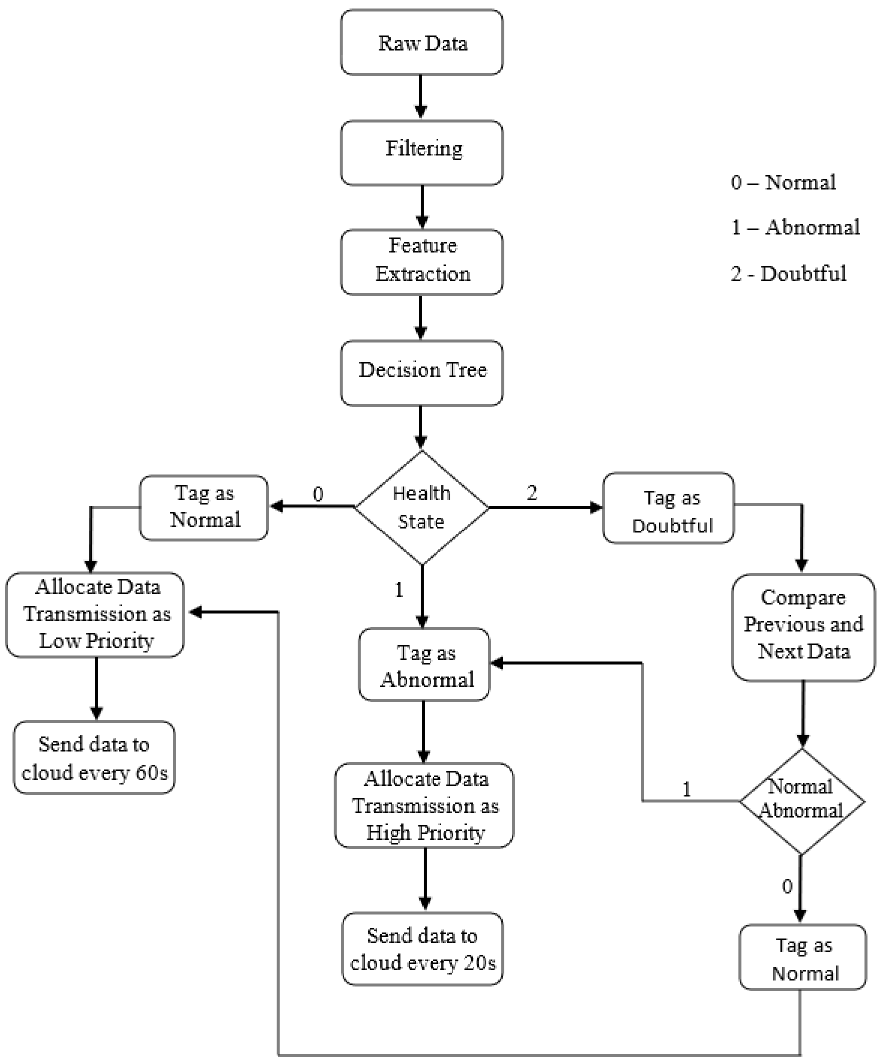

Figure 3.9 Smart Data Transmisson Process

This algorithm is created to decide how to take the action for data transmission after deciding the health status. According to the health status analyzed every 20 seconds, it is decided how often the data will be sent to the cloud dynamically. If the health status is normal after 20 seconds of analysis, data is tagged as normal. This data is held and the system continues to analyze the new data.

If the state of health is normal for 60 seconds, data transmission is allocated as low priority and it is sent to the cloud every 60 seconds. If health status is regarded as abnormal, this data is tagged as abnormal. Because these data are critical, they are not held for analysis of new data. Data transmission is allocated as a high priority and it is sent to the cloud every 20 seconds. In some cases, the state of health may be classified as neither normal nor unhealthy. If such a situation is observed, the system is tagged as suspicious. The system compares the suspicious data with the previously analyzed and newly analyzed data. As a result of the comparison, suspicious data are labeled as normal or abnormal.

3.5 5G Throughput Calculation

Smartphone-based healthcare systems transmit small-sized data in a way that is latency-sensitive and meets various QoS requirements. For 5G data transmission, physical resource blocks are allocated, which is the smallest radio resource. It is important to use these resources efficiently [47].

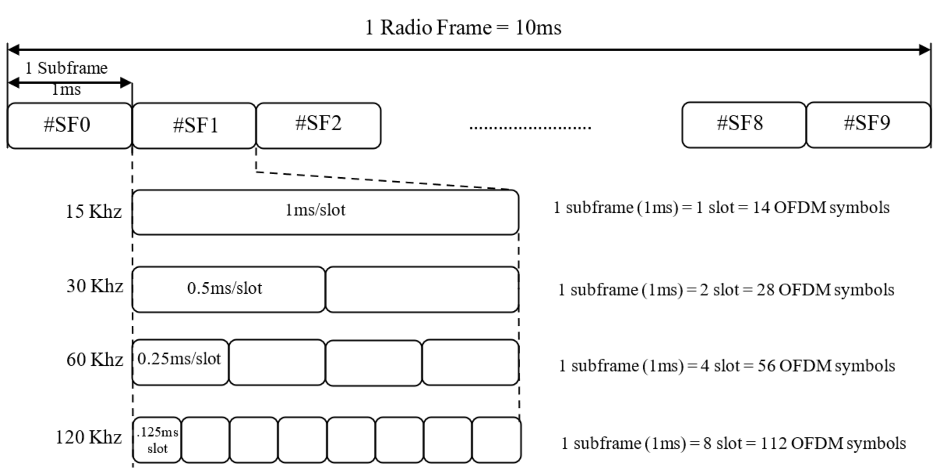

Figure 3.10 5G NR Frame Structure

According to 3GPP, 5G technologies use different frequencies in various parts of the frequency spectrum to provide much higher bandwidth or support higher data rates in 5G mobile communication. The frequency bands for 5G NR are divided into FR1 and FR2 frequency ranges that are 4.1 GHz to 7.125 GHz and 24.25 GHz to 52.6 GHz band of frequencies, respectively [48]. The most notable difference compared to LTE is that 5G NR supports multiple different types of subcarrier ranges while LTE has only a 15 KHz subcarrier range. 5G frame structure is illustrated in Figure 3.10.

In 5G NR, as in LTE, one radio frame is fixed at 10 ms and has 5 different subcarrier structures. Numerology 0 is the same as LTE, the rest are different carrier structures provided by 5G NR. The theoretical data rate for a given number of aggregated carriers in a band or band combination is calculated using the below formula [49]. The following fields are used in 5G NR throughput calculation

$$Data\,rate\,(in\,Mbps) = 10^{-6} \cdot \sum_{j=1}^{J} \left(v_{layers}^{(j)} \cdot Q_m^{(j)} \cdot f^{(j)} \cdot R_{max} \cdot \frac{N_{PRB}^{BW(j),\mu} \cdot 12}{T_s^{\mu}} \cdot (1 - OH^{j}) \right) \qquad 3.4$$

where J represents sum of carriers, $v_{layers}^{(j)}$ is number of layers, $Q_m^{(j)}$ is modulation order, $f^{(j)}$ is scaling factor, T_s^{μ} is numerology, $N_{PRB}^{BW(j),\mu}$ is resource block allocation, and OH^{j} is overhead.

Chapter 4: Evaluation

This section aims to show the results of simple feature extraction and classification. The dataset was obtained using the open-access MIT-BIH dataset at the PhysioBank ATM shown in Figure 4.1 [54].

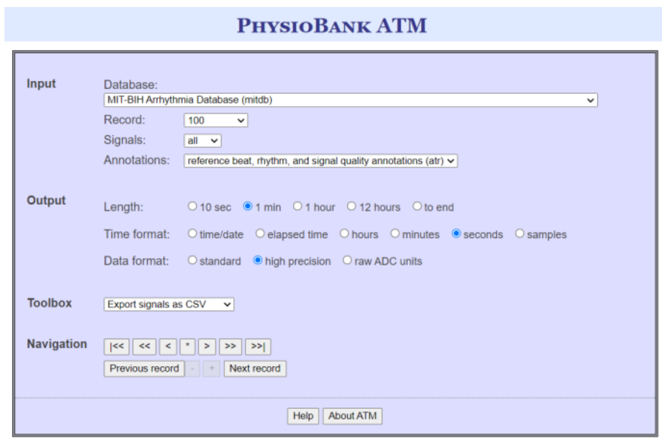

Figure 4.1 Data Preparation. (The screenshot of interface is obtained from https://archive.physionet.org/cgi-bin/atm/ATM). Reprinted with fair use.

ECG feature extraction is critical to enable us to successfully analyze the signal and diagnose heart conditions. Determining the QRS complex and calculating the RR value is used to detect changes in heart rate and abnormalities in heart signal. The successful acquisition of these features helps to have higher precision in the classifications to be made with the help of machine learning and deep learning algorithms. The noise components of the ECG signals must be removed before the feature extraction can begin. Baseline wanders and power line interference (50 Hz or 60 Hz) are the main noise sources for raw ECG signals. This process is shown in Figure 4.2 and is performed on the saved datasets via MATLAB and Python.

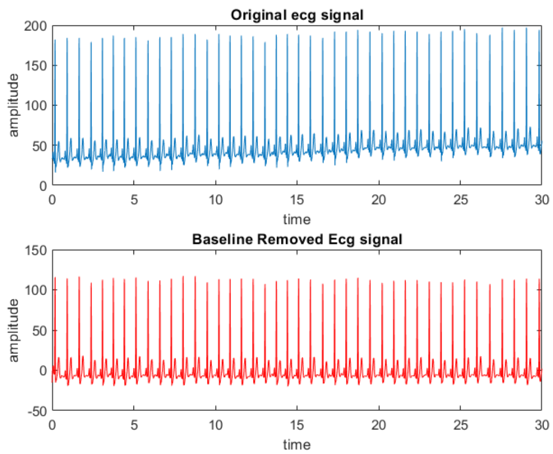

Figure 4.2 Raw ECG and Removed Baseline Wander from ECG. (This figure is plotted using https://www.mathworks.com/matlabcentral/fileexchange/61784-remove-baseline-wander-using-for-ecg-or-pppg)

As seen in Figure 4.2, a second order IIR notch filter was used to remove noise components from the ECG signal. signals. The notch filter has the desired bandwidth with the notch located at 50 Hz.

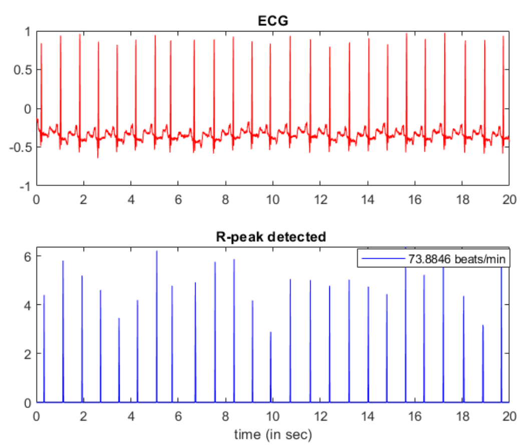

Figure 4.3 R-Peak Detection For Normal ECG. (This figure is plotted using https://github.com/prateekrajgautam/ECG-wavelet-feature-extraction)

FFT and wavelet methods are widely used to extract the characteristics of the ECG signal. While the wavelet method localizes both in time and frequency, the Fourier Transform only localizes in frequency. Testing was done with both FFT and Wavelet to extract the R-peaks and other features of the signal. Detection of R peaks of ECG data and calculation of heart rate is shown in Figure 4.3 and Figure 4.4 for two different data sets.

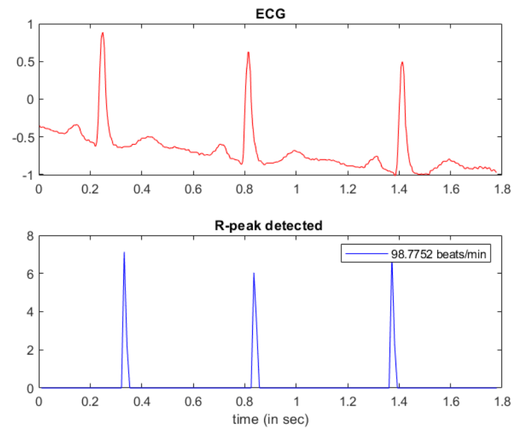

Figure 4.4 R-Peak Detection For Anormal ECG. (This figure is plotted using https://github.com/prateekrajgautam/ECG-wavelet-feature-extraction)

In Figure 4.3, FFT was applied to normal ECG data and the heart rate was calculated as almost 74. In addition, FFT was applied to abnormal ECG data in Figure 4.4 and the heart rate was calculated as approximately 98.

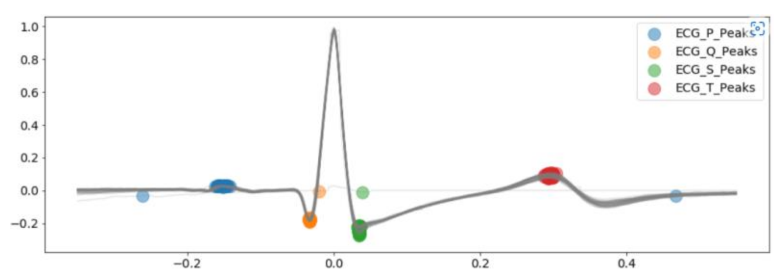

Figure 4.5 ECG Peak Positions. (The figure is plotted using https://github.com/neuropsychology/NeuroKit)

Figure 4.5 shows that other peaks of the ECG signal are detected. These obtained features are critical for classification and are sent to the model.

Chapter 5: Conclusion

In this thesis, we proposed an IoT e-health system. First of all, the requirements of this system were explained in detail, then the modeling of the proposed system was shown step by step. Finally, the BLE package structure used for the design was shown, and the expected amount of efficiency was calculated. Afterward, a smart system was proposed by making use of the data sent to the smartphone, and it was focused on intelligently adjusting the data transmission according to the health status. Finally, the frame structure required for sending data over 5G was examined and the data throughput calculation was emphasized.

In the evaluation phase, feature extraction applications were made for the ECG signal using ready-made data sets, and these extracted samples were tried to be used for classification.

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Analysis and Performance Evaluation of Bluetooth Low Energy Piconet Network

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Open Access Review

Performance Evaluation of Bluetooth Low Energy: A Systematic Review

by Jacopo Tosi [1,2,*], Fabrizio Taffoni [1,2], Marco Santacatterina [3], Roberto Sannino [3] and Domenico Formica [1]

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Abstract

Small, compact and embedded sensors are a pervasive technology in everyday life for a wide number of applications (e.g., wearable devices, domotics, e-health systems, etc.). In this context, wireless transmission plays a key role, and among available solutions, Bluetooth Low Energy (BLE) is gaining more and more popularity. BLE merges together good performance, low-energy consumption and widespread diffusion. The aim of this work is to review the main methodologies adopted to investigate BLE performance. The first part of this review is an in-depth description of the protocol, highlighting the main characteristics and implementation details. The second part reviews the state of the art on BLE characteristics and performance. In particular, we analyze throughput, maximum number of connectable sensors, power consumption, latency and maximum reachable range, with the aim to identify what are the current limits of BLE technology. The main results can be resumed as follows: throughput may theoretically reach the limit of ~230 kbps, but actual applications analyzed in this review show throughputs limited to ~100 kbps; the maximum reachable range is strictly dependent on the radio power, and it goes up to a few tens of meters; the maximum number of nodes in the network depends on connection parameters, on the network architecture and specific device characteristics, but it is usually lower than 10; power consumption and latency are largely modeled and analyzed and are strictly dependent on a huge number of parameters. Most of these characteristics are based on analytical models, but there is a need for rigorous experimental evaluations to understand the actual limits. View Full-Text

Keywords: Bluetooth Low Energy (BLE); performance evaluation; wireless sensor network; wearable technology; Internet of Things (IoT)

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Author: Guanglou Zheng

Publication: IEEE Journal of Biomedical and Health Informatics

Publisher: IEEE

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