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Integrating Various Sensor Readings from MySignals into a Standalone Mobile Health App

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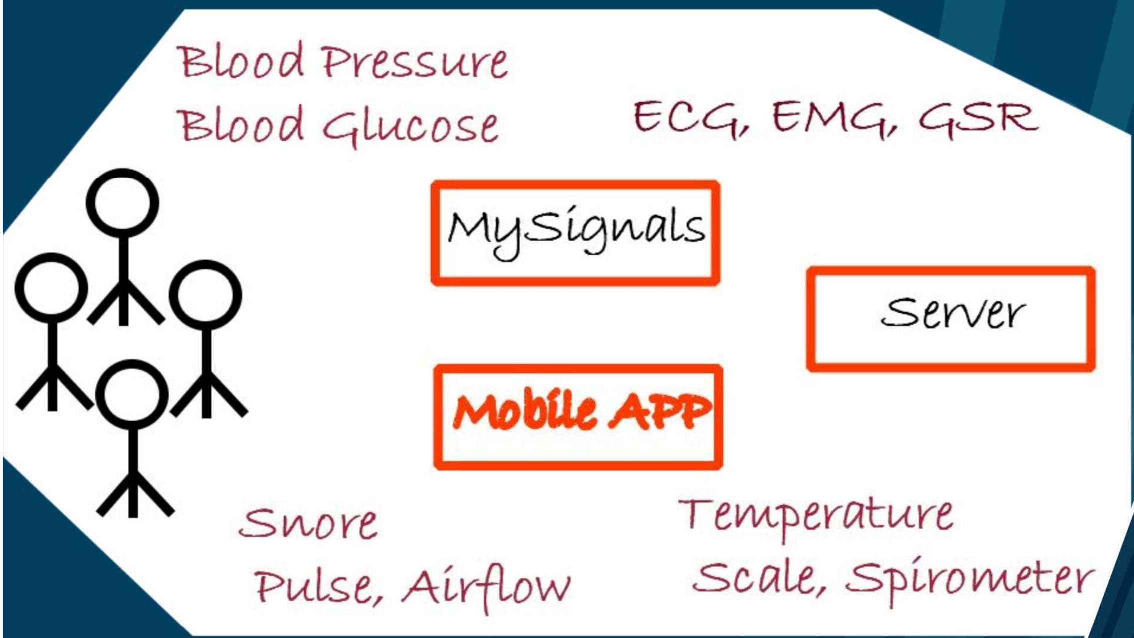


Dedication

To my Family

Preface

There are a number of apps related to health in the market. Each of them has their own purpose-mostly presenting health parameters and giving guidance for a healthier life to the patients. The number of chronic diseases such as diabetes, blood pressure, asthma, etc., are on the rise. There are different apps which are specifically made for each of these types of conditions. However, apps which present many different parameters that can aid in more efficient monitoring and decision making, along with the parameters of interest are not found. Presenting not just a single parameter related to the diseases but other parameters like temperature, stress levels, body position, weight and many more which can help health workers making better decisions is relatively new.

Initially it was decided that this project would be developed to integrate with Master's project done by Ashenafi Zebene Woldaregay. His thesis is titled "Electronic Disease Surveillance System Based on Inputs from People with Diabetes: An Early Outbreak Detection Mechanism". His thesis has some limitations such as it cannot detect Holiday Effect and outbreak detection can be more accurate if temperature, blood pressure and count of white blood cells are also provided. As this project can provide with values for temperature and blood pressure, it can help to reduce the limitations. But as there are many more parameters such as ECG, EMG, SpO2, airflow, and snore, halfway it was decided that the project would focus on presenting these parameters in a comprehensible way and making deeper analysis. Because of this change, some of the theoretical concepts, and functional requirements were changed. However, this did not affect the implementation because by that time the app was only able to retrieve the values from server and further implementation was still underway.

The initial steps started with the testing of a set of hardware sensors from MySignals. Testing of the sensors was a bit difficult. The sensors do not work when they have low battery even if they turn on. Some of the sensors do not give a realistic reading such as ECG may show 90 bpm for a user with 50 bpm. Blood Pressure sensor works only when the battery is full. It had to be charged for 2 consecutive days before it started working. The most difficult part was configuration of BLE sensors in main device which has to be done with repeated restart and takes time. Although, MySignals guide explains almost all the technical aspects of their device but does not talk about these inconsistencies and difficulties in measuring and configuring. Next challenge was to read the BLE sensors into the app because MySignals do not provide any documentation about how to directly read BLE sensors through mobile app and was resolved with multiple experiments and observations of the notifications from sensors.

These sensors can measure blood pressure, blood sugar level, heart signals, lungs capacity, blood oxygen level, weight, body position, muscle strength, body temperature, snore rate and emotional state.After finishing the successful tests of these sensors, a paper prototype was developed, followed by the implementation of the app. The GUI of the app is kept as simple as possible so that it will be easier for patients with chronic cases as they have to use it regularly. Focus on presentation of the data has been made by the use of different colors for normal and abnormal range. Also users can see the data in graphical forms, as graphs are a great way to comprehend the parameters at a glance. Further, deeper analyses of some of the parameters have also been presented. Overall, the project presents many different parameters in a simplistic, comprehensible way along with analysis which can help to understand patient's health conditions better than just showing the normal or abnormal values.

There are many people who helped me to make this project successful. It would never be complete without a continuous support and guidance of these kind and very helpful people. First, I would like to express my heartfelt gratitude to my supervisors. I am very thankful to my supervisor Professor Gunnar Hartvigsen, and co-supervisors Professor Eirik Årsand and Research scholar Ashenafi Zebene Woldaregay. Their continuous support, guidance and inspiration constantly propelled me towards the completion of the project. The weekly supervision meetings helped me to get better and more profound ideas from the supervisors. It also helped me to write and implement more precisely, and develop an understanding of how ideas need to be supported by references, and linked up with the whole purpose of the thesis.

Also, my sincerest thanks go to our coordinator and Senior Advisor Jan Fuglesteg, who helped with various issues during the study period. Moreover, Chief Engineer Kai-Even Nilssen is another person to whom I am very thankful. License for testing the MySignals cloud was provided by him. Also, I am very thankful to Senior Engineer Ken-Arne Jensen for providing me with batteries for the MySignals sensors.

Tromsø, May 6, 2021
Madhu Koirala

Abstract

Purpose

The purpose of this project was to build a mobile health app, which can integrate all the important bio-parameters and present them in the most comprehensible manner. There are 14 parameters MySignals sensors can measure. They are snore, temperature, ECG, heart rate, breathing rate, blood pressure, glucose level, Peak Expiratory Flow (PEF), Forced Expiratory Volume (FEV), Galvanic Skin Response (GSR), body position, weight, Electromyogram (EMG) and oxygen saturation (SpO2)with the help of different sensors. As there are many parameters, there needs to be a way by which the users find it easy to visualize their parameters and understand it quickly. As such, different techniques such as colors for different ranges of values, graphs and analysis have been used to present the data.

Motivation

People's health has not shown remarkable improvements despite huge technological advancements.There is a need to be constantly aware of one's health and act upon any abnormalities as quickly as possible. Also, rise of chronic disease, increase of elderly population and chronic diseases related to old people have clearly demanded a system which can monitor various health parameters and notify as soon as any abnormal readings are found. Not only the parameter of interest but if we have more parameters which can reflect upon the overall health status of the patients, it will help the care givers and doctors to give even more effective treatment. All these necessities form a strong basis for the motivation to develop a mobile app that continuously gathers information from patients and present them in a simple and comprehensible way.

Methods

To develop such an app, various steps like testing of sensors from MySignals, building the app and finally testing and verifying the results were taken. The testing of MySignals sensors was done as the first step. After having sufficient knowledge of how the sensors work, secondly, the app LifeSignals was built using C Sharp programming language. Xamarin framework was used, which works on Microsoft Visual Studio platform. This provides a cross-platform development, where most of the code can be shared among Android, iOS and Windows operating system. The developed system was tested for performance using Android Studio profiler for CPU, Network, Energy and Memory usage. It was also tested for its functional requirements manually to see all the pages show the desired results and display results according the requirements set.

Results

The sensors are listed on a vertical menu. It is combined with a tabbed menu for more

navigation. All the sensors show their data properly with the respective colors for normal and abnormal ranges for easy comprehension of the parameters. The graphs between two desired parameters can be plotted by choosing the required range of dates facilitating better understanding of the relationship between the parameters. Also analysis for blood sugar and ECG are displayed in the form of Glucose Variability and Heart Rate Variability. The performance evaluation using Android profiler shows minimum usage of the parameters CPU, Memory and Energy when the app is running without performing any tasks. When it performs certain tasks such as launching a new page, there is light usage of these parameters and no abnormally high usage of any of the parameters was found.

Conclusion

The app downloads real time data from the server and shows them in a way where abnormal and normal values are easy to figure out. Also, if there are any abnormal values, the caretakers and doctors get an SMS message about the health status of the patient and thus can be immediately taken care of. Use of color, graphs and various analysis help patients with better and quick understanding of their health conditions.

Contents

List of Figures

List of Tables

List of Algorithms

1 Introduction

1.1 Background and Motivation

Remote monitoring using various biosensors is increasingly becoming popular these days. The recent advancements in the development, easy and cheap availability of such technologies is one of the reasons why people are adopting these devices. The most popular ones are the smart watches which monitor heart rate, steps, sleep patterns, and various other health parameters depending upon its brand. Besides, some of them even show notifications and messages from mobile phone. In addition, there are crucial necessities as well which is encouraging general public to use some form of monitoring. The first is the steady increase of chronic diseases such as asthma, blood pressure, blood sugar, etc., because of which people need to check their parameters regularly. And the second is rise of geriatric population all over the world. A large population of old people is affected with chronic diseases like blood pressure and diabetes. In addition, they are prone to falls and many other medical conditions. Both of these reasons, there is a need of a robust and trustworthy remote monitoring to ensure their vital parameters are monitored on a regular basis and actions taken on time in case of any emergency.

Non-Communicable diseases like diabetes, cancer, diseases of the heart and long-term respiratory diseases are the main causes of death worldwide(WHO,n.d.-a).These diseases are growing all over the world , and at a greater and alarming rate in the developing countries (WHO,n.d.-b). Similarly, there is a constant increase in the geriatric population. The proportion of elderly people is estimated to reach 12% by 2030 and 16% by 2050[1]. Both of these cases are going to cause a surge in the medical costs and number of medical professionals required. Remote monitoring is a necessity which can help reduce the costs in terms of tests, medical visits, and number of practitioners.

There are ample of mobile apps and remote monitoring systems which can send the bio-signals being at the ease of home and distantly examined by the health care professionals. These apps are mostly specific to a particular bio-parameter. But to the best of the author's knowledge there is no app which can gather many different signals like blood glucose, blood pressure, snore, temperature, ECG (Electrocardiogram), EMG (Elecromyogram), respiration rate, GSR (Galvanic Skin Response), body positions, spirometer values, oxygen saturation (SpO2), and weight . Integrating all these sensors into a single app is one of the new concepts of the project. The project is also unique in that it facilitates the user to see the line graphs of two signals they choose in the same

[1]https://population.un.org/wpp/Publications/Files/WPP2019_Highlights.pdf [Accessed 27/02/2021]

graph. This enables users to understand the relation between various parameters rather than just looking at the values. Also, a deeper analysis of the values such as calculation of Glucose Variability (GV), and Heart Rate Variability(HRV) are done. This is motivated by the fact that these sort of analyses provides a greater understanding of the health conditions.

Measuring more parameters rather than just a single parameter to be monitored gives us more insight to the real cause of the disease. For instance, there can be a number of causes for the rise in blood pressure. Stress is one of them [2]. This system uses Galvanic Skin Response(GSR) to measure stress levels. So, the relationship between stress and blood pressure can be used by the caretakers to suggest the patient to involve in activities such as mindfulness, meditation to reduce the stress.

So, taking into consideration the fact that elderly population is increasing, and chronic diseases are on the rise there is clearly a necessity of a system which can continuously monitor the required parameters, and inform the concerned personnel about the threatening abnormalities on time. Even though there are a lot of systems which can monitor patients, but a system which incorporates many supporting sensors to make more effective decisions are not found. This brought about the concept of multi sensor monitoring system and thus gave birth to this thesis.

1.2 Scope and Research Problem

The main goal of this thesis is to develop a system which collects all the vital signs of a patient and present it in an easy-to-understand way. The app for the chronic patients must be simple to use and easy to comprehend.

As such, the following problems may arise.

How can we design a mobile health app that ensures all vital parameters are collected and presented in a simple and comprehensible manner?

This problem is divided into two below problems to make the scope and boundaries of this thesis more clear and definite.

1. Design of Application : The application should be easy to use and the transfer of bio-parameters should be as automatic as possible, necessitating very few active participation of the patients. This ensures that all the data readings are transferred all the time automatically. The below questions should be answered to address this problem.

[2]https://www.mayoclinic.org/diseases-conditions/high-blood-pressure/in-depth/stress-and-high-blood-pressure/art-20044190 [Accessed April 12, 2021]

a) Question 1: How can we make the application automatic so that patients will need the least interaction with it?

b) Question 2: How can we make it easy to use for chronic patients?

2. Presentation of the parameters: As there are many parameters, there is a need to think about how the parameters should be presented. If the parameters are presented randomly, then it will simply overwhelm the users with a lot of readings. So, an effective way of presentation must be implemented. The below questions should be considered to focus on this problem.

    a) Question 1: How can we present the parameters so that it will be easy for the user to detect any abnormal values?

    b) Question 2: How can we present the parameters so that the most important ones are easily seen by the users?

    c) Question 3: How can we present the parameters so that the users can understand how one parameter can affect the other?

1.3 Summary of Goals

The major goals of the thesis are summarized below.

(a) The thesis should find out the effective ways of presenting various bio-parameters.

(b) The thesis should consider the age factors of the patients and their psychological structure for better design and user interfaces of the application.

(c) The presentation should be clear to the users and it should also show probable relations between the signal parameters.

(d) The thesis should try to present analysis of the parameters based on a single value or relations between the parameters.

(e) The thesis should provide with a way for further research, as such it should give suggestions on how it can be extended for a more useful project.

1.4 Assumptions and Limitations

One of the main limitations is the application(apk of the app) was tested only on Samsung Galaxy A20e (Android version 10, 3 GB RAM). It has not been tested on other Android devices.

The assumptions made are related to the security concerns. The first one is that the patients data are stored in the internal memory of the phone and accessing the phone is secured the users. Next is that the mobile phones are Android based.

1.5 Methods

The following steps were followed to complete the project presented in this thesis.

- Test the sensors from MySignals.
- Review the related past works.
- Develop a paper prototype of the system to be built.
- Develop the mobile application.
- Test the app and improve the features until they meet the requirements.

Initially, literature review was done to know how related works were performed. It also helped to understand state-of-the-art and paved a way to steer this project in the proper direction. Papers and projects dealing with mobile health monitoring and how various body parameters are related to each other were studied.

Next, simple paper prototype was developed to realize the basic functioning of the app. Later, it was extended to understand how a full-fledged app can be implemented. Along with the paper prototype, the application was also built simultaneously.

Finally, the features were tested using a mobile device and continuously improved until the final version was ready.

1.6 Significance and Contribution

The major contribution of the project is that it integrates almost all of the major vital parameters into an app and present them in an simple and comprehensible way for the patients. Unlike other health apps which have a few parameters only, the project assimilates all the important parameters required to understand the health situation of a patient fully. Presenting further analysis of some of the parameters is the second contribution of the project. Also, plotting graphs between the chosen parameters, which can give insight to their relations, comprise the third contribution.

1.7 Organization

The rest of the writing has been organized into the following chapters.

Chapter 2.Theoretical Framework

This chapter explains various sensors,in general, that have been used in the project. It then explains the same sensors from MySignals. It describes theoretical concepts of the Bluetooth Low Energy technology, and also make a comparison of some most popular health apps.

Chapter 3.Literature Review

This chapter presents how the articles related to the project has been chosen, using the exclusion and inclusion criteria. Also it presents the summary of some of the important articles that has been included in the thesis.

Chapter 4.Materials and Methods

Various materials and methods used for the development of the project from its initial stage to completion have been discussed in this chapter.

Chapter 5.Requirements Specification

This chapter explains the source of requirements and their functional and non-functional aspects, along with use-case diagram.

Chapter 6.Design and Implementation

It talks about design of the application-its look and feel and how the design has been implemented to realize the application in practice.

Chapter 7.Test and Results

This chapter deals with different tests done on the MySignals sensors, and the application developed and the results it produced.

Chapter 8.Discussion

It presents analyses of various aspects of the project and discusses the results produced.

Chapter 9. Future Work

This chapters shows various ways of extending the project further. It mentions many future prospects of the thesis.

Chapter 10. Conclusion

It makes concluding remarks about the works and achievements and contribution of the current project.

2 Theoretical Framework

This chapter governs various theoretical concepts required for the understanding of sensors, and implementation of the application. These concepts include knowledge of health sensors, functioning of MySignals sensors (BLE and wired), API to communicate with the server, knowledge of various types of popular health apps, persuasive techniques and usability of the app.

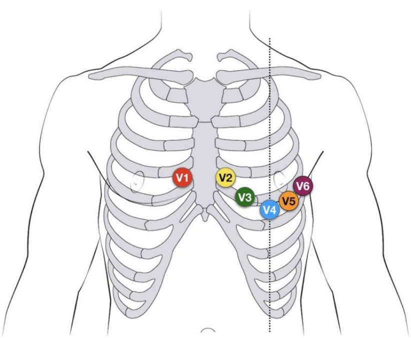
2.1 Various Health Sensors

The project measures many different bio-signals with the help of various sensors. Below is a description of various sensors in general followed by sensors from MySignals used in the thesis.

2.1.1 Electrocardiogram(ECG)

ECG is a test of the heart's rhythm and electrical activity[3]. ECG can detect arrhythmia, coronary heart disease, heart attacks, and cardiomyopathy. Even though there are 3- or 5-lead ECG, the 12-lead ECG is the most popular one. The placement of electrodes is shown in Figure 1 [4]. The figure shows 6 electrodes position on chest; rest of the 4 electrodes are placed on hand and legs-one each. There are 10 electrodes only in a 12-lead ECG. Figure 1 also shows a normal ECG curve known as QRS complex[5]. Looking at the abnormalities in the curve, various heart diseases can be diagnosed.

(a) 12-lead ECG Placement



(b) ECG QRS Complex

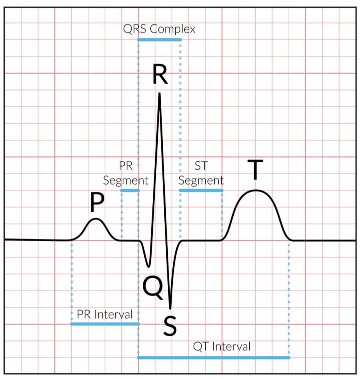


Figure 1: Electrocardiogram
Source[4]

[3]https://www.nhs.uk/conditions/electrocardiogram/#:~:text=An%20electrocardio-gram%20 [Accessed 21/01/2021]
[4]https://litfl.com/ecg-lead-positioning/ [Accessed 21/01/2021]
[5]https://www.amboss.com/us/knowledge/ECG [Accessed 21/01/2021]

2.1.2 Body Position

Wong et al. describe that body position sensors generally use accelerometers and gyroscopes (Wong et al., 2007). The accelerometers can also be used for movement tracking, gait analysis, limb movement analysis besides knowing body positions. These sensors offer advantages such as miniature in size, portability and low power consumption. Body positions are mainly supine, prone, left lateral, right lateral and fowler's as shown in Figure 2.[6]

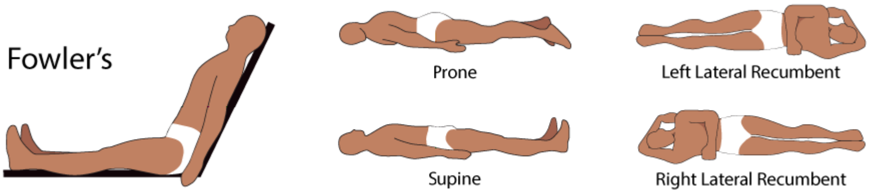


Figure 2: Body Positions
Source:MySignals Technical Guide[6]

2.1.3 Electromyogram(EMG)

EMG measures the electrical activity of the nerves and muscles [7]. An EMG is generally performed when there is muscle weakness in the body. EMG can help detect various diseases such as muscular dystrophy, inflammation of the muscles, disc herniation, etc. There are generally two aspects of an EMG test-nerve conduction test and needle EMG[8]. The first test involves placing surface electrodes on the skin to assess how fast motor neurons can pass electrical signals. The second one requires insertion of needles into the muscles to measure electrical activity of muscles during rest and contraction. In surface EMG there are positive, negative and reference electrodes. Current passing through positive and negative electrodes is analyzed for time and magnitude[9]. A needle EMG may require a number of needle insertions (5 or 6) in the muscles and a reference needle[10].

[6]MySignals SW Technical Guide, www.libelium.com/development/mysignals/documentation/mysignals-sw-technical-guide/?action=download [Accessed 11/13/19]

[7]https://www.medicinenet.com/electromyogram/article.htm [Accessed 22/01/2021]

[8]https://www.healthline.com/health/electromyography#procedure [Accessed 23/01/2021]

[9]https://lermagazine.com/article/surface-emg-a-how-to-guide-for-practitioners [Accessed 23/01/2021]

[10]https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/electromyography-emg [Accessed 23/01/2021]

2.1.4 Pulse Rate

Pulse rate is the number of times the heart beats per minute[11] . Generally, a resting heart has 60-100 beats per minute. In clinical practice, mostly pulse rate is measured by putting index and middle finger on patient's wrist and is called radial pulse[12] .

2.1.5 Blood Pressure

Blood pressure is the pressure of the blood in the arteries[13]. When heart pumps blood throughout the body, it contracts and the pressure generated is called systolic and when it relaxes after contraction, the pressure is called diastolic. Normal pressure is different for different age group of people. For adults, pressure below 120/80 mmHg is considered normal. If it drops below 90/60 then it is called hypotension or low blood pressure[14]. Systolic 130 to 139 and diastolic 80 to 89 is considered as first stage of hypertension for adults [15]. Blood pressure is measured with sphygmomanometers. They can be aneroid or digital. A study shows that digital sphygmomanometers are less accurate compared to aneroids(Shahbabu et al., 2016).

2.1.6 Blood Glucose

When food is ingested, acid and enzymes act on it and convert it into glucose. Insulin produced by the pancreas helps to convert the glucose into energy[16]. But if enough insulin is not produced or the insulin becomes incapable to convert the glucose into energy then glucose remains in the blood stream for a long time and such condition is called diabetes. Normal blood sugar level before eating is 4 to 7 mmol/l and 2 hours after eating is under $<$ 8.5 mmol/L for Type 2 diabetes[17]. Blood glucose can be measured using a regular glucometer or CGM (Continuous Glucose Monitoring) devices. The former requires pricking finger tip with a lancet and putting the blood on a test strip inserted into glucometer, while the latter continuously measures blood glucose with the help of a sensor put on the body and a receiver to read the values[18].

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[11] https://www.bhf.org.uk/informationsupport/heart-matters-magazine/medical/ask-the-experts/pulse-rate [Accessed 23/01/2021]

[12] https://www.ncbi.nlm.nih.gov/books/NBK542175/ [Accessed May 6, 2021]

[13] https://www.medicinenet.com/blood_pressure/definition.htm [Accessed 23/10/2021]

[14] https://www.nia.nih.gov/health/high-blood-pressure [Accessed 23/01/2021]

[15] https://www.healthline.com/health/what-considered-high-blood-pressure#healthyreading [Accessed 23/01/2021]

[16] https://www.webmd.com/diabetes/glucose-diabetes [Accessed 23/01/2021]

[17] https://diabeteson.com/normal-blood-glucose-sugar-levels/ [Accessed 23/01/2021]

[18] https://www.healthline.com/health/type-2-diabetes/best-devices-type-2#blood-glucose-meter [Accessed 23/01/2021]

2.1.7 Scale (Weight)

Weight is measured using a weighing scale. Maintaining a normal weight is crucial for health. A normal weight is calculated with the help of BMI(Body Mass Index)[19]. BMI is defined as weight in kilograms divided by square of height in metres[20]. A normal BMI lies between 18.5 and 24.9. An overweight person always has a risk of developing various health issues such as diabetes, heart diseases, certain cancers, musculoskeletal disorders, gout, etc.

2.1.8 Oxygen Saturation

There is oxygen in blood and is carried by a molecule called hemoglobin. Oxygen saturation is a measure of how much oxygen is present in blood and is calculated in percentage. Oxygen saturation is measured by a simple device called pulse oximeter (SpO2). It is tested by putting the device on a fingertip or earlobe. There are many SpO2 sensors available in the market but they do not substitute the ones used in hospitals. A study compares 8 non medical use (NMU) pulse oximeters with one MU oximeter sensor (Hudson et al., 2018). The study shows that NMU SpO2 are accurate only when SpO2>90% so can be useful to rule out hypoxemia(low oxygen in blood) but cannot be used to decide if one needs oxygenation.

2.1.9 Galvanic Skin Response (GSR)

Emotional states such as happiness, fear, a startling event, a demanding task bring about changes in sweat glands activity, which is directly related to skin conductance. GSR is a measure of skin conductance which in fact reflects the inner state of a person[21] [22] [23]. A GSR signal is typically measured in hand (palms) and foot (soles) regions because they have the most sweat glands in the body. An increase of intensity of positive(joy) or negative(sadness) internal state can increase sweat activity and thus conductance. So, GSR measures intensity but cannot differentiate between types of emotions. The response is not much affected by sweating due to activities as the glands found on palms and soles are highly sensitive to emotional stimuli. Ahuja et al. designed a system with GSR and HRV (Heart Rate Variability) which can be effective in the treatment of phobias and

[19] https://www.drgsweightloss.com/blog/the-importance-of-maintaining-an-ideal-body-weight [Accessed 23/01/2021]

[20] https://www.cdc.gov/healthyweight/assessing/bmi/index.html [Accessed 23/01/2021]

[21] https://imotions.com/blog/gsr/ [Accessed 24/01/2021]

[22] https://www.media.mit.edu/galvactivator/faq.html [Accessed 24/01/2021]

[23] Galvanic Skin Response (GSR), https://www.brainsigns.com/en/science/s2/technologies/gsr [Accessed 11/13/2019]

anxiety by continuously looking at their GSR and HRV values (Ahuja et al., 2003). Thus GSR can be used for relaxation training, treat certain fears and anxieties.

2.1.10 Temperature

Temperature is a measure of body's ability to maintain heat within itself[24]. When body is hot it tries to reduce temperature by widening blood vessels thus allowing excess heat to the skin. Similarly, when cold, it tries to save heat by narrowing the blood vessels. Temperature can be generally measured in the mouth, ear, armpit or rectum. Body temperature can vary from person to person or at different times of the day but 36.1 to 37.2° Celsius is generally considered as normal temperature[25].

2.1.11 Airflow

Airflow is the number of breaths per minute. For adults, 12 to 20 breaths per minute is considered normal[26]. Inhaling supplies all the organs with oxygen and exhaling helps to throw out carbon dioxide from the body. Marjanovic et al. points out to the fact that respiratory rate (RR) is the most sensitive parameter to detect any clinical deterioration. The study mentions a need for more research due to drawbacks present in current RR monitors (Marjanovic et al., 2020).

2.1.12 Snore

Snore is a sound produced while breathing when the throat tissues vibrate due to air flow[27]. Snoring sometimes is normal but some people snore on a regular basis, which can cause further complications such as obstructive sleep apnea, daytime sleepiness, high blood pressure, etc. Arnardottir et al. compared various types of snore sensors-audio-based, cannula and piezoelectric. The study suggests not to use cannula as a snore sensor and audio-basesd sensors are the most sensitive and accurate ones (Arnardottir et al.,2016).

2.1.13 Spirometer

It is used to measure lungs capacity. It is helpful in performing pulmonary function test (PFT). It can be helpful in detecting lungs disease such as asthma, pulmonary fibriosis

[24] https://www.uofmhealth.org/health-library/hw198785 [Accessed 24/01/2021]
[25] https://www.health.com/condition/cold-flu-sinus/what-causes-fever [Accessed 24/01/2021]
[26] https://www.medicalnewstoday.com/articles/324409#adults [Accessed 24/01/2021]
[27] https://www.mayoclinic.org/diseases-conditions/snoring/symptoms-causes/syc-20377694 [Accessed 24/01/2021]

and COPD (Chronic Obstructive Pulmonary Disease)[28].

2.2 Mysignals Sensors

MySignals is a development platform on which health applications or new type of medical devices can be developed [29]. They have kits for software development and also for new hardware development. In this project, software development kit has been used to implement a mobile health app. All the sensors that Mysignals is using are depicted in Figure 3.

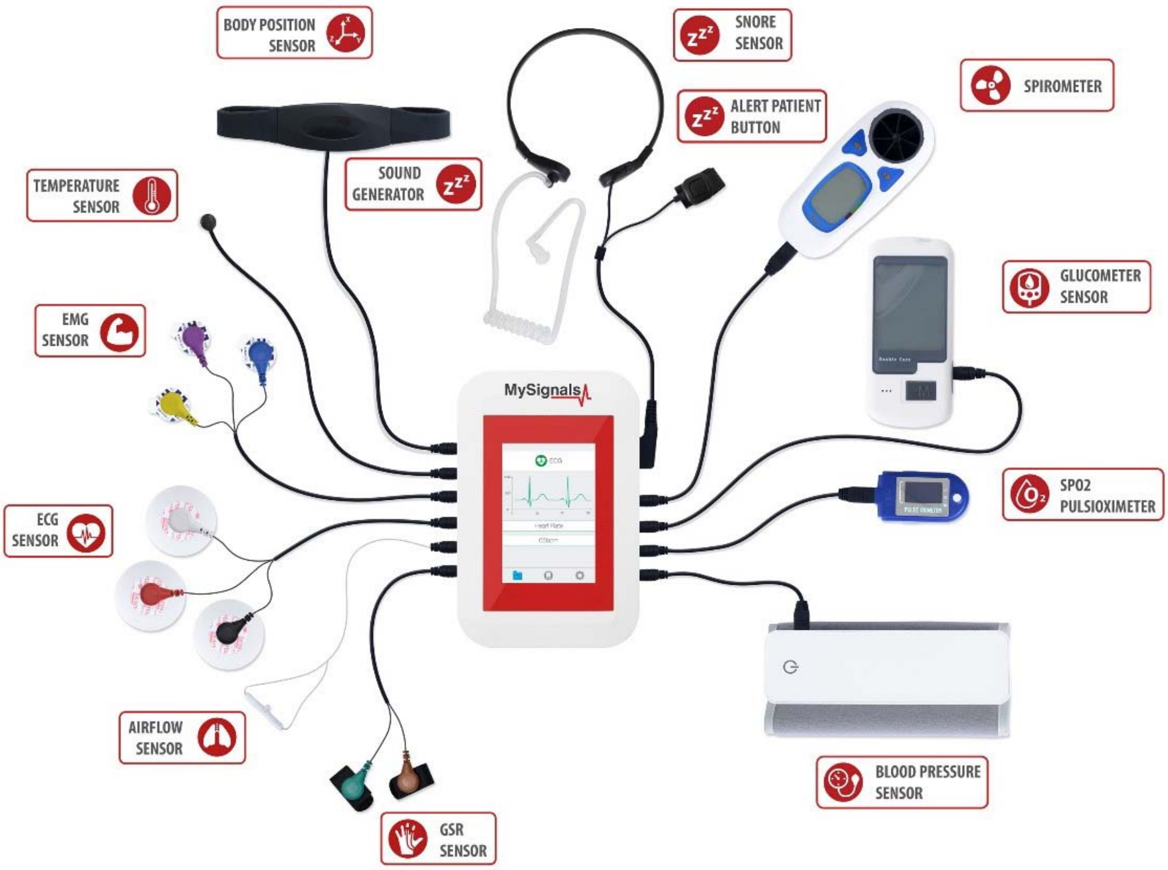


Figure 3: Mysignals Sensors
Source:MySignals Technical Guide[6]

2.2.1 Electrocardiogram (ECG) Sensor

Mysignals ECG sensor has three electrodes colored red, white and black which are connected in the chest and stomach as shown in Figure 4. The patient has to lie on their back, not stand or sit on a chair.

[28]https://www.mayoclinic.org/tests-procedures/spirometry/about/pac-20385201 [Accessed 19/05/2021]

[29]http://www.my-signals.com/

(a) ECG Sensor

(b) ECG Electrode Position

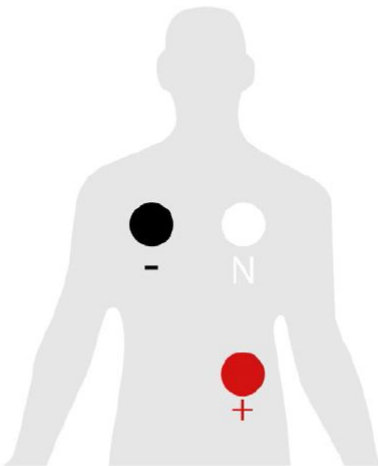
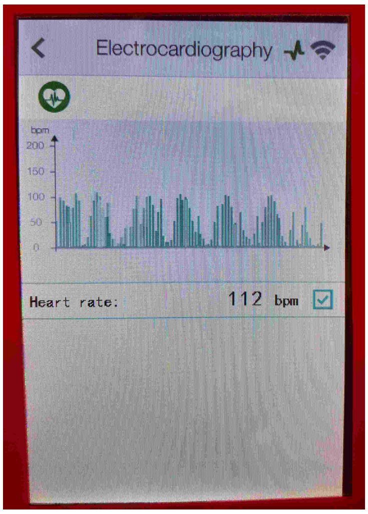


Figure 4: Mysignals ECG
Source:MySignals Technical Guide[6]

Some sample ECG readings are shown in Figure 5. ECG measures heart rate in beats per minute and shows heart's electrical activity in the form of wave as shown in Figure 5.Besides, it is also possible to get the raw values of ECG through cloud API to make a graph . The ECG graphs nowhere resemble a general ECG curve and heart rate is also much higher compared to the real heart rate of the person (measured using fingers on wrist).

(a) ECG Reading



(b) ECG Reading

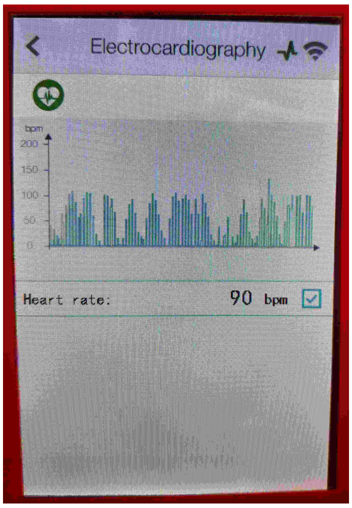


Figure 5: ECG Readings

2.2.2 Body Position Sensor

This sensor detects five different body positions: supine, prone, left, right and standing/sitting. This information is helpful to know if an old or disabled person has fallen or fainted. The sensor is worn around the lower chest as shown in Figure 6. It uses triple axis accelerometer to find the patient's position.

(a) Body Position Sensor

(b) Body Position Sensor Positioning

Figure 6: MySignals Body Position Sensor
Source:MySignals Technical Guide[6]

Sample readings of body position sensors are depicted in Figure 7. The positions correspond to the values of acceleration. -1 G along X axis, indicate standing position, -1 G and 1 G along Z axis indicate Supine and Prone respectively. Similarly, 1 G and -1G along Y axis indicate left and right lateral recumbent respectively.

(a) Body Position Reading

(b) Body Position Reading

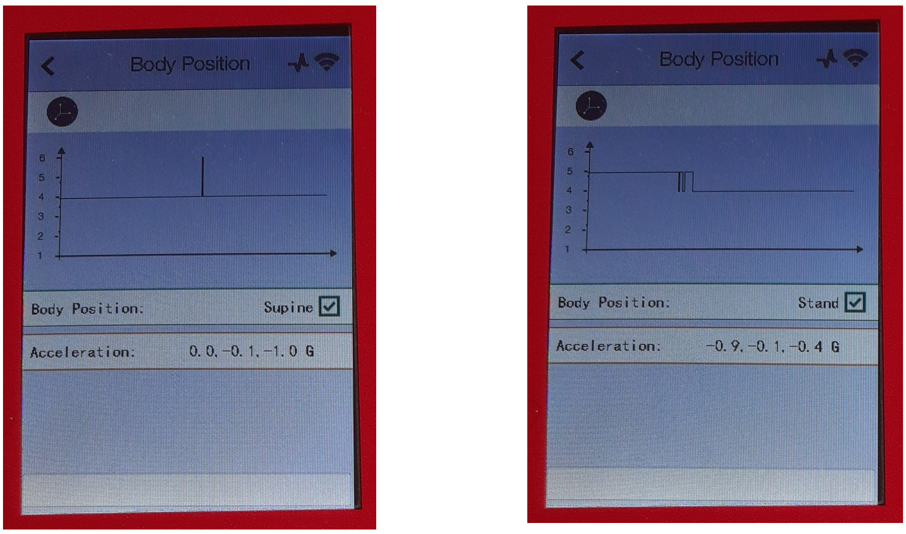


Figure 7: Body Position Readings

2.2.3 Spirometer Sensor

MySignals spirometer has a mouthpiece which is placed on the device as in Figure 8 and taking a deep breath in, air is exhaled forcefully through the mouthpiece.

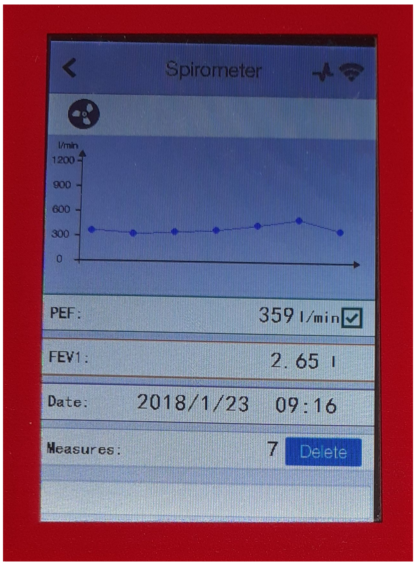
(a) Spirometer Sensor

(b) Spirometer with Mouthpiece

Figure 8: MySignals Spirometer
Source:MySignals Technical Guide[6]

Some sample readings from spirometer are provided in Figure 9. It gives values for two parameters, Peak Expiratory Flow(PEF) and Forced Expiratory Volume(FEV). PEF is the measure of maximum rate of expiration with respect to time and FEV1 gives the maximum volume of air exhaled forcefully in the first second (1 second)after taking in deep breath.

(a) Spirometer Reading



(b) Spirometer Reading

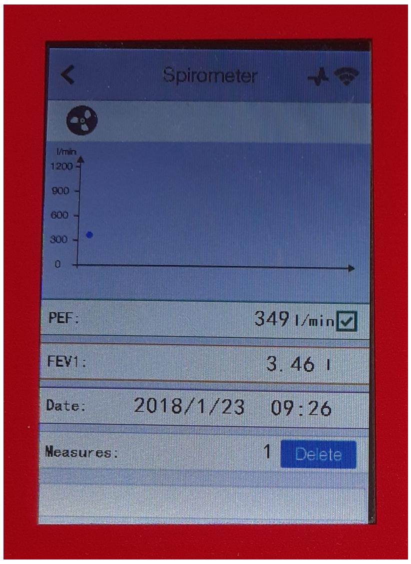


Figure 9: Spirometer Readings

2.2.4 Electromyogram (EMG) Sensor

Electromyography is a test done to detect neuromuscular abnormalities[30]. It measures the electrical activity of the muscles under examination. MySignals EMG sensor has three electrodes, which are placed on the muscles which need to be tested (Figure 10).

(a) EMG Sensor (b) EMG Positioning

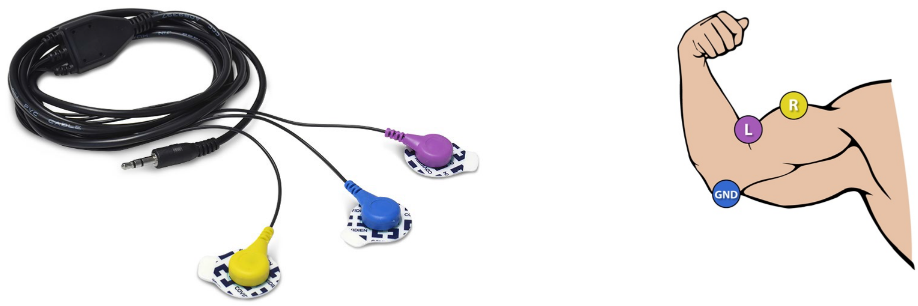


Figure 10: MySignals EMG
Source:MySignals Technical Guide[6]

Some sample EMG readings are shown in Figure 11. The electromyogram shows muscle strength in contractions per minute(cpm). The electrical activity in muscles can also be plotted in graphs by accessing its raw values.

(a) EMG Reading (b) EMG Reading

Figure 11: EMG Readings

[30]https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/electromyography-emg [Acessed 11/13/2019]

2.2.5 Blood Pressure Sensor (BLE)

Like other ordinary pressure measuring devices, the cuff is wrapped in the arm and it is turned on to take the measurement (Figure 12).

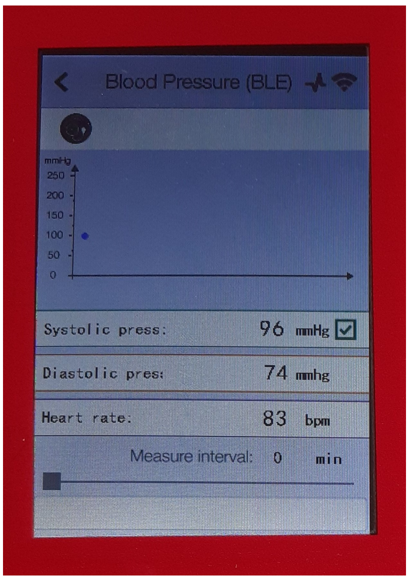
(a) Blood Pressure Sensor

(b) Blood Pressure Sensor Positioning

Figure 12: MySignals Blood Pressure Sensor
Source:MySignals Technical Guide[6]

Some sample readings from blood pressure sensor are provided in Figure 13. This sensors measures systolic and diastolic pressure in mmHg along with heart rate in bpm.

(a) Blood Pressure Reading



(b) Blood Pressure Reading

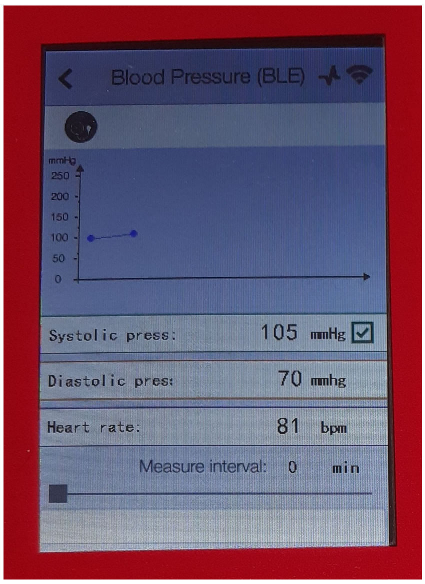


Figure 13: Blood Pressure Readings

2.2.6 Glucometer Sensor(BLE)

This device measures the glucose level in blood. It uses an invasive method; a lancet is used to prick the skin and a drop of blood is placed on a disposable test strip to measure the sugar level (Figure 14).

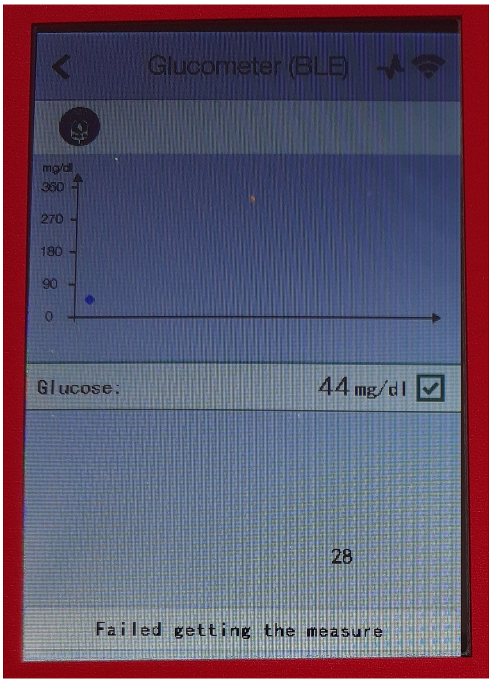
(a) Glucometer Sensor

(b) Glucometer Measurement

Figure 14: MySignals Glucometer
Source:MySignals Technical Guide[6]

Some sample readings from Glucometer are provided in Figure 15. As soon as the Glucometer is on, the main device waits for the blood on the strip. After blood is put on the strip, it sends the value after a few seconds. The glucose value is measured in mg/dL.(milligrams per deciliter)

(a) Glucometer Reading



(b) Glucometer Reading

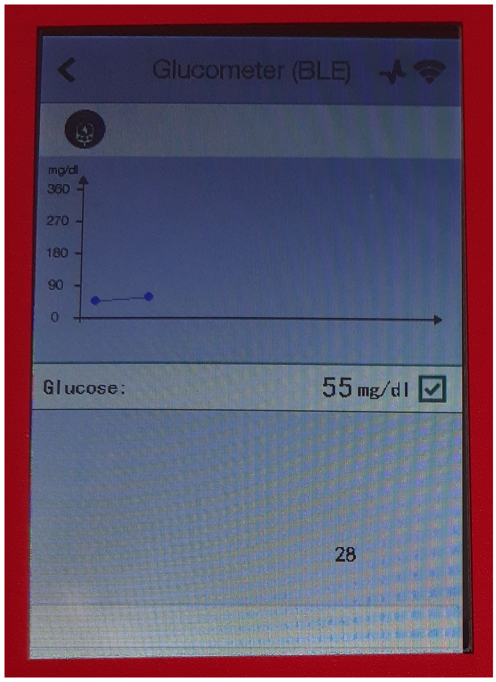


Figure 15: Glucometer Readings

2.2.7 Scale Sensor (BLE)

It measures the weight or body mass of a patient. As soon as the patient steps on the scale, it turns on and sends the measurement to the MySignals main device (Figure 16).

(a) Scale Sensor (b) Scale Measurement

Figure 16: MySignals Scale Sensor
Source:MySignals Technical Guide[6]

Some sample readings from Scale Sensor are provided in Figure 17. It shows weight in kilograms(kg), body fat, and bone mass in percentage. Also, muscle mass, visceral fat, water and calories can be accessed using Cloud API.

(a) Scale Reading (b) Scale Reading

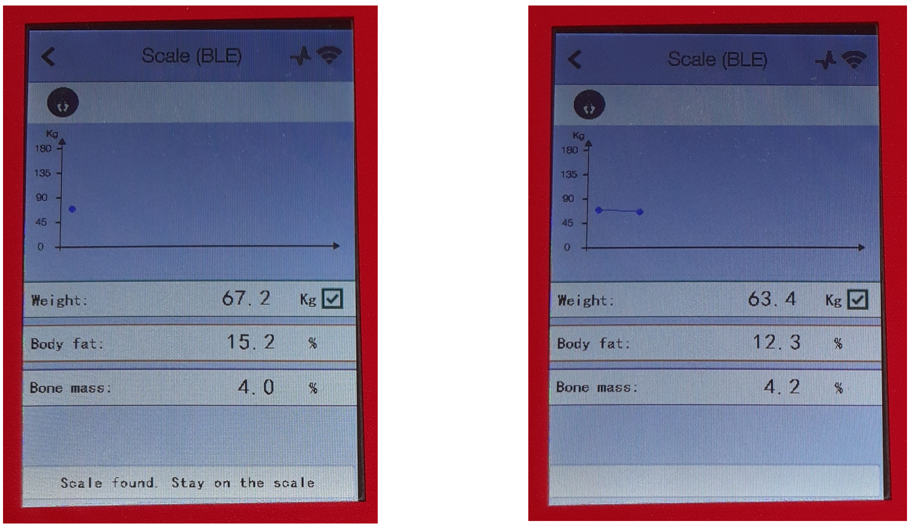


Figure 17: Scale Readings

2.2.8 Pulse Oximeter Sensor (SpO2 BLE)

It measures the pulse rate and oxygen in blood. This sensor gives a measure of oxygen saturation level in blood. A finger is placed in the sensor and turned on to measure the SpO2 values as shown in Figure 18.

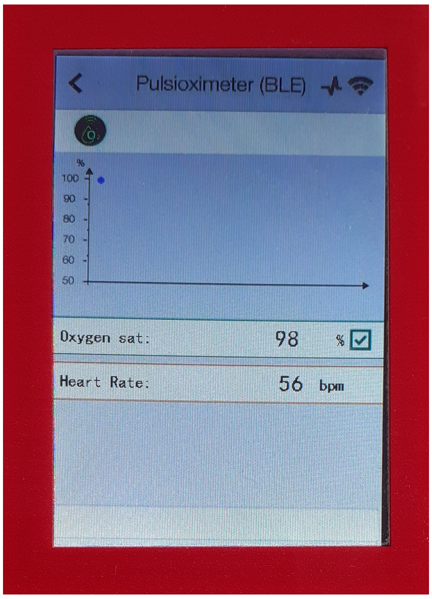
(a) SPO2 Sensor

(b) SPO2 Measurement

Figure 18: MySignals SpO2
Source:MySignals Technical Guide[6]

Some sample readings from SpO2 are provided in Figure 19. SpO2 measures Heart Rate in beats per minute and oxygen saturation in percentage.

(a) SpO2 Reading



(b) SpO2 Reading

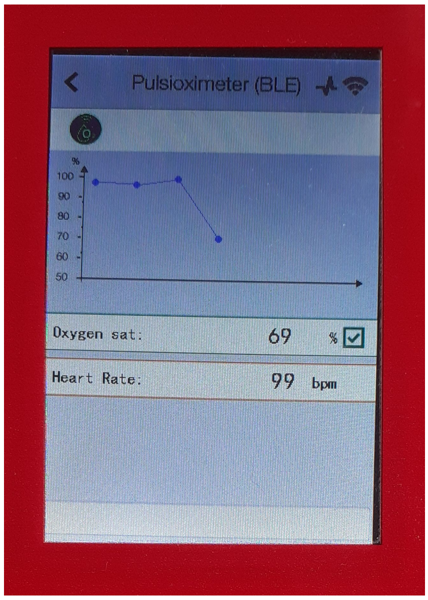


Figure 19: SpO2 Readings

2.2.9 Galvanic Skin Response (GSR) Sensor

GSR sensor measures the conductance of skin with the help of two electrodes placed across skin at two points as shown in Figure 20.

(a) GSR Sensor (b) GSR Measurement

Figure 20: MySignals GSR
Source:MySignals Technical Guide[6]

Some sample readings from GSR sensor are provided in Figure 21. It measures the skin conductance in micro Siemens(µS). It also shows the opposite of conductance which is called resistance in ohms.

(a) GSR Reading (b) GSR Reading

Figure 21: GSR Readings

2.2.10 Temperature Sensor (BLE)

This device is equipped with Exacon D-S18JK sensor. Temperature is one of the vital parameters of the body. It is measured by pushing in the sensor under a band placed in the arm as depicted in Figure 22.

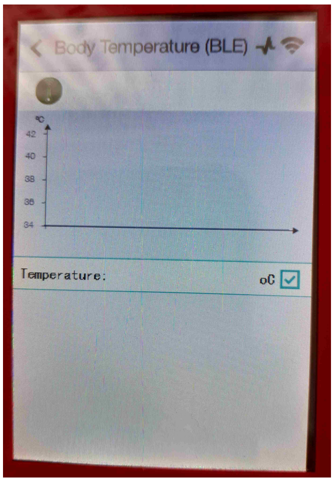
(a) Temperature Sensor

(b) Temperature Measurement

Figure 22: MySignals Temperature Sensor
Source:MySignals Technical Guide[6]

The attempt to give some sample readings from temperature sensor in Figure 23 became unsuccessful when the device constantly failed to detect the sensor. It displays temperature readings in degree Celsius.(°C)(which has been verified previously).

(a) Temperature Reading



(b) Temperature Reading

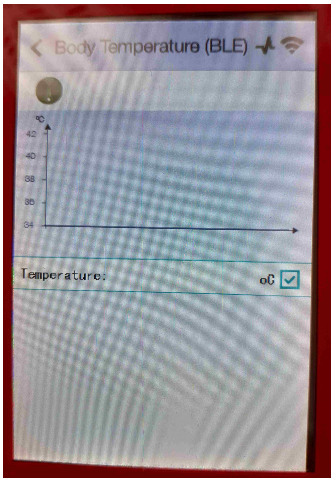


Figure 23: Temperature Readings

2.2.11 Airflow Sensor

This sensor measures the breathing rate. There are two prongs which are placed in the nostrils to measure the rate, and the cannula is wrapped around the head to hold the sensor as portrayed in Figure 24.

(a) Airflow Sensor (b) Airflow Measurement

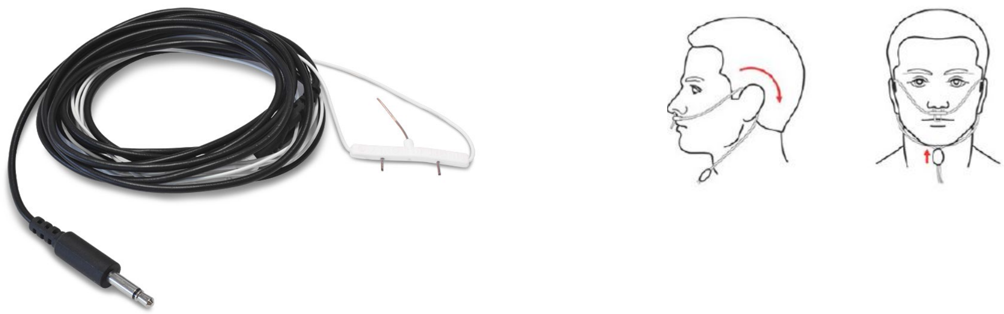


Figure 24: MySignals Airflow Sensor
Source:MySignals Technical Guide[6]

Some sample readings from Airflow Sensor are provided in Figure 25.It measures the value of airflow in peaks per minute(ppm). Raw values are also available for airflow sensor, which can be plotted for a quicker understanding of the airflow values.

(a) Airflow Reading (b) Airflow Reading

Figure 25: Airflow Readings

2.2.12 Snore Sensor

This is used to measure the snore rate. It is based on Hidden Markov Model, and detects snoring using piezo sensor. The sensor is worn around the neck and measures snore per minute (Figure 26).

(a) Snore Sensor (b) Snore Measurement

Figure 26: MySignals Snore Sensor.
Source:MySignals Technical Guide[6]

Some sample readings from snore sensor are provided in Figure 27.Its unit of measurement is snore per minute(spm). Snore values can be plotted by extracting raw data from MySignals cloud.

(a) Snore Reading (b) Snore Reading

Figure 27: Snore Readings

2.2.13 MySignals Cloud API

There are following API to communicate with the MySignals cloud. They were tested on a webpage[31] before implementing in the application.

[31]https://cloud.libelium.com/mysignals_documentation/api_web/

1. **auth** : It is a POST request with headers content type 'x-www-form-urlencoded' and accept 'application/x.webapi.v1+json'. It also includes data with username and password and url 'https://.libelium.com/mysignals/auth/login'. It returns a token string which is used to authorize the user. It is used to log in to the cloud.

2. **members** : It is a GET request that lists the details of all the members associated with a device. It has headers Accept and Authorization. Accept header is same as in API auth and Authorization header is the string Bearer combined with the token returned by API auth.

3. **departments** : It is a GET request that lists the details of all the departments. There are Accept and Authorization headers same as in API members and url 'https://api.libelium.com/mysignals/departments'.

4. **values** : It is a GET request that retrieves values of a sensor associated with a member within a certain time frame. There are Accept and Authorization headers along with a url with values for sensor id, member id, starting time, ending time, limit, cursor and order.It has also an option to get all the last values of all sensors for a particular member.

5. **raws** : To get the raw values (for plotting graph), there is a need to send two different requests to the server. First GET request lists all the details of the measured values. It does not however show the values. It just indicates that a particular value has been recorded. It also has Accept and Authorization headers, and a url with values for sensor id, member id, starting time and ending time. Then values can be retrieved with the help of id found from the first request.

2.3 Bluetooth Low Energy

Bluetooth Low Energy(BLE) is a wireless communication technology which has a very low power consumption. It is ideal for situations where we need messages and data to be transferred periodically, not continuously. The actual communication time is very short with a high data rate. The BLE devices remain in sleep mode most of the time and remain awake only when communication happens. MySignals uses a combination of wired and BLE devices for monitoring health status. BLE devices transfer data back and forth using GATT(Generic Attribute) profile. The smallest piece of information or data in a GATT server is called an **attribute**. The attributes are grouped into **services**, each of which can contain zero or more **characteristics**. Similarly, each characteristic can have zero or more **descriptors**[32] [33]. These concepts allow structuring of data to be supplied by the GATT server. A service is made up of attributes that serves one particular functionality. A characteristic is a part of a service and it gives some specific information like battery level of the device. Descriptors contain some explanation about the characteristic value.

2.4 Mobile Apps Comparison

A brief comparison of popular mobile apps about diabetes and their important features are tabulated below. The apps are chosen based on the list provided in these websites[34] [35] [36] [37].The main purpose of the comparison is to have a deeper insight of the important features and user interfaces of the current health apps. Also effectiveness of the current features of the app being developed can be assessed and a way for further improvement can be found.

[32]https://www.novelbits.io/bluetooth-gatt-services-characteristics/ [Accessed 19/11/ 2019]
[33]https://www.oreilly.com/library/view/getting-started-with/9781491900550/ch04.html [Accessed 20/11/2019]
[34]https://diabetesstrong.com/diabetes-apps/ [Accessed 12/01/2021]
[35]https://www.androidauthority.com/best-diabetes-apps-android-1121038/ [Accessed 12/01/2021]
[36]https://www.everydayhealth.com/hs/type-2-diabetes-care/diabetes-apps/ [Accessed 12/01/2021]
[37]https://www.healthline.com/health/diabetes/top-iphone-android-apps [Accessed 12/01/2021]

Table 1: Comparison of Apps

Apps Name	Features				
	Charts	**Data Export (format)**	**Logs**	**Rem-inder**	**Others**
Diabetes Diary	Graph	CSV	Blood sugar, exercise, weight, Kcal		Goals setting
Blood Sugar Tracker	Graph, statistics	Charts, logs in TXT, PDF, XLS	Blood sugar, medications	can be set	Different advice each day
mySugar		Logs in PDF, CSV or XLS	Blood sugar, pills, activities, steps, blood pressure		User manual, support and feedback, calculates HbA1c
Beat Diabetes					A lot of information about diabetes, exercises, diets, complications, tests
Diabetes:M	Graphs, charts	Import/ex-port in CSV, XLS	Glucose, carbs, pressure, exercise	can be set	Cloud data, pattern analysis, estimate HbA1c, remote monitoring
Diabetic Recipes					A lot of recipes for diabetic cakes, dessert, main dish, etc.
Diabetes	Graphs, statistics	Import, export in PDF	Glucose, weight	can be set	
Glucose-Buddy	Graph	Report	Glucose, food, insulin activity		Plan
Dia-betesCon-nect	Graph, statistics	Export in CSV, PDF	Glucose, meal, pressure, weight, activities	can be set	
One Drop		Report	Glucose, weight, pressure, activity, medicines, carbs	can be set	Food Library, chat with an expert, news, community, calculates HbA1c
Diabetes Tracker	Graph, Statis-tics	Export in PDF	Sugar, weight, pressure, medicines		

Referring to the above comparison table (Table 1), it can be seen that the apps maintain logs of sugar level, food and medications intake, exercise and other parameters such as weight, pressure,etc., in general. Some of them have all these features while others have only the minimum parameters required. One of them (One Drop)has a food library so users can choose their food from the library avoiding the burden of knowing the calories and carbs associated with a food. Many of the apps have representation of the data on graph, statistics or charts. This facilitates visualization and understanding of the parameters better. Most of them support exporting the data in pdf, csv or excel formats. One of them produces report also. The report has not been evaluated due to the fact that it is not available in trial version of the app but assumed that is should be a summarized form of the data. In almost all of them reminders for pills intake or any other activities can be set. Some of them calculates HbA1c value based on inputs provided. HbA1c is glycated hemoglobin (hemoglobin and glucose joined) which gives an average value of blood glucose levels over a period of weeks or months. This differs from blood glucose level that blood glucose is the glucose present at a particular instant [38]. Two of them (Diabetic Recipes and Beat Diabetes) just provide information and advice about diabetes and food recipes for diabetics lacking all the features explained above.

2.5 Principals of Persuasion Design

Principles of Persuasion Design has been described based on Mobile Persuasion Design (Marcus, 2015). Some of these principles have been implemented in the project like choice of colors, simple navigation, metaphors in the form of familiar images of sensors, and personas from scenarios.

Metaphors: The concept of using a established fact or knowledge to clarify an unfamiliar/new fact is called a metaphor. In the design of this project, various metaphors are used in the form of images to understand various life signals at a glance.

Mental Models: It refers to the beliefs not facts of users about a particular system. Understanding a mental model helps designers to develop their design such that it will be easy to comprehend for the users.

Navigation: Poor navigation features may hinder a user from finding the relevant pages and information. So, a consistent navigation with established convention may be helpful.

Interaction: It includes how users interact with the app. As such, interaction refers to the input from users and how the results are displayed.

Appearance: It governs all the perceptual characteristics such as choice of fonts, colors.

[38] https://www.diabetes.co.uk/what-is-hba1c.html [Accessed 25/01/2021]

Personas: Personas typically mean type of a user. An app is developed specific to particular personas so that it will serve the purpose and interests of the personas it has been developed for.

2.6 Security

Security is the process of protecting data from any unauthorized access. He et al. present a comparison of various android health apps with a purpose of finding if proper security measures have been adopted (He et al., 2014). It was found that many of the apps lack encryption while saving data on mobile phone and sending over to cloud. Also, most of them do not encrypt data when third party storage is used.

Data collected by mHelath apps do not only contain health-related data but also other information like habits, location and movements (Adhikari et al.,2014), which makes all sensitive information at the risk of being stolen if appropriate security measures are not adopted. The study presents a comparison of 20 mobile health apps focusing on privacy and security concerns. Most of the apps have privacy policy but majority of them have not implemented any security measures. The methods suggested for security are encryption and authentication. Most of the mHealth apps available in the market do not follow General Data Protection Regulation (GDPR) or Health Insurance Portability and Accountability Act (HIPPA) and are insecure(Braghin et al.,2018).

BLE uses AES-128 encryption for security and uses a combination of short and long-term keys to make a secure connection[39]. However, BLE sensors from MySignals used in this project can be easily read and the data has been successfully interpreted as shown in figures 32 and 33. So anybody nearby can listen to the BLE devices and get the bio-parametric readings from sensors.

2.7 Usability

Different users have different experiences when they use a product or a system. The quality of their experience determines the usability aspect of the system[40].

A study tested the usability of health apps in Bangladesh using Nielsen's usability heuristics and System Usability Scale (SUS) (Islam et al., 2020). The study finds more than 50% of the apps below acceptable SUS score and the acceptable ones have score just above the threshold value.

[39] https://www.arrow.com/en/research-and-events/articles/security-for-bluetooth-low-energy [Accessed 17/01/2021]

[40] https://blog.hubspot.com/service/system-usability-scale-sus [Accessed 26/01/2021]

Leijdekkers et al. have designed an app that can capture many different bio-parameters and present to the user (Leijdekkers et al.,2013). They gave adopted ease of use as one of the prime factor for User Interface. Simplicity and motivation are considered as two factors for accepting any mHealth apps.

Simplicity and ease of use are two important factors considered in the development of the app in this project also.

3 Literature Review

3.1 Introduction

There are ample of researches deploying health monitoring systems based on various types of sensors, a gateway to transfer the bio-parameters to the server and a cloud for analysis. They have a primary purpose to provide immediate or as-quick-as-possible support to the patients in the form of advice such as changes in drug dosage or cautioning about probable future diseases.

To have a thorough understanding of the existing systems related to health monitoring using sensors and cloud, many articles were studied. The following paragraphs describe a few of them and their main functionalities.

Earlier researches have also deployed BLE or wearable sensors for collecting the vital parameters. Data have been collected in real time and various micro-services are used at the front end, storage and data management (Renta et al., 2017). A smartphone acts as a gateway for the data collected from sensors to be transferred to the cloud. A healthcare monitoring system for diabetics (Alfian et al., 2018) uses similar architecture with a phone collecting data and transferring to the server. They have incorporated machine learning algorithms for Blood Glucose (BG) prediction. A similar approach has been presented in a BLE-based Smart Home solution (Porjazoski et al., 2019). The BLE sensors are continuously scanned by a back-end application on an android device and the results sent to the front-end for the users. Besides it has alarm system too in case the measured values go beyond normal levels.

A home-care system has been designed (Power et al., 2018) using BLE sensors and a mobile application as a receiver. The research focuses on the accuracy of BLE beacons as an Indoor Proximity System. The project accomplished by Schobel et al. incorporates heterogeneous sensors (Bluetooth or USB) communicating with a native mobile app (Schobel et al., 2013). For this, they have developed a sensor framework which can be used to communicate with the sensors. Another project also uses BLE devices for localization and environment data collection with a purpose to enhance operation management by integrating these data into BIM (Building Information Modeling) (Teizer et al., 2017). Smartphone acts as a gateway to deliver the data to the cloud.

A similar but more comprehensive approach (Petrakis et al., 2018) has been implemented in the project iTaaS(Internet of Things as a Service). They have adopted the concept of making the mobile device a fog and not just a gateway for transferring the data to cloud. Depending upon situations, some computations and analysis are also made on the smartphone. Implementing the real time data collection and analysis, they have also focused on security and privacy of patient's data. Mougy & Kerdany have proposed a reliable data transfer protocol for the design consisting of BLE sensors for data collection and smartphones as gateway to the cloud(El Mougy & El-Kerdany, 2016).

An app called "Few Touch Application" was designed and implemented(Årsand et al., 2010) with the main goal of monitoring blood glucose, food habits and physical activity and inspiring the patients to improve their activity and nutrition habits based on the goals they achieve. The name Few Touch comes from the purpose of making the app as automatic as possible requiring only a few human interventions. It uses Bluetooth to automatically transfer glucose values to a mobile phone and is equipped with functionalities like goal setting, feedback and advice for patients.

A system that transfers blood glucose readings automatically through a glucometer equipped with a Bluetooth adapter to a mobile phone and then to an EHR(Electronic Health Record) in the form of SMS was implemented (Årsand et al., 2005) with a purpose of early outbreak detection.

Klasnja & Pratt have discussed various approaches on how patients can be better monitored and motivated towards achieving health goals using mobile technology (Klasnja & Pratt, 2014). Tracking and feedback, goal setting, social influence, and exergames (physical activities through technology)are considered as the factors that can lead to behavioral change. Similarly, symptom monitoring, self-management coaching and automated decision support are the tools the paper discusses for better patient care.

In a project called SMARTDIAB, they have implemented a system useful for patients with T1DM, capable of transferring glucose reading automatically along with food and exercise data to a central system with the help of a mobile phone or PC/laptop (Mougiakakou et al., 2009). The system consists of Diatebetes Database Management System (DDMS), Decision Support System (DSS) and Insulin Infusion Advisory System (IIAS). It has the ability to make adjustment in the volume of insulin infusion according to the recommendation made by IIAS.

Al-khafajiy et al. have designed a remote care system for elderly people which monitors heart rate using a pulse sensor, and Arduino UNO assisted with a Bluetooth device and a smartphone as gateway (Al-khafajiy et al.,2019). The system sends the collected data to a data center which is accessible by care givers. It also sends notifications if the value is beyond normal.

A continuous monitoring system called PhysioDroid has been designed using Equivital Eq01 system which measures heart rate, respiration, motion and body temperature (Banos et al., 2014). An android device equipped with an app acts as a gateway to send the collected date to the persistent remote storage.

Sim discusses how mobile health is evolving from a mere monitoring tool to diagnostics and therapeutics tools and the major challenges that have to be addressed to make it a technology for all (Sim, 2019). The challenges include validation of meaningful biomarkers and integrating them into the current health care systems.

Seshadri et al. present a review of the current attempts towards better managing the ongoing pandemic of COVID-19 (Seshadri et al., 2020). They suggest a way to exploit the wearable technology to measure clinically relevant physiological metrices and use an early detection algorithm to detect COVID presence even before the symptoms show up.

West discusses how health can be improved using mobile technology as it enables continuous monitoring of patients using various sensors and medical devices and allows care providers and medical professionals to intervene appropriately even distantly (West, 2013).

Majumder et al. have presented a summary of around 200 articles related to wearable sensors for remote health monitoring (Majumder et al., 2017). There are a number of wearable sensors based on many different technologies which can measure various bio-parameters such as heart rate, respiration rate, activities, skin conductance and many more. Because of increasing life expectancy all over the world, there is a clear need of more care for old people. This can be addressed with remote monitoring using wearable sensors at a comparatively low cost. Even though there are a number of wearable sensors available, there are many challenges also related to remote monitoring. There are not many systems which can measure all the vital parameters needed for monitoring.They state accuracy of the methods used, interoperability, information privacy and data security as some of the other challenges that need to be solved.

Jovanov et al. have designed and implemented WISE (Wireless Intelligent Sensor) which has a personal sensor network(PAN) consisting of wireless sensors (which measure ECG, breathing rate and motion) and a DSP-based personal server which collects and sends the data to the main server (Jovanov et al.,2001). The project is considered as a leap from wired sensors to wireless sensors for health monitoring.

A system with continuous monitoring of ECG, body temperature, environment temperature and humidity wirelessly has been implemented which focuses on low-cost and energy-efficient sensor and gateway nodes (Gia et al, 2017) . It implements the gateway as a fog equipped with data processing, analysis, notifications features. Fog is particularly important to achieve low latency.

Rodgers et al. discuss various types of wearable sensors such as activity monitors, physiological monitors and environment monitors (Rodgers et al.,2015). They also present use cases of monitoring for Parkinson's disease, stroke and neck and head injuries. The paper suggests a need for more accurate measurements from the devices and research towards establishing business models to cover the costs incurred to make these systems ubiquitous for elderly people and patients with chronic conditions.

A survey conducted in New Zealand among diabetic patients and health professionals show that the most desired feature of an app for diabetes management is blood glucose diaries (Boyle et al.,2017). And the most wanted feature for the future is insulin dosage calculation. The authors point to the direction of ensuring apps are safe and regulated before they can be prescribed by health professionals with confidence.

Brown & Brown try to make a cost analysis of continuous monitoring of diabetic patients and the cost that complications can cause, in the USA, India and Brazil (Brown & Brown, 2013). The authors find a positive indication that continuous monitoring of glucose levels will eventually outweigh the complications in terms of monetary values.

Kasmeridis & Vassilakopoulos have designed an android application that allows users to input their blood glucose levels and select foods from a database (Kasmeridis & Vassilakopoulos, 2015). Based on these information, it calculates insulin dosage. It has also the facility to send the records to doctors for further evaluation. One of the novel features they claim is the use of practical units of measurements for food instead of a scale.

Koottunkal et al. present a mobile app that can record food, glucose level and diets input from a user and focus on preparing a summarized report of the same for the health practitioners (Koottunkal et al.,2019). It will help the doctors to make more efficient decisions on a patient as they have the information of a patient in an organized form.

Miele et al. present a system consisting of a mobile diary that records blood glucose levels, meal composition and activities for Type 1 diabetics (Miele et al., 2015). It also has a web dashboard for visualizing the data.

A survey study of individuals with Type 2 diabetes living in rural communities show that lack of awareness of apps is a prime reason for them not to use the apps (Peng et al.,2016). They want an app which is easy to use(takes less time and effort), has a feature which converts the virtual rewards to tangible incentives. The other desired features are customized educational information and personalized feedback system.

Preuveneers & Berbers present a mobile application that captures context data based on location of patients and infer activities associated to the location (Preuveneers & Berbers,2008). Combining these data with blood glucose inputs from patients, it can calculate the daily drug dosage for the patient.

Shin & Holtz design an android application that helps children with Type 1 diabetes to have a smoother transition towards managing their diabetes themselves freeing the parents or caregivers from their responsibility to check their children's diabetes (Shin &

Holtz,2019). The app allows a seamless connection between the children and parents and the latter are able to see the glucose values as soon as the child records them.

There are more articles but these were specifically helpful to have an overview of how the project could be structured and what kinds of features are desirable and how they can be realized. Other articles are mentioned and described as per the need of the content.

3.2 Method

Searches related to integrating BLE sensors into mobile app, maintaining quality, privacy and security of the bio-metric values thus collected, relationship between bio-parameters, sensors used in hospitals were made in various databases and search engines. The databases used were Google Scholar, ACM Digital Library, IEEE , PubMed, Science Direct, MEDLINE, PLOS ONE, Munin, a database of the Arctic University of Norway(UiT). The keywords used were" BLE", "sensors", "mobile", "app", "health", "mysignals", "wearable sensors", "BLE sensors", "mobile app", "diabetes", "relationship between health parameters", "instruments in clinical practice". Various combinations of these keywords were used. The screening was carried out first by looking at the title and then afterwards going through the abstract and conclusion and the whole text.

3.3 Exclusion and Inclusion Criteria

Below are the inclusion criteria:

- Papers with evaluation and testing.
- Papers with health monitoring apps related to any disease.
- Papers with surveys about mHealth.
- Papers that describe relations between the health parameters.
- Papers that describe instruments which are used in hospitals.

Below are the exclusion criteria:

- Papers prior to 2000 AD.
- Papers in any other language than English.

4 Materials and Methods

Materials are the tools and resources that are used during the project and methods refer to how these tools were used, and implemented to achieve the goals and testing of the system. Various materials and methods have been used for the completion of the project.

4.1 Research Paradigm and Tools

The engineering approach described by Denning et al. has been used in this thesis (Denning et al.,1989). This approach presents fours steps for design: state requirements, state specifications, design and implement the system and test the system. The first steps requires setting the requirements of the project. The requirements states what exactly the project should do by dividing the main goal into smaller requirements. Then system design takes place which shows the blocks or modules of the system and how they intercommunicate. The theoretically designed system is then implemented using various tools , frameworks and programming language. Finally, the developed application is tested for performance, usability, and security using different tools.

4.2 Materials

Different software and hardware tools have been used for the thesis.

- Krita Version 4.2.8 and online tool (draw.io) were used for paper prototyping and logo design.
- Visual Studio (Community 2019) - It is an integrated development environment (IDE), which has been used for application development. Visual Studio Version 16.9.3 has been used.
- Microsoft .NET Framework - .NET framework Version 4.8.03752 has been used as a platform to compile and run applications.
- Xamarin : It extends .NET framework to make cross-platform applications for iOS, Android and Windows (cross-platform). The programming language used is C Sharp (C#). Xamarin Version 4.8.0.1560 has been used in the project.
- Android Emulator (OS Pie 9-API 28, Processor x86, Memory 1 GB) : Android emulator has been used to run and test the application before testing in a real device.

- Android Studio : Android Studio Version 4.1.3 has been used to test the performance of the developed app.
- The hardware device used to test the apps is Samsung Galaxy A20e android phone.
- Other hardware devices used is MySignals complete Software Development Kit. It consists of a main device which receives signals from various BLE and wired sensors and sends the signals to the MySignals server.
- MySignals Cloud[41] is used to store and retrieve data.

4.2.1 Rationale for Choosing Cross-Platform

The main advantage of cross-platform development is the facility to use the same code base for different platforms(Xanthopoulos & Xinogalos,2013). With a variety of mobile platforms, companies need to build separate mobile app for each platform if they want to target a wide customer base. And the main disadvantage of native development is they have to build everything from scratch as code reuse is not possible(Xanthopoulos & Xinogalos,2013). This situation has given rise to choosing of cross-platforms over native app development. But finding the right platform that suits the needs of a project is really difficult. Every platform has their own pros and cons and one may be better in fulfilling a particular need than the other.

Frameworks that support multiple platforms can be classified into hybrid and cross-platform[42]. Hybrid are web apps but equipped with native app container that allows to access device hardware and other native platform features[43]. Cross-platforms are similar to hybrid in code shareability but closer to native in user experience,device access and ease of implementation.

Xamarin is a tool that uses C# as programming language to develop apps in Windows, Android and iOS with more that 90% of the code reuse, providing almost native look and feel.[44]. Xamarin.Forms is a separate product for simple mobile apps with almost 100% code sharing.

Most widely used mobile operating systems are iOS and android. Cross platform framework Xamarin supports iOS, Android and Windows. So the platform the author

[41] https://cloud.libelium.com/login

[42] https://dzone.com/articles/native-vs-hybrid-vs-cross-platform-how-and-what-to [Accessed 05/11/2020]

[43] https://www.upwork.com/resources/should-you-build-a-hybrid-mobile-app [Accessed 05/11/2020]

[44] https://www.altexsoft.com/blog/mobile/pros-and-cons-of-xamarin-vs-native/ [Accessed 05/11/2020]

has chosen helps to increase the use the system by a majority or the population. Xamarin.Forms has been used in the project to develop the app.

4.2.2 Cross-Platform Architecture

Xamarin is built on top of Visual Studio. The cross platform architecture is shown in Figure 28[45].

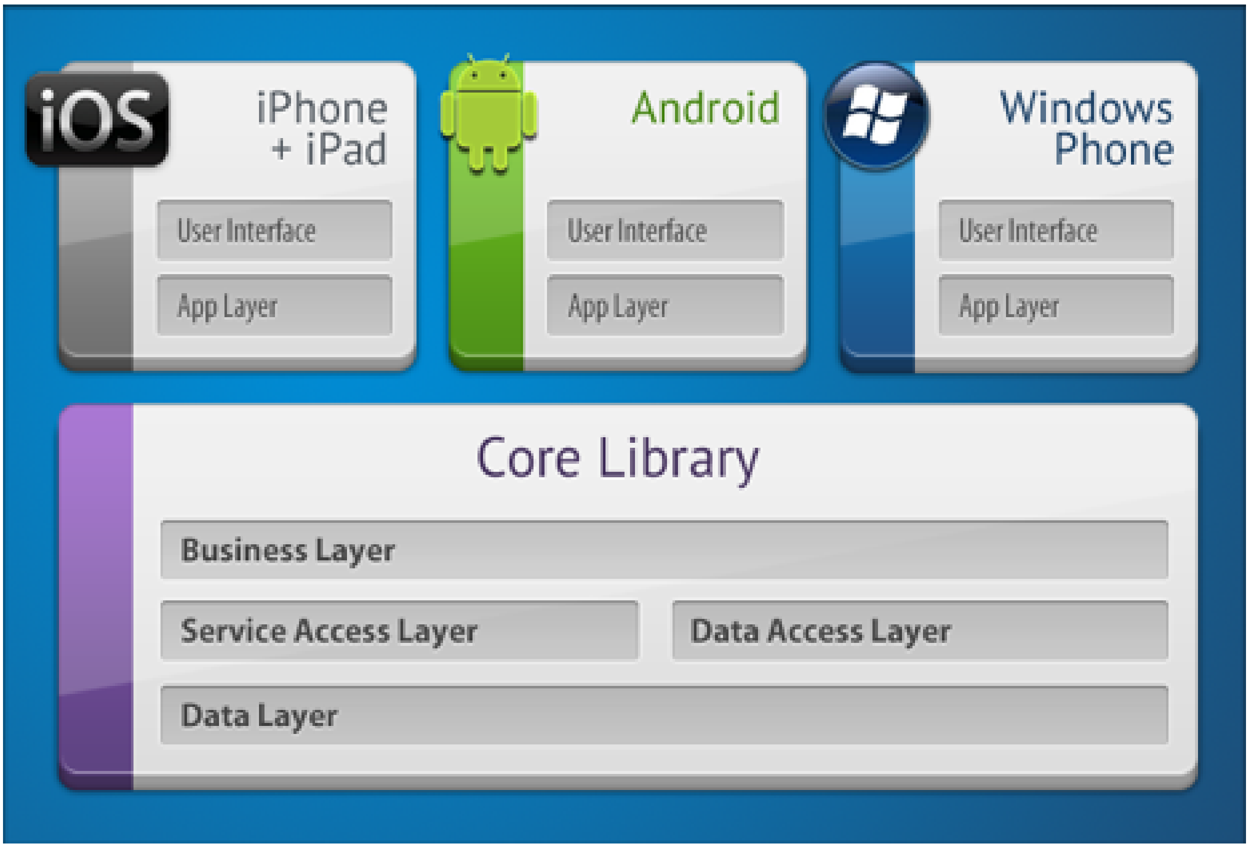


Figure 28: Cross Platform Architecture

- **Data Layer**: It is a layer in which database is formed.
- **Data Access Layer** : This provides various access to data such as Create, Read, Update, Delete.
- **Business Layer** : This layer defines business entities and business logic.
- **Service Access Layer** : It provides access to services in cloud, like web services (REST, JSON, WCF), and retrieval of data and image.

[45]https://docs.microsoft.com/en-us/xamarin/cross-platform/app-fundamentals/building-cross-platform-applications/overview [Accessed 06/11/2020]

- **Application Layer** : It contains code that is platform specific, which is generally not shareable.

- **User Interface Layer** : It is the layer faced directly by the user.

Data layer, data access layer, business layer and service access layer are same for all three platforms-Android, Windows and iOS. These layers entertain the facility of code sharing in all three platforms. Only in app layer and user interface layer, there are implementation which are specific to a platform and code cannot be shared.

4.3 Data Collection and Experimental Methods

Firstly various related articles were collected and theoretical aspects of the project were reviewed. According to review and discussion with supervisors, functional requirements were set. Based on the requirements, application prototype and android version were developed. As for the data to be shown by the app, data were regularly uploaded to the server from each sensor from the start of the project.

4.4 Evaluation Methods

For evaluation, Mysignals sensors were tested a number of times and results documented. Also, some other aspects of MySignals such as configuration of BLE sensors in main device has been tested and documented with a purpose of making it easier for future users. For the application developed, all the pages have been thoroughly tested to see if they meet the functional requirements. For performance of the app, Android Studio has been used to check CPU, memory, network and energy usage by the app.

4.5 Critics of the Method Used

The methods used has some limitations. Data collection is done by a measuring a single person's parameters. If data were collected using multiple persons, more analysis could be done and results and conclusion drawn would have become more trustworthy. In the beginning of the project, if there were meetings with the experts for their opinion of the system's usability then the usability aspect could have been even better. Performance test such as CPU utilization, Memory utilization, Network usage and Energy consumption of the apps has been done but no usability and security tests has been performed.

5 Requirements Specification

This chapter discusses the functional and non-functional requirements of our system. The functional and non functional requirements are defined with the help of Volere Requirements (Robertson & Robertson, 2006).

5.1 Functional Requirements

A functional requirement states what a system should do(Robertson & Robertson, 2006). It describes the behavior of the system in terms of function, tasks or services[46], which a system must perform. A function converts the inputs into outputs. The source of these requirements is literature reviewed, discussion with the the supervisors and the author. A few scenarios where and how the project can be useful are explained below.

Scenario 1:

John Dahl is an elderly man (70 years old) with stage 1 high blood pressure and Type 2 diabetes. He has been given a treatment plan by his doctor and is taking medicines for both diabetes and blood pressure. There is a need to constantly monitor both blood pressure and sugar level. He needs to check sugar level everyday once and blood pressure every week once. The values need to be monitored by the health care professionals to see if any intervention is needed. This system can provide the doctors with the latest values of Blood Glucose and Pressure. Let us assume, there is an abnormally high value of Blood Pressure on particular week. The system immediately alerts the patient and the doctor by sending an SMS. The patient, caregivers and doctors can then check the values and take necessary precautions and decisions.

Scenario 2:

Oliver Carter, a 62 year male has a severe asthma and stage 2 high blood pressure. It is difficult to administer drugs for him as the medicines for high blood pressure such as non-selective beta blockers[47] can actually aggravate asthma. In such case, an optimum solution is needed which can reduce blood pressure but without affecting asthma. Such conditions can be handled if both lungs and blood pressure can be monitored. This system can provide both spirometer readings and pressure values and help doctors make the right course of action for the patients. If any complications arise, then both diseases can be monitored again and another course can be finalized. As the system can provide with many bio-parameters, it can help in cases which need consideration for drug interaction,

[46]https://www.guru99.com/functional-vs-non-functional-requirements.html [Accessed 17/03/2021]
[47]https://www.verywellhealth.com/the-effects-of-high-blood-pressure-medication-on-asthma-1764113 [Accessed 30/04/2021]

where a drug used for one condition can worsen the other conditions present in the patients.

Scenario 3:

Mandy Wood is woman,75 years of old living in a remote village. One a certain day, she collapsed all of a sudden while going to her bed after dinner. Hospitals with health equipment are not available in her place and the nearest one requires 2 and a half hours of drive. There are only local health posts and health assistants. In this case, the proposed system can be used to monitor her vital parameters, which can be checked by a doctor from a distant place and drugs administered with the help of local health care givers. Once her condition stabilizes, she can be brought to the hospital nearby for full checkup.

Scenario 4: Consider a school where there are students who are interested in health technology. The whole MySignals set and the app designed can be used as a learning tool to teach the student about the sensors in a more interesting way than just teaching them the theoretical concepts of the same. There are sensors which measure temperature, respiration rate, blood pressure, blood sugar, lungs capacity, heart rate, heart cycles, snore, muscle strength, skin conductance, weight, and oxygen saturation. There are both wired and BLE devices. So, it can provide with a hands-in experience to the students to understand various sensors. Also, through the app they can see the values that have been measured, in table and graphs form, can plot the graphs between parameters they want. Because of these reasons, it can be an effective tool to teach the students about various health sensors, BLE communication, server, and APIs needed to communicate with the server.

With the help of these scenarios, the following functional requirements are set. UML use case diagram and table below lists out all the functional requirements.

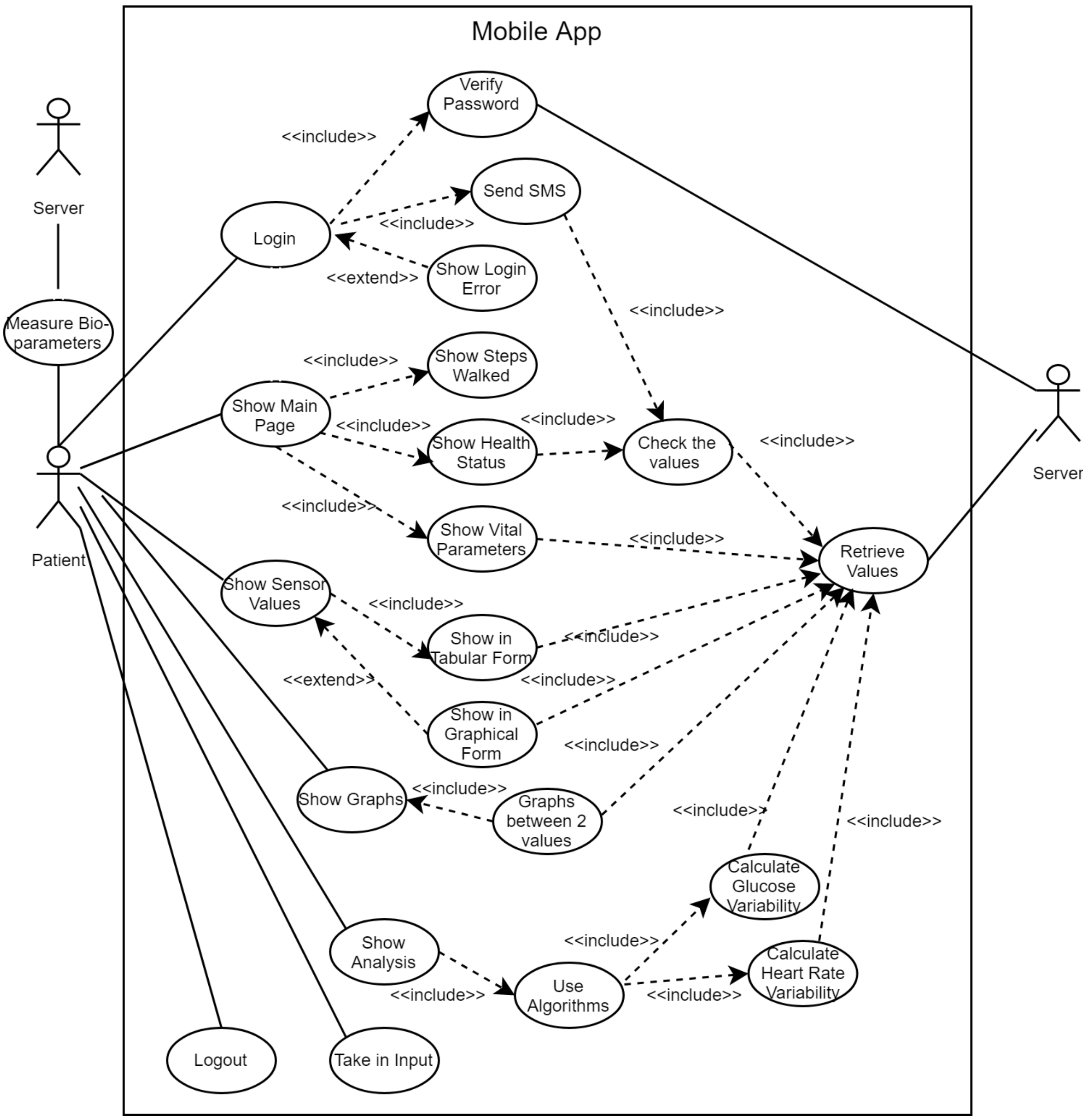


Figure 29: UML Use Case Diagram

Based on the use cases shown in Figure 29, the following functional requirements have been tabulated.

Table 2: Functional Requirements

S.No	**Use Cases**	**Requirements of the App**	**Purpose**	**Source**	**Fit Criteria**
1	Login to app.	It should avail the users to login to the app.	Access the values	Author	Provide login screen.

2	Verify pass-word.	It must verify the password of the user before letting the user in.	Make the app secured.	Author	Allow login only if both username and password are correct.
3	Show login error.	The app must show error to the user if the user credentials are incorrect.	Let the user know if they have a typo.	Author	Shows error for wrong credentials
4	Send SMS.	The app has to send SMS to the caregivers and relatives if any value is abnormal.	Ensure patient gets proper care before it is too late.	Literature	SMS should be received for any abnormal values.
5	Show main page.	The app should launch the main screen after login .	Show health status, vital parameters.	Author	Show screen with health status, vital parameters, and steps.
6	Show health status.	The main screen should show overall health status in different colors, based on values of vital parameters.	Let user know overall health at a glance.	Discussion with supervisors	Show health with different color for different status.
7	Show vital pa-rameters.	The main page must show all the vital parameters (blood pressure, HR, RR)	Let the user know their main parameters without navigating further.	Literature	Show all the vital parameters on the main page.

8	Show steps.	The main screen should display the steps walked by the user.	Measure physical activity.	Author	Show the steps walked.
9	Check values.	The app must check the values to find if there are any abnormal readings.	Find abnormalities .	Author	Show in red only if the values are abnormal.
10	Retrieve values.	The values has to be retrieved from the server.	Display and make analysis.	Author	The values in server and retrieved should be same.
11	Show in tabular form.	The values by default will be shown in a table.	Show the values the user wants to see.	Author	Show values in a table.
12	Show in graphical form.	The users should be able to choose if they want to see the values in a graph, within desired date.	Graphs help to understand the values better.	Discussion with supervisors	Depict the values in a graph.
13	Graphs between 2 values.	The user has the facility to choose any 2 parameters and see their graph.	Help to see relation between 2 parameters.	Discussion with supervisors	Display line graph between 2 chosen values.

14	Show analyses.	The app should present analysis of the various parameters, thus providing more deeper information besides the values measured.	Helps in understanding the overall health status better.	Discussion with supervisors	Show results by calculating parameters that can give more information.
15	Use algorithms.	The analyses should be based on formula for deeper analysis	Make analysis.	Discussion with supervisors	Results should be based on the formula.
16	Calculate HRV	Further calculations should be made based on formula.	Make deeper analysis.	Literature	Results should be based on formula
17	Calculate GV	Further calculations should be made based on formula.	Make deeper analysis.	Literature	Results should be based on formula
18	Take input.	The app should have the facility to take in various input parameters from the user.	Use them in the app as per need.	Literature	Take input from the input page.
19	Logout of the app.	The app should be able to exit to the login screen.	Exit the app.	Author	Exit the app and show login screen.

5.2 Non-functional Requirements

These requirements govern the quality aspect of the application. They are a set of standards to evaluate the functional requirements. A system does some specific functions but how well it performs is set by its non functional requirements.

Below are the non-functional requirements that have been set for the project.

1. Presentation: The values collected from sensors should not be simply displayed but

there should be some better form of presentation such as graphs, or some indicators that can help patients understand the parameters with the least effort. There should be some sort of analysis of the values, and useful, more clear information displayed for the users.

2. Usability: The user interface should be as simple and clear as possible. The usability of the app should consider the requirements set by the scenarios. It must try to display the values with minimum interaction from the patients as chronic patients have to use the app on a regular basis. Also, some form of notification or use of colors should make it easy for the patients to know their abnormal values at a glance.

3. Security: The app collects sensitive patient data from the sensors. These data should be secured. It has to ensure there are no unauthorized access of the data. The data security should be considered while receiving data from the BLE devices to the mobile application, while downloading the data from MySignals cloud and also while presenting the data to the users.

4. Legality: The app should be aware of the legal issues that can arise if private data is leaked. So, it must avoid sending data over insecure channel or giving access to third parties.

6 Design and Implementation

This chapter describes theoretical design aspects and how they are implemented later on. Various types of designs such as app logo, GUI, architecture of the project, different modules and their interaction are necessary before they are implemented. For app development, first paper prototypes were designed and then they were slowly developed with many versions until final version was ready.

The title of the app has been chosen LifeSignals(inspired from MySignals) signifying that it deals with the parameters/signals related to life. The logo was designed in a photo editing and design software Krita 4.2.8 and it portrays a human body with ls(LifeSignals) written at the center. Figure 30 shows the logo.

Figure 30: App Logo

6.1 App GUI

Graphical User Interface (GUI) has to consider a design which is easy to use and have the ability to change the behavior of the users towards a better health. Such ideas are governed by persuasive design techniques. Persuasive designs are motivated by the facts that a design does not simply limits to usability of the app but also extends to features such as emotional impact, and social and cultural interaction.

6.1.1 Paper Prototypes

Initially, a few simple paper prototypes were designed in draw.io so as to visualize what various screens should contain and how the navigation should take place. Later on, they were implemented with more features, colors and designs. Figure 31 shows the paper prototype of login screen and the main screen after logging in. The login screen contains entry fields to enter username and password and login button. After the login screen, the main screen shows the important vital parameters along with images of healthy foods and person running so as to motivate the user to engage in activities and healthy eating habits.

(a) Login Screen

(b) Main Screen

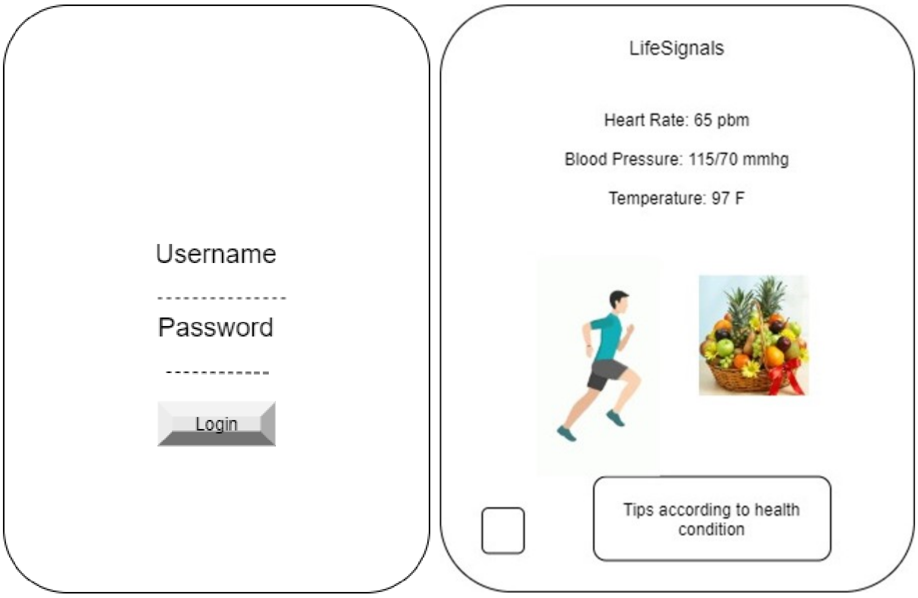


Figure 31: Paper Prototypes I

Figure 32 shows more about how various sensors will be available to the users in the form of a simple vertical menu. The purpose was to implement a simple navigation menu easy to use for the users. Also, it shows how data will be displayed in the Display page. The Display screen should display 10 latest entries in tabular form and there should be options to choose if data needs to be tabulated or shown in graphical form. This was the initial design but it changed a bit later as the app developed.

(a) Navigation Page (b) Display Page

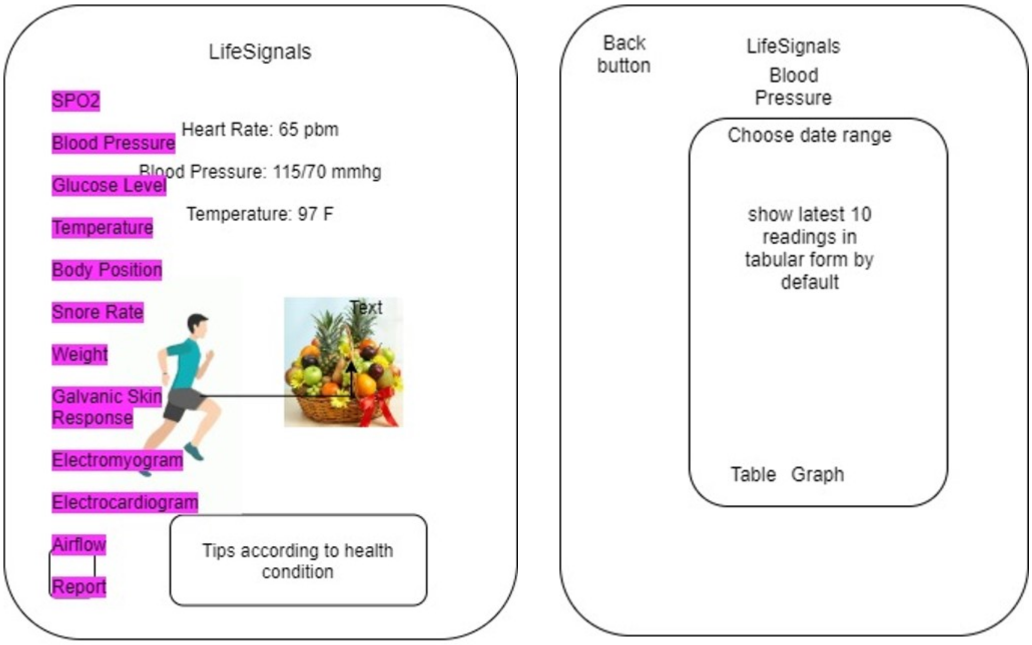


Figure 32: Paper Prototypes II

6.1.2 Login Screen

There are many different steps of implementation but only one of the preliminary versions and the final version of the app GUI have been shown for each page. The APIs mentioned in Section 2.2.13 were tested before implementing them in the app development.

The login screen has been designed with the help of Krita(V 4.2.8) and the entry form and button implemented on top of it. The login screens are depicted in Figure 33. Figure a (old version) has been improved with an activity indicator implemented later on (Figure b). As it takes a few seconds to enter the main screen, an indicator helps the users to know that some processing is going on. Also, while entering the main screen, the app asks the user for location and SMS permissions. As location permission is required for step counter and SMS sending permission is needed to send SMS to caretakers if any value is abnormal.

(a) Login Screen I (b) Login Screen II

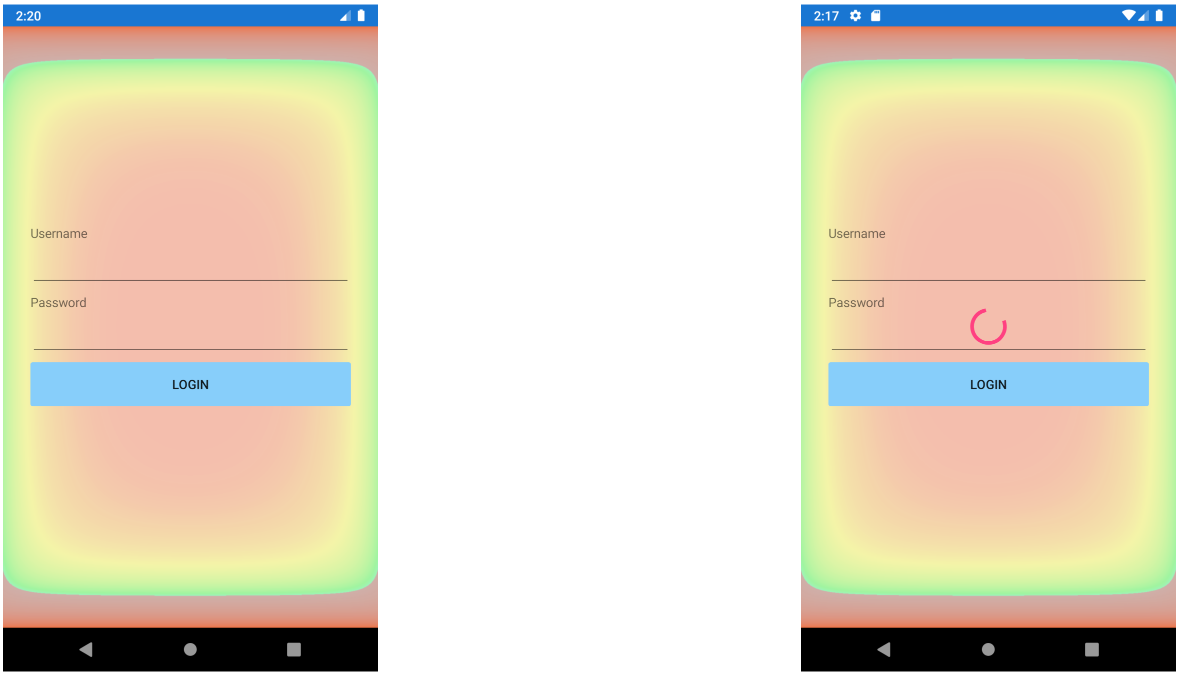


Figure 33: Login Screen

6.1.3 Home/Main and Menu Screens

The main/home screen contains the four most vital parameters with its latest values (Figure 34). The four most important vital parameters chosen are temperature, heart rate, respiration rate and blood pressure [48].

Before launching the main screen, the app asks if the patient suffers from blood pressure and blood sugar. The purpose of this was to have a customized main screen in which the parameters blood pressure and sugar level both will be displayed if the patient has both. This has not been implemented though, but it can be implemented in future so that it increases the usability of the app.

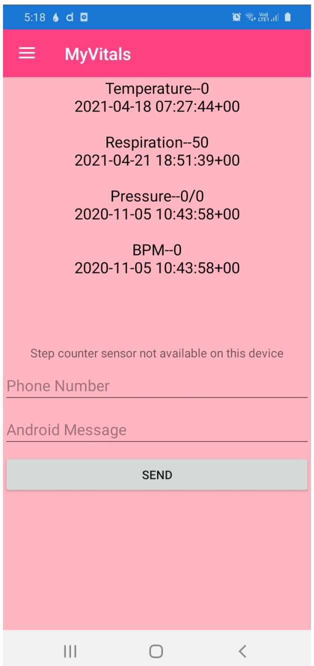
It also shows the overall health status of the user in the form of a circle. The circle changes its color according to the health condition. The circle has green for normal, orange for slight deviation from the normal and red if the values differ from the normal by large range. The algorithm is a simple check of the most vital four parameters for their abnormality. Rather than checking the individual values, this helps the users to grasp their health status at glance. The concepts of master-detail-page/flyout-page[49] have been

[48] https://www.hopkinsmedicine.org/health/conditions-and-diseases/vital-signs-body-temperature-pulse-rate-respiration-rate-blood-pressure
[Accessed 20/05/2021]

[49] https://docs.microsoft.com/en-us/xamarin/xamarin-forms/app-fundamentals/navigation/master-detail-page [Accessed 06/06/2020]

used to implement the home and menu screens. A flyout page typically shows a list of items. Additionally, tabbed pages[50] are also used which show tabs in the bottom. The first version of the app only had flyout page implemented and tabbed page was integrated later on. The displayed values inside the four quadrants of the circle are either in red, orange or green colors. Instead of showing the date when the values was measured, how long ago it was measured is displayed so that it is easy to grasp for the users. Also, a logout button appears on the top right in the final version, which takes the users to the login screen after resetting the authorization token value. There are other buttons by the side of the circle for health status which can directly launch the corresponding screen. They launch display pages which display the values in table and graphs. They are present in the vertical menu list as well but a front screen showing all the sensors is capable of showing one of the main purposes of the app-to integrate many different sensors into a standalone application. The color of the buttons are however chosen randomly, but a better approach would be to get the latest values of each sensor and show the color of the buttons according to the range of the values. There is an input button (blue circle with white plus) also in the final version. It gives user the facility to input different information.

(a) Home Screen I



(b) Home Screen II

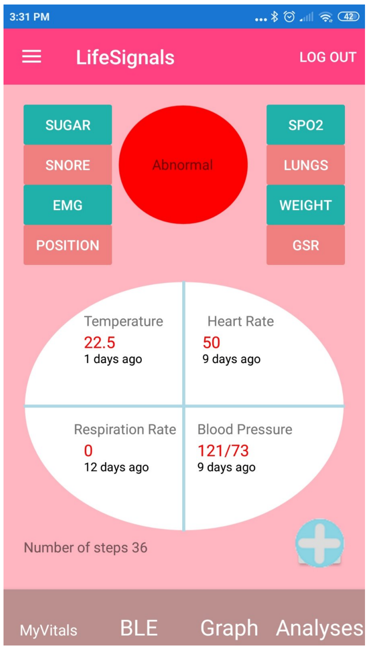


Figure 34: Home Screen

[50] https://docs.microsoft.com/en-us/xamarin/xamarin-forms/app-fundamentals/navigation/tabbed-page [Accessed 05/02/2021]

Figure 35 shows the menu screen with all the menu items. As soon as an item in the menu is tapped, it launches the corresponding screen which shows the values of the selected item. Old menu screen has slightly been changed in color of the text and background to maintain consistency with the rest of the pages.

(a) Menu Screen I (b) Menu Screen II

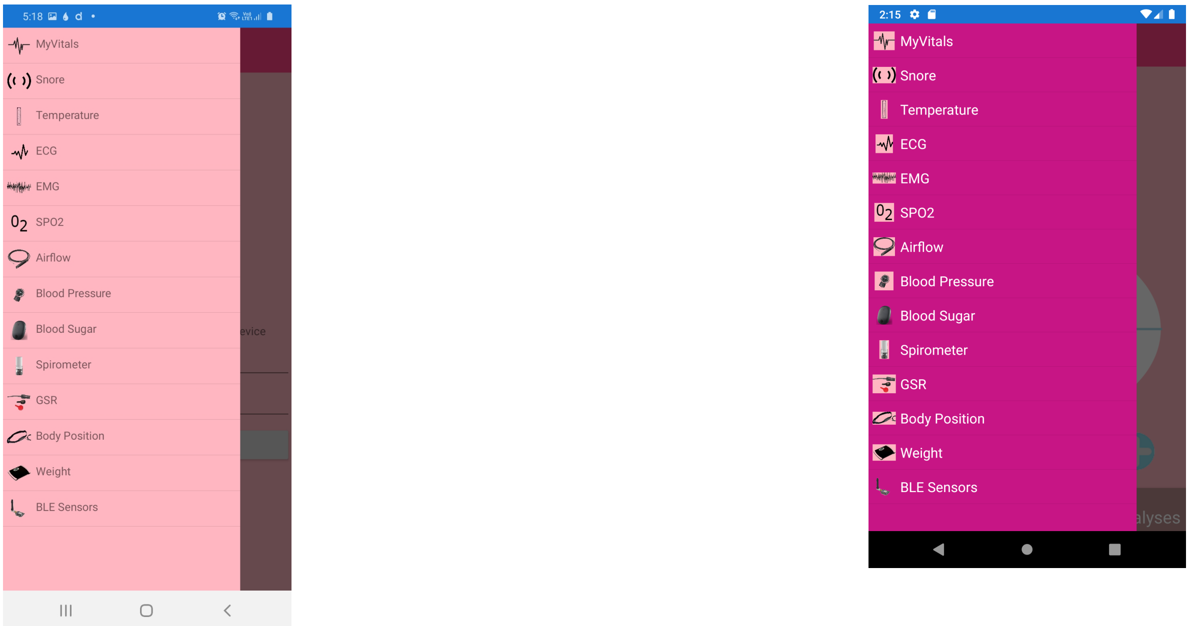


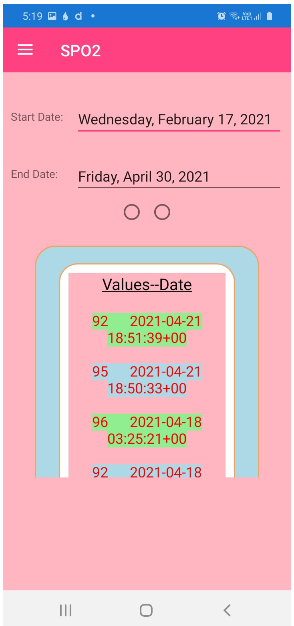
Figure 35: Menu Screen

6.1.4 Display Screen(Table)

The Display page shows the latest value of the item(sensor) selected, by default as soon as it launches. And the users can also choose a date range according to which the values will be displayed in a tabular form. In addition, the users can choose to see the values plotted in a graph. Graph has been implemented using MicroCharts [51]. Below figures(Figure 36) show the Display pages. The final version shows data and colors the background according to its value.(normal or abnormal). The color is orange, red or green.

[51] https://github.com/dotnet-ad/Microcharts

(a) Display Screen I(Table)



(b) Display Screen II(Table)

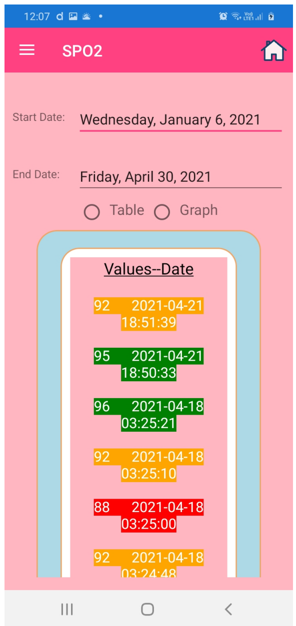
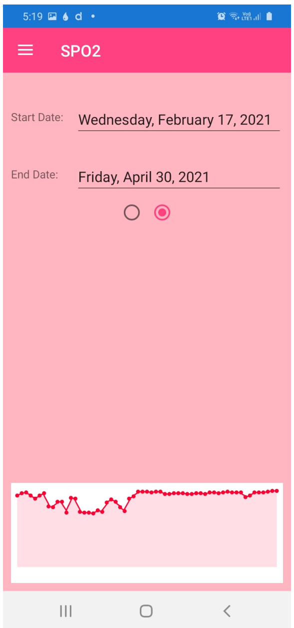


Figure 36: Display Screen(Table)

6.1.5 Display Screen(Graph)

The values shown in table can also be plotted in a graph. The final version has been improved to show a clear graph with its labels (Figure 37).

(a) Display Screen I (Graph)



(b) Display Screen II(Graph)

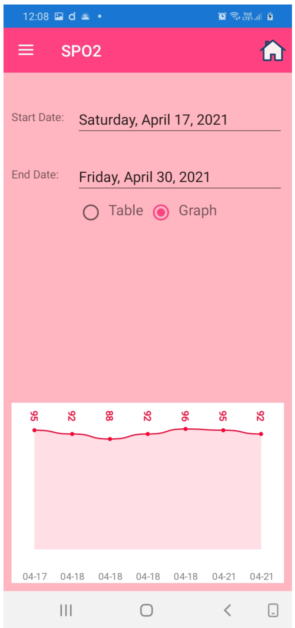
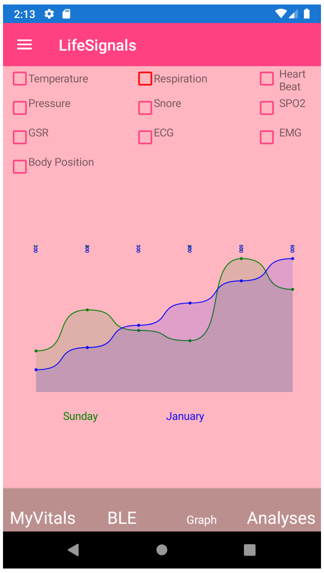


Figure 37: Display Screen(Graph)

6.1.6 Graphs

Line graphs have been implemented with a purpose of providing an easy means to understand the vital parameters (Figure 38). The users can choose which parameters they want to see plotted on the graph. They can choose two parameters and see the relationship between them. The first figure(Graph Screen I) is just a demonstration of how it can be plotted (two arrays have been plotted)and the second figure was improved to retrieves the values from server and plot the two parameters according to the selected date and selected parameters.

(a) Graphs Screen I



(b) Graphs Screen II

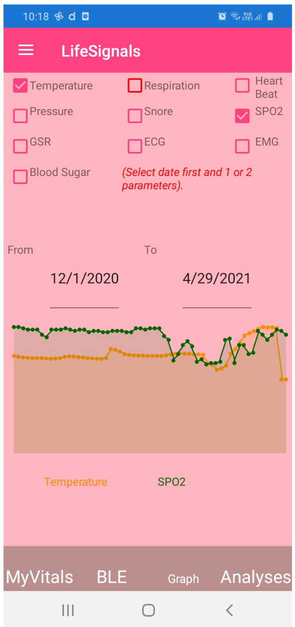


Figure 38: Graphs Screen

6.1.7 Input and Analyses Screen

The input page (Figure 39) allows the users to enter the information about their health and the numbers they want SMS to be sent in case of emergency. The health information inputted by the users can be used for customized display. For example, if the user needs to show values of spirometer and weight, then the same values can be shown in the first screen. This has not been implemented, only the input page is implemented and can be useful for customized display. The analyses screen (Figure 40) is used for giving some analysis of the measured values. It shows HRV and GV with their color. There can be many more analysis based on a single parameter as well as on multiple parameters which can be very useful for the patients.

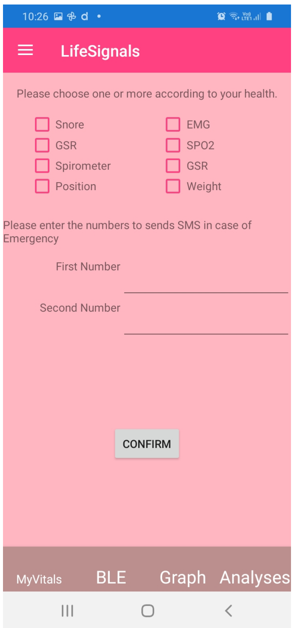


Figure 39: Input Screen

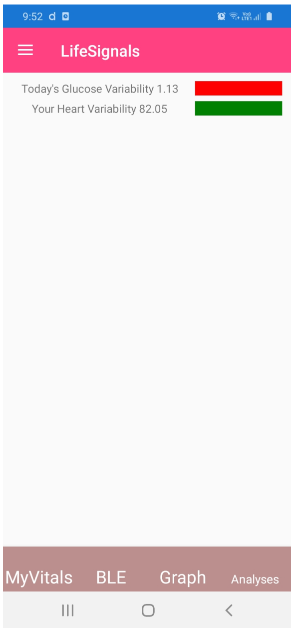
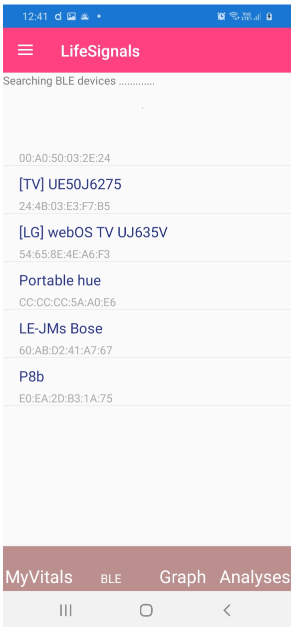


Figure 40: Analyses Screen

6.1.8 BLE Screen

This screen (Figure 41))lists out all the BLE devices in range and allows to connect the desired one. Once connection is successful, "show value" is clicked which shows the values of the corresponding sensor. The "Notify " button can be used to enable or disable notifications. One of the goals of the project is to have least intervention from the users. The connection and reading of the BLE sensors should be made as automatic as possible. So, in the second version of the app, an attempt was made to make it automatic. To make it automatic, various click events are converted into functions and they are called in one after the other. But one event ItemTapped (event created when a particular sensor is tapped in a list of sensors)could not be converted because of which it still requires one tap to receive the values. This has been tested only on SpO2 sensor as it continuously sends notifications and was easier to implement than other sensors. For glucometer sensor, it will be harder as it sends notification only once and time factor has to be well managed to automate it.

(a) BLE Search



(b) BLE Value

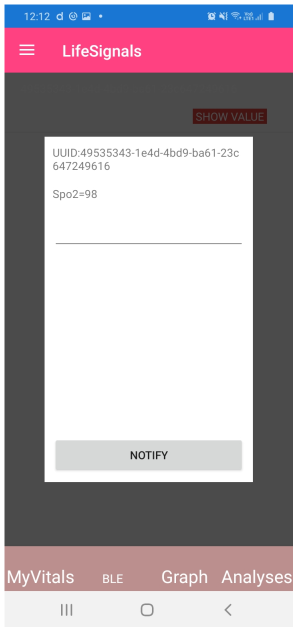


Figure 41: BLE Screen

6.2 Algorithms and Other Features

6.2.1 Analyses

Rather than simply displaying the data for the user, further calculations have been made so that the users can have better understanding of their data. Also relations among parameters have been used to formulate algorithms that can reflect more of the health status. Analyses of the bio parameters require the knowledge of the normal range of the values. Table 4 lists out the normal and abnormal ranges of the sensors used.

Table 3: Normal Range of the Health Parameters

S.No.	**Parameter**	**Normal Range**	**Abnormal Range**	**Source [Accessed 19/03/2021]**
1	Blood Glucose (Type 2 Diabetes)	4 mmol/L to 7 mmol/L(before meal) <8.5 mmol/L(at least 90 minutes after meal)	<4 mmol/L-Hypoglycemia >11.1 mmol/L-Hyperglycemia(2 hours after meal) >7 mmol/L when fasting	Diabetes and Hypoglycemia Blood Sugar Level Ranges Diabetes and Hyperglycemia

2	Blood Pressure	90/60 mmHg to 120/80 mmHg	Systolic 120-129 & Diastolic > 80-Elevated Systolic 130-139 & Diastolic 80- 89 –Stage 1 High >140/90 mmHg-Stage 2 High <90/60-Low	Blood pressure chart What is blood pressure
3	Heart Rate	60 to 100 bpm	<60 bpm-Bradycardia >100 bpm-Tachycardia	Target Heart Rates Chart Bradycardia: Slow Heart Rate Tachycardia: Fast Heart Rate
4	Forced Expiratory Volume 1	>=80%-Normal	70% to 79 %-Mild 60% to 69 %-Moderate <60 %-Severe	Understanding Your Breathing Test Results
5	Peak Expiratory Flow	400 to 700 liters/minute	50% to 80 % of Your Best-Mild <50% of Your Best-Severe	Breathing and lung function tests Peak Flow Measurement
6	SpO2	95% to 100%	<90%-Hypoxemia <85%-Cyanosis	What is Oxygen Saturation?
7	Body Mass Index	18.5 to 24.9	Below 18.5-Underweight 25 to 29.9-Overweight 30.0 and Above-Obese	About Adult BMI
8	Temperature	36.1 °C to 37.2 °C	<35 °C-Hypothermia >39.4°C-High fever(serious)	How to Tell When a Fever in Adults Is Serious? Hypothermia

9	Respiration Rate	12 to 20 per minute		What is a normal respiratory rate?
10	HRV	SDNN: 18.43-92.55 ms RMSSD:14.66-100.02 ms		(Sammito & Böckelmann., 2016)

RMSSD:Root Mean Square of the Successive Differences (Refer to Heart Rate Variability same Section)

SDNN: Standard Deviation of NN intervals, also called SDRR(Standard Deviation of RR intervals (Refer to Heart Rate Variability same Section)

The HRV values are provided in the form of percentiles in different aged male and female(Smmito et al., 2016). The lowest value of 5^{th} percentile and highest value of 95^{th} percentile have been taken as the range of HRV. There are no standard values for HRV and the values taken in this project can be different from some other findings. Also, these values are found considering a 24 hour period of ECG and may not apply to the HRV calculated using a 5 secs period in this project. But due to lack of data to compare in case of variability calculated using short interval, same has been used.

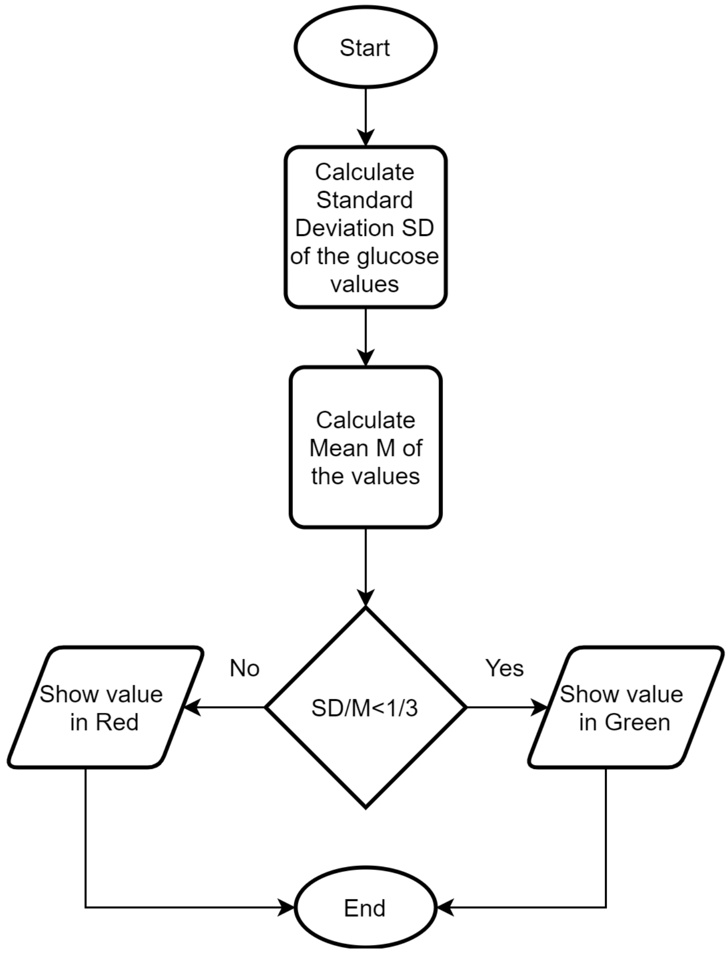
- Glucose Variability (GV): GV has been chosen as one of the parameters for analysis because diabetes is one of the most common chronic diseases. GV gives a measure of variation of glucose values over a period of time. This can be useful to decide what kind of glucose control scheme should be chosen. Even if the HbA1c(Hemoglobin A1c-gives average level of blood sugar over last 2-3 months) value is normal, there could be variations in the level of glucose which are abnormal. So, variability is a more effective factor to make sugar control more successful [52].GV has been taken as a more efficient measure for glycemic control (Umpierrez & Kovatchev, 2018). Compared to the traditional methods which focus only on bringing down the sugar level, as GV considers the fluctuations, it can assess both hypo and hyperglycemia. This is calculated using Coefficient of Variation (DeVries, 2013). Coefficient of Variation(CV) is defined as standard deviation divided by mean of the glucose

[52]http://www.diabetesincontrol.com/teaching-patients-about-glycemic-variability-and-why-its-important/ [Accessed 12/04/2021]

level[53]. Coefficient of Variation less than 1/3 is considered normal. Increased CV is linked with an increased risk of hypoglycemia(Uemura et al.,2018). Algorithm 1 shows the calculation of GV.

$$Coefficient\ of\ Variation(CV) = \frac{Standard\ Deviation}{Mean}$$

Algorithm 1 Glucose Variability



- Heart Rate Variability (HRV): HRV is considered a parameter which can provide information on overall health [54]. HRV is another parameter chosen to present as an analysis because heart disease is also very common chronic disease. HRV is the variation of time between successive heart beats . It is considered an important parameter to find any imbalances in the autonomic nervous system (ANS). A higher value of HRV indicate good overall health while a lower value may signify increased risk of cardiovascular disease, anxiety and depression.Two methods have been used

[53]https://diatribe.org/understanding-average-glucose-standard-deviation-cv-and-blood-sugar-variability [Accessed 27/02/2021]

[54]https://www.health.harvard.edu/blog/heart-rate-variability-new-way-track-well-2017112212789 [Accessed 12/04/2021]

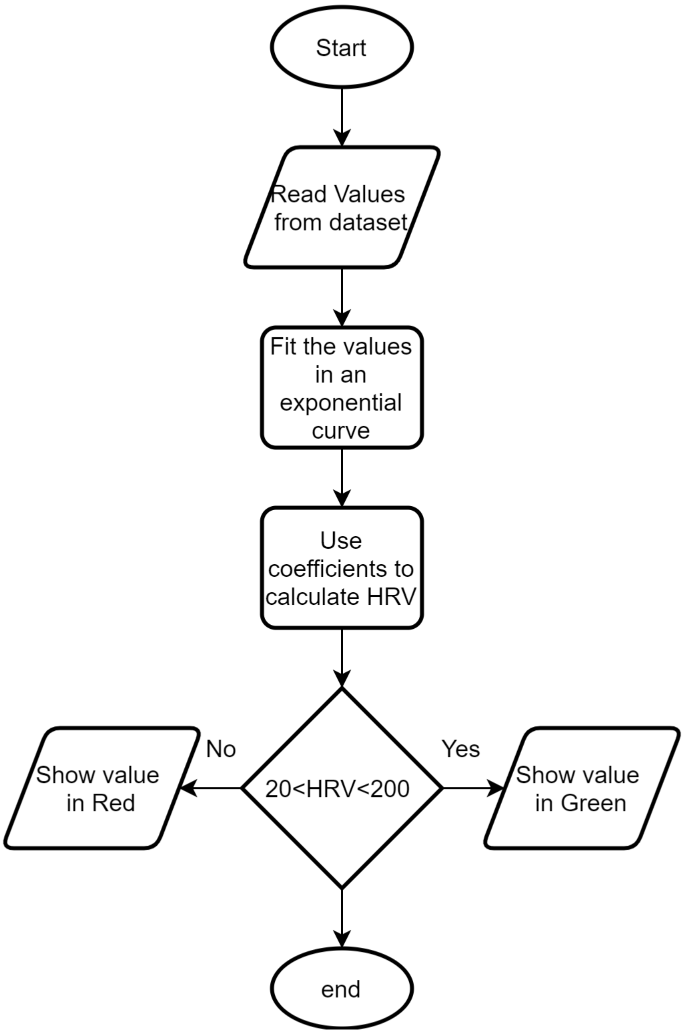
for calculating HRV. One is using the relationship between heart rate and HRV and the other is using the ECG graph. A study concludes that there is a non-linear relationship between heart rate variability(HRV) and heart rate (Monfredi et al., 2014). They have shown an exponential decay of heart rate variability with an increase of heart beat. The standard way of calculating heart rate variability requires RR interval of an ECG curve. But ECG curve produced by MySignals device is not so reliable, so HRV was also calculated using this method. A small portion(50 entries) of the heart rate variability dataset[55] has been used to find a fitting exponential curve. Non-Linear Regression using least squares method[56] has been used to find a fitting curve for the data points. Algorithm 2 shows how HRV is calculated using non-linear regression. Exponential functions are used to fit the curve. Non-linear regression is used when the exact nature of the curve is not known. How exactly the dataset would fit is not known so, non-linear method is better than linear methods. The normal value here is taken as 20-200 ms based on the information given in this page [57]. But later on, a more reliable normal range was found (Sammito & Böckelmann., 2016).

[55] https://www.kaggle.com/qiriro/swell-heart-rate-variability-hrv Accessed[07/03/2021]

[56] https://www.extremeoptimization.com/QuickStart/CSharp/NonlinearCurveFitting.aspx [Accessed 04/03/2021]

[57] https://support.ouraring.com/hc/en-us/articles/360025441974-An-Introduction-to-Heart-Rate-Variability [Accessed 13/04/2021]

Algorithm 2 Heart Rate Variability



- HRV from RR interval: MySignals provide an API to get the raw values of the ECG signal (Figure 42). Using the raw values, RR interval can be found and thus HRV can be calculated as below. The raw values provide the amplitude of the wave every 1 ms. The raw values for 5 sec has been taken to calculate HRV.

Figure 42: ECG Signal

To calculate HRV, first of all, squares of the successive differences of the RR intervals is found out. Then the squared differences are added and their mean is taken. The square root of mean of the squared differences give HRV, which is called RMSSD(Root Mean Square of the Squared Differences) [58].

$$Heart\ Rate\ Variability(HRV) = \sqrt{\frac{(RRInterval1-RRInterval2)^2+(RRInterval2-RRInterval3)^2}{2}}$$

HRV can also be calculated as SDRR(Standard Deviation of RR intervals). In the above ECG graph, formula can be applied as below.

$$HRV = \sqrt{\frac{(RRInterval1-Mean)^2+(RRInterval2-M)^2+(RRInterval3-M)^2}{2}}$$

M is the mean of the intervals Interval1, Interval2 and Interval3.

From the graph, Interval1=68 ms, Interval2=70 ms,Interval3=187 ms

$$M = \frac{68+70+187}{3} = 108.33ms$$
$$HRV = \sqrt{\frac{(68-108.33)^2+(70-108.33)^2+(187-108.33)^2}{2}} = 68.13ms$$

6.2.2 SMS (Short Message Service)

The app entertains the facility to send SMS texts to the caregivers or/and relatives in case one of the vital parameters is beyond normal values. SMS is better than sending an email as notification because SMS open rates are as high as 98% compared to emails at 20%[59]. To make sure the message is read and acted upon by the caretakers in case of emergency, SMS has been used. SMS has been implemented using the concepts and code from github [60].

6.2.3 Steps Counter

The inbuilt feature of the Android to count the number of steps has been implemented[61]. This is native to Android and does not support the code shareability feature of Xamarin.

6.2.4 Bluetooth Low Energy (BLE)

Initial Test

Initially Raspberry Pi 3 was used to read the BLE sensors. The hardware connection has been depicted in Figure 43. Bluepy is a python module which helps in communication using BLE technology. Bluepy has been used to read the BLE sensors using a python program (Appendix 1). Notifications is enabled by writing hexadecimal value 0100 on

[58]https://imotions.com/blog/heart-rate-variability/ [Accessed April 17, 2021]
[59]https://www.zipwhip.com/blog/the-pros-and-cons-of-texting-vs-email/ [Accessed 29/01/2021]
[60]https://github.com/officialdoniald/Xamarin.Forms.SendAndReceiveSMS [Accessed 20/11/2020]
[61]https://overton.dev/blog/native-api-access-in-xamarin-forms [Accessed 30/11/2020]

the handle of the required characteristic. Once the notification is enabled, the sensors keep on sending the updates. This feature, however, has been successful only with the BLE SpO2, temperature and glucometer sensors. Remaining two BLE sensors, scale and blood pressure seem to work slightly differently. They do not send the notification values upon enabling notification. But as they connect to Mysignals, they start measuring and show a stable value. This preliminary implementation was done to learn how to read the BLE sensors using a program before implementing it in the main project.

This was tested using a program in Raspberry Pi 3, Model B. NOOBS version 3.2.1[62]has been used to install Raspbian on Raspberry Pi. A python program that captures notification from BLE devices confirmed similar data as read by other apps (which can read BLE devices). As MySignals does not provide us with API to collect data directly from the sensor, the purpose of this test using a Rapberry Pi was to understand how data can be collected from BLE sensors before implementing it in the application.

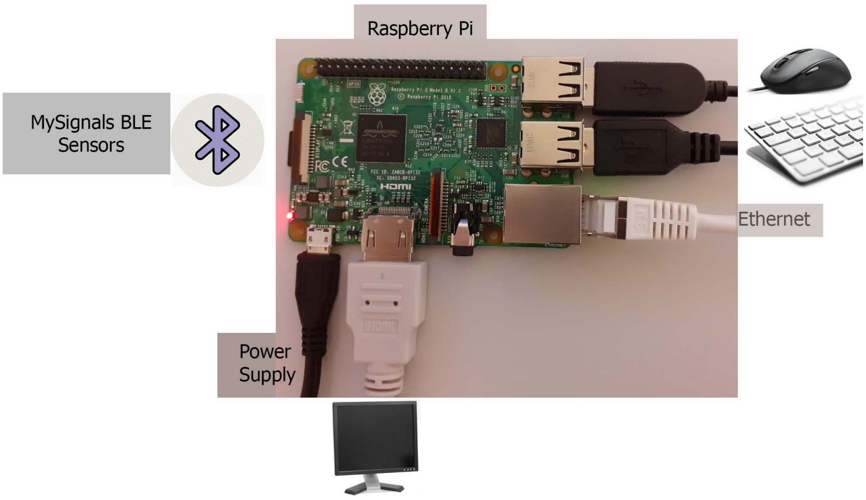


Figure 43: Raspberry Pi-BLE Sensors Connection

The app can read the values directly from BLE sensors-SpO2 and temperature and glucometer.[63]. However, only SpO2 and glucometer values were successfully interpreted. Temperature values even though can be read but could not be interpreted.

6.3 Architecture of the System

The main goal of this thesis is to develop an app which can integrate all the MySignals sensors, present it to the user and make analyses and give more useful information. The BLE sensors can be connected to the app directly. The sensors without BLE cannot

[62]https://www.raspberrypi.org/downloads/noobs/ [Accessed 18/11/2019]
[63]https://github.com/4a0g0085/Quick.Xamarin.BLE [Accessed 03/11/2020]

be integrated directly with app. To connect with the BLE sensors directly, a code from Github has successfully been used.. This code lists out all the characteristics of the BLE devices. Code has been written on top of it to turn on notification of the required services and extract the value from the sensor.

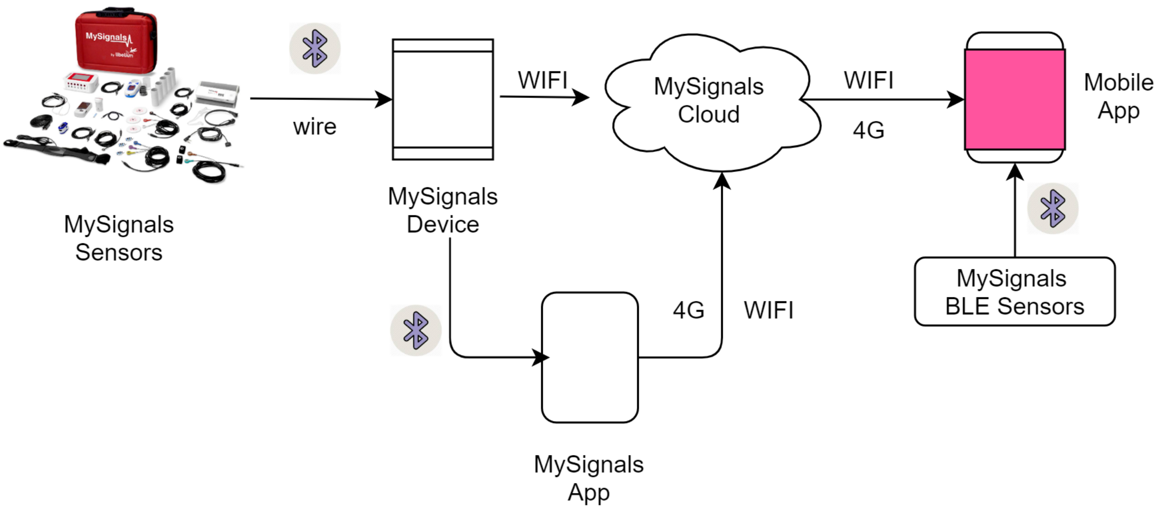


Figure 44: High Level Architecture

The app is built in Microsoft Visual Studio 2019 using Xamarin. The software development stack is shown in Figure 45. Using the same platform and the API for Mysignals Cloud, the values from other sensors stored in cloud are retrieved.

A high-level architecture of the system is show in in Figure 44.The values are measured with wired and BLE sensors. MySignals main device measures the values of wired sensors as well as BLE sensors and upload them to MySignals cloud using WiFi mode of operation. The BLE sensors values can be uploaded using MySignals app also, which uses 4G or WiFi to upload the data. BLE sensors can be directly read by the developed app as well using Bluetooth communication. The data on cloud are downloaded and presented by the mobile app to the users using 4G or WiFi.

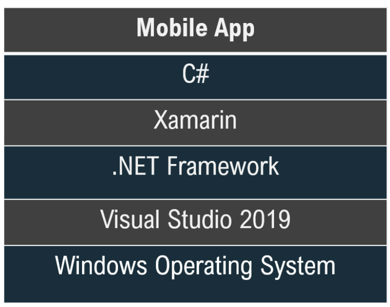


Figure 45: Software Development Stack

7 Test and Results

Below sections present various tests made before and after implementation of the app and their results. Tests were required before implementation to understand how the sensors work and afterwards to check if the developed system meets the functional and non-functional requirements.

7.1 Interpretation of BLE Notifications

As MySignals does not provide with API for App development, it was really difficult to find out which service, characteristic and descriptor gives the values of a sensor. Every service was explored with the help of standard GATT profile reading apps. The apps used were GATTBrowser[64], BLE Analyzer[65], BLE Scanner[66], and Bluetooth Scanner[67]. These apps were used to read the GATT profile of the sensors.

While accessing the BLE sensors for values, it was found that the sensors might not have been built strictly following the BLE protocols. The name of glucometer sensor is “BLE to UART_2” and there is a service called Heart Rate Measurement. This added to the confusion, so, the author decided to check every service irrespective of the service name using all these four apps. The general rule followed is that the **read** or **notification** values should show some changes in the next reading because the values are likely to change in every different tests. If a stream of byte is same in three consecutive readings then that particular service is discarded. After a particular a characteristic is found, which keeps showing different values in each test, the whole stream of bytes was analyzed to find out which byte or set of bytes are giving the measurement values. Below is a description of how values were read for the BLE sensors.

7.1.1 SpO2 Sensor

There is only one characteristic with **notification** property in SpO2 sensor and there are a number of **read** characteristics. After testing each of these characteristics, it was found that only the **notification** property shows a change of value. The notification byte appears as shown in Figure 46. The sensor gives heart rate in beats per minute(bpm) and oxygen saturation in percentage. The values for a person does not show major change for a short period of time. So the values which were close to the values shown on the device were chosen. The fourth byte represents heart rate and the next SpO2 value (Figure 46).

[64]GATTBrowser, https://play.google.com/store/apps/details?id=com.renesas.ble.gattbrowser
[65]BLE Analyzer, https://play.google.com/store/apps/details?id=com.keuwl.ble
[66]BLE Scanner, https://play.google.com/store/apps/details?id=com.macdom.ble.blescanner
[67]Bluetooth Scanner, https://play.google.com/store/apps/details?id=com.pzolee.bluetoothscanner

While displaying, they need to be converted into decimal values from hexadecimal. So the heart rate is 44 (Hex 2C)bpm and SpO2 is 97% (Hex 61).

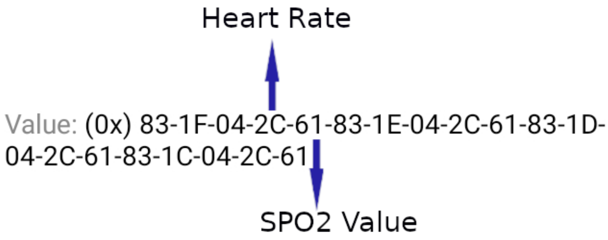


Figure 46: SpO2 Notification

7.1.2 Glucometer

There are five **notification** properties and a number of **read** properties in the glucometer. Each of these were tested using all the four apps mentioned above. No useful information was found with the **read** properties. The first four notifications in the list do not show any **notification** values even after enabling the **notification**. The last in the list shows a stream of bytes as shown in Figure 47. The bytes are continuously streamed in SpO2 sensor as long as the device is on and finger is inside the sensor but in glucometer, the notification is sent only once.

Figure 47: Glucometer Notification

The notification values are sent in mg/dL format but shown in mmol/L in the main device. It was difficult to relate the notification bytes to 5.2 mmol/L(equivalent of 94 mg/dL). But it became easier when the app BLE Scanner did not only show notification but also the unit in mg/dL, while other apps did not show the unit. It was found that the bytes between 3D and 6D give the glucose measurement as shown in Figure 47.

7.2 Testing MySignals Sensors

Before testing the sensors, there is need to understand the Configuration menu which is the first screen when MySignals device is turned on. The menu has four options: Offline mode, Bluetooth mode, WiFi mode and Settings. Bluetooth mode is used to read the signals through MySignals App, which is not required for this project and so not discussed. Offline mode and WiFi mode are used to read the sensor values but with a different purpose. Offline mode is useful in monitoring the values without sending them to server, but WiFi mode also sends the value to the server besides facilitating the offline monitoring. All the sensors have been tested in both Offline and WiFi modes and found that their values can be read in the main device and uploaded to the server.There is an option for EEG also in the “Select Sensors” screen, but the EEG sensor is not available in the provided set. Similarly, there is a port for wired connection for sensors SpO2, blood pressure and temperature but these sensors are BLE and the wired ones for these sensors are not available.

The test results of MySignals presented below would not be necessary but as the testing and configuration is a bit difficult due to inconsistency of results and a need of repetitive trials, the tests below might help further users to understand the sensors and device better.

7.2.1 BLE Configuration

There are some issues with MySignals device while configuring and measuring the values-specifically while configuring the BLE device on the MySignals main device. A BLE device is detected by the main device only if its MAC ID has been properly configured on the Bluetooth settings and this process has a very low success rate. So success rates of the BLE configuration has been tabulated below (Table 4)with a purpose to help the users to use it.SpO2 and temperature(Temp) sensors have been chosen for the test results, however all the BLE sensors have been tested.

Table 4: BLE Configuration

S.No.	Sensor	Paired(Y/N)
1.	SpO2	N
2.	SpO2	N
3.	SpO2	N
4.	SpO2	N
5.	SpO2	Y

(a) SpO2 Configuration

S.No.	Sensor	Paired(Y/N)
1.	Temp	Y
2.	Temp	N
3.	Temp	N
4.	Temp	N
5.	Temp	Y

(b) Temp Configuration

It was observed that success is achieved if device is restarted and BLE devices are configured first before using any features of the devices each time. If the device shows message “Scanning <device name> 10 sec..”, then the device is properly working. Otherwise, it needs to be restarted and tried again. For SpO2 sensor, it did not show any name but just some unreadable characters adding up to the difficulty. In temperature sensor, it showed “MySignals Temp”. However, there were four “MySignals Temp” instead of one. It is also advisable to tap on the device immediately after it shows up or else tapping does not occur and configuration fails.

7.2.2 BLE Measurement

There are also issues while measuring the BLE sensors, sometimes the measurement fails for no reason. Table 5 presents the measurement success rate. SpO2 and Temp sensors were chosen randomly. Measurement of SpO2 shows that it needs frequent restart. Y denotes a successful measurement and N a failure. It cannot measure continuously. There are 8 or 9 consecutive measurements before the device needs restarting. Temperature sensor looks a bit more consistent . But if Temp is turned off and another BLE sensor is measured (blood pressure sensor was used), then Temp sensor is not detected by the main device and a restart is needed.

Table 5: BLE Measurement

S.No.	Sensor	Measurement(Y/N)
1	SpO2	3 N before 1st restart (Main Device)
2	SpO2	1 N, 8 Y, 3 N after 1st restart
3	SpO2	5 N, 9 Y, 3 N after 2nd restart
4	SpO2	10 N after 3rd restart
5	SpO2	3 Y, 10 N after 4th restart

(a) SpO2 Measurement

S.No.	Sensor	Measurement(Y/N)
1	Temp	35 Y before another BLE measurement
2	Temp	30 Y after restart, before another BLE measurement
3	Temp	25 Y after restart, before another BLE measurement
4	Temp	30 Y after restart, before another BLE measurement
5	Temp	30 Y after restart, before another BLE measurement

(b) Temp Measurement

7.2.3 Wired Sensors Measurement

Measurement using wired sensors have the most success rate, but sometimes they also may fail to take the measurement. Table 6 presents the data for the same. Airflow and position sensors were randomly chosen for the test results. Both of them show a continuous measurement without fail. But if a BLE measurement takes place during these measurements, then both of them stop responding and a restart is needed.

Table 6: Wired Sensor Measurement

S.No.	Sensor	Measurement(Y/N)
1.	Airflow	Continuous until BLE measurement
2.	Airflow	Continuous until BLE measurement
3.	Airflow	Continuous until BLE measurement
4.	Airflow	Continuous until BLE measurement
5.	Airflow	Continuous until BLE measurement

(a) Airflow Measurement

S.No.	Sensor	Measurement(Y/N)
1.	Position	Continuous until BLE measurement
2.	Position	Continuous until BLE measurement
3.	Position	Continuous until BLE measurement
4.	Position	Continuous until BLE measurement
5.	Position	Continuous until BLE measurement

(b) Position Measurement

7.3 Performance Evaluation of Mobile App

7.3.1 Android Studio Profiler

An analysis of the app has been done using the android profiler available on Android Studio 4.1.3. Xamarin profiler is available only for Visual Studio Enterprise and not for Visual Studio Community, because of which Android Studio has been used. The option debuggable=true has to be set in the application for profiling. Also, option "Enable developer instrumentation (debugging and profiling)" has to be ticked while releasing the apk. In the mobile device, USB debugging needs to be enabled.

The profiler shows CPU, Memory, Network and Energy consumption of the app. Profiling for each of the functionalities has been assessed to check if there are any abnormal performances of the app. Figure 48 shows profiling of memory, network, energy and CPU while logging in. It can be seen from the graph that at the time of login, there is a surge of Network, CPU and Energy usage while Memory usage is almost constant. After logging in, the consumption of Memory, CPU and Battery is very low. CPU has reached around 20% for a very brief period of time and energy consumption is "Light". Received bytes/sec is higher than sent bytes/sec.

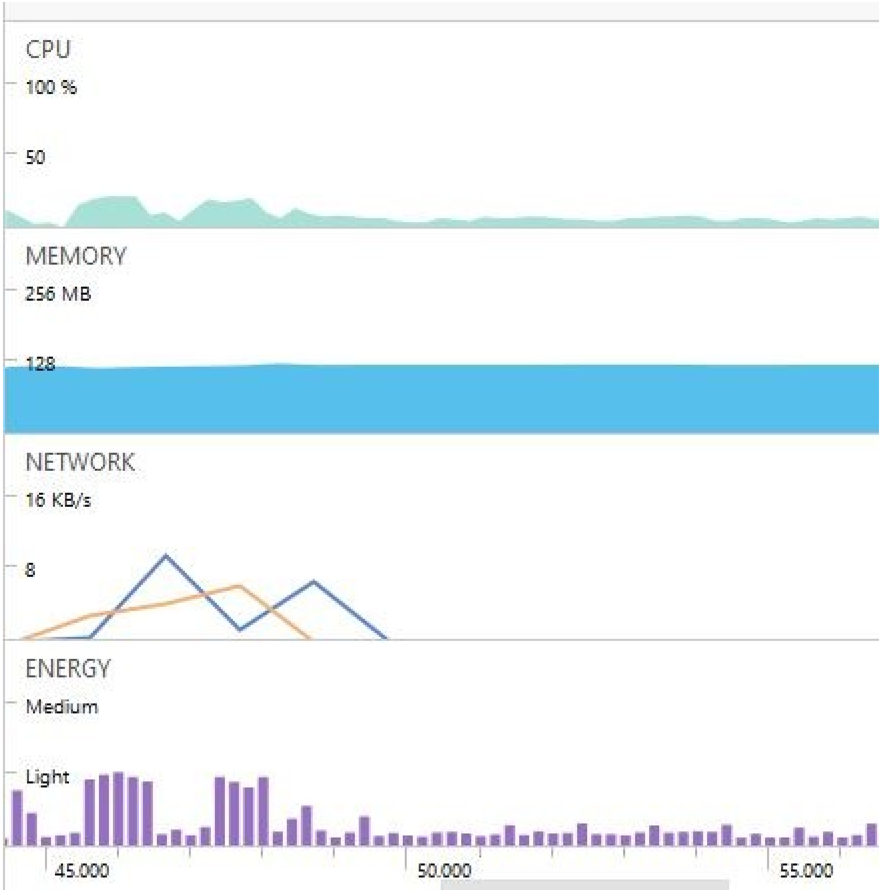


Figure 48: Login Profile

Figure 49 shows SMS profile. For ease of test, time to check the latest values of the most vital parameters temperature, respiration rate, pulse rate and blood pressure is set to 2 minutes. So, every 2 minutes, the system checks these parameters and if one of them is abnormal, sends SMS to the number input by the user. Below Figure shows 2 instances of SMS profiles. There is no clear increase in Memory, CPU or Energy usage while sending SMS, but there is an increase in the Network usage.

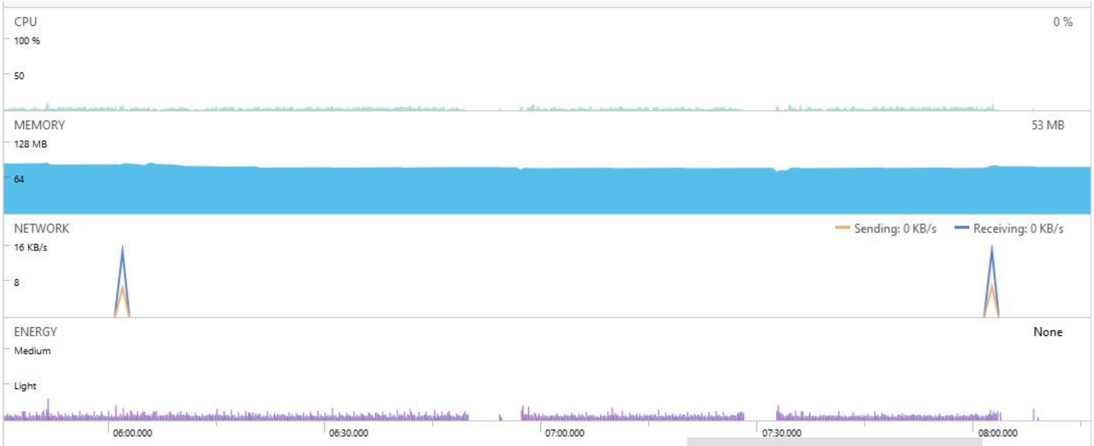


Figure 49: SMS Profile

Figure 50 shows various types of usages when a BLE sensor is measured. There is no significant increase in CPU and Memory usage, and no usage of Network as BLE does not require to use internet, but small rises in Energy consumption at different times of the measurement can be seen.

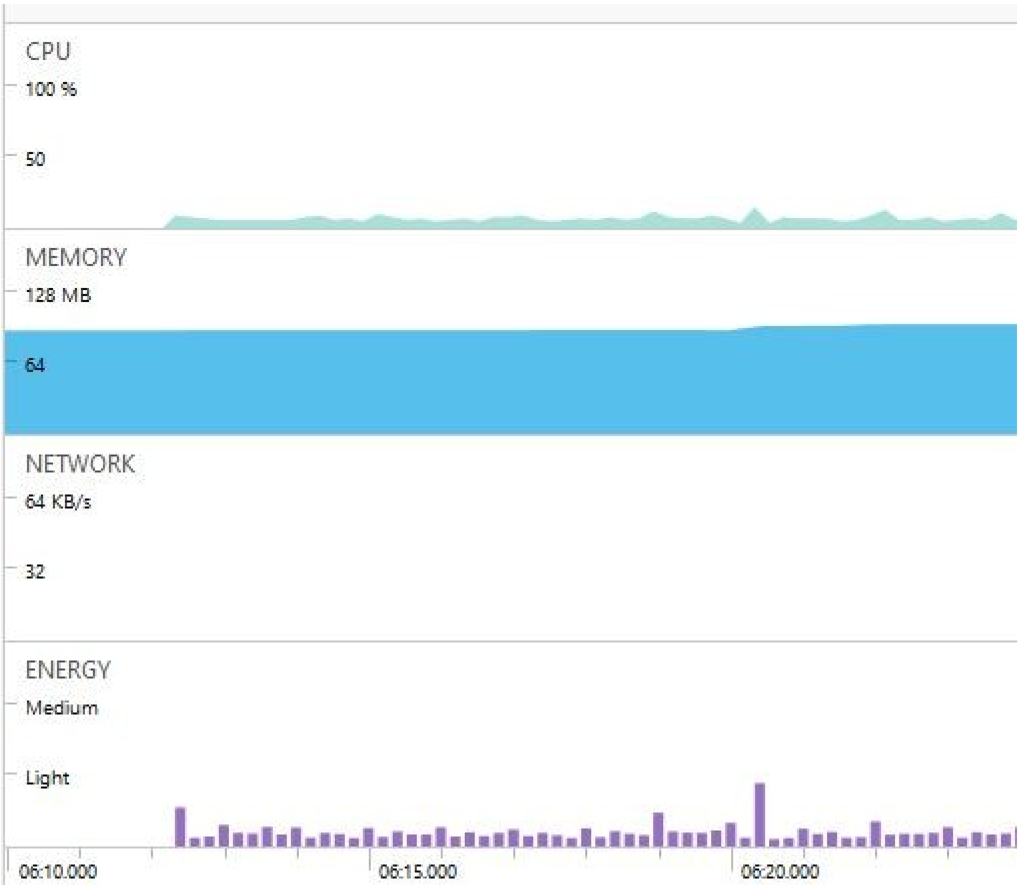


Figure 50: BLE Profile

Figure 51 shows the profile while displaying the values in tabular and graphical form.

There is a clear rise in CPU, Network and Energy consumption. Also there is a rise in Memory usage when dates were chosen. The CPU usage has reached around 22 % and Energy consumption slightly above "Light". The Network usage is clearly more than the usage of Network in any other cases. The first increase in the figure is while displaying in tabular form and the second increase is for graphical form. In both cases there is similar increase of usages.

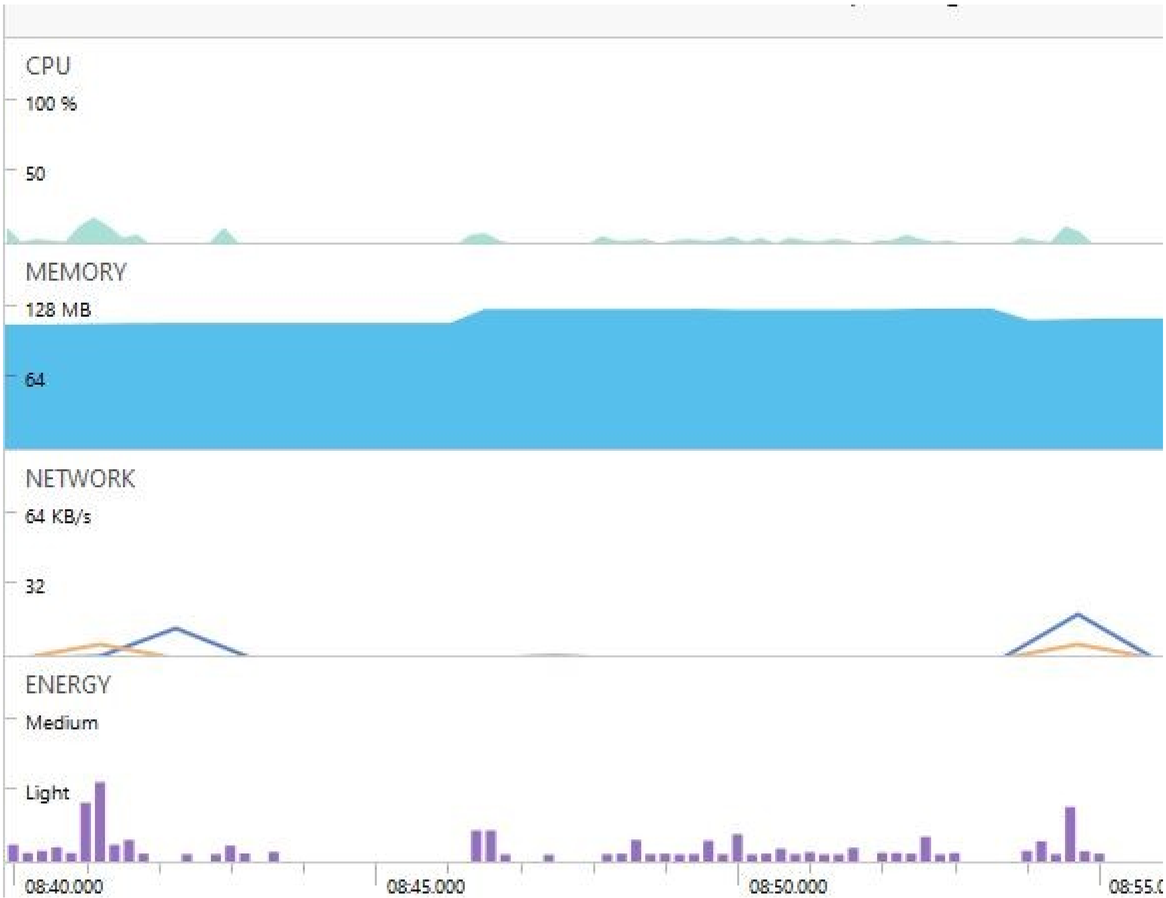


Figure 51: Display Values Profile

Figure 52 depicts profiling when plotting two graphs. There is similar type of increase as in the case of displaying the data. All fours profiling parameters have an increased usage in this case also.

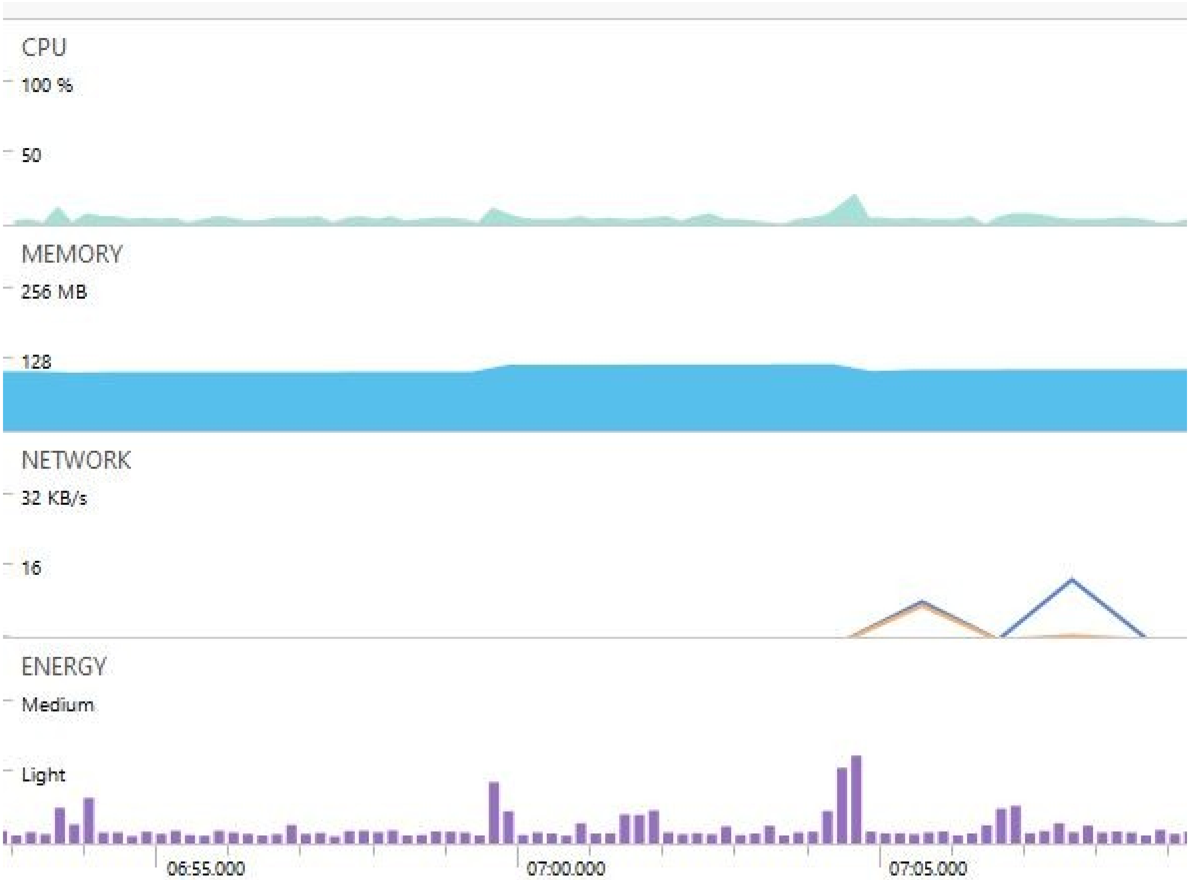


Figure 52: Graph Profile

7.3.2 Manual Test of Pages

Each page of the application has been navigated 10 times to see if it continuously gives the desired results (Table 7). To check if it becomes unresponsive or does not show the values as required, this test was performed. Y indicates the page displayed desired result, N indicates there was some problem displaying the result. As can be seen from the below table, all the pages showed the results without fail, except BLE page which kept on searching for devices failing to list out the devices 5 out of 10 times. Each time it failed, the Bluetooth of the device had to be turned off and on again for BLE page to work properly.

Table 7: Responsiveness of Pages

S.No.	Page/Functionality	Response(Y/N)
1	Main Page	10 Y
2	Display Page (All Sensors)	10 Y
3	Graph Page	10 Y
4	Analyses Page	10 Y
5	Input Page	10 Y
6	Logout Button	10 Y
7	Home Button	10 Y
8	BLE Page	5 Y, 5 N

7.3.3 Steps Counter

Table 8 presents a comparison of the number of steps walked and steps measured by the app. All the tests were done on Samsung Galaxy A20 e but as steps counter was not found on this device, steps counting test was done on Xiaomi Redmi Note 4(Android 7, 3 GB RAM).

Table 8: Steps Comparison

S.No.	Steps Walked	Steps Measured I	Steps Measured II
1	200	175	193
2	400	371	395
3	600	588	598
4	800	801	802
5	1000	1020	1001

8 Discussion

Continuous health monitoring is slowly becoming a part of daily life. One reason is the steady rise in the prevalence of chronic disease for which regular tests and monitoring is very essential. Monitoring ensures that the values of the parameters are normal and an immediate measure is taken in case they go beyond the standard ranges. The second cause is the growing population of the elderly people. With the availability of advanced technology and medicines, the population of old people has been increasing to a number that has never occurred in the history of humankind. These people need a constant care because of which health monitoring has become a necessity. Last is the easy availability of the monitoring devices such as smartwatches and an awareness of people for constant tracking of the health parameters which can have many benefits. These people may not necessarily be suffering from any disease. For such people, monitoring can bring about more health awareness and can create a lasting positive effect on overall health and may serve as a means to decrease the occurrence of chronic disease also.

There are many different applications that can collect and display the bio-parameters for the patients. They have many features like notifications(notifying the users, caretakers of abnormal values), exporting the values , reports, sharing the values among the people with similar health problems, etc. But, none of them, to the best of author's knowledge, has tried to gather many different parameters (temperature, blood pressure, blood sugar, ECG, EMG, snore, airflow/respiratory rate, GSR, SpO2, weight and body position) and present them in an easy-to-understand way through graphs,tables, and deeper analyses. A collection of all the useful parameters into an app and an analysis to make these parameters understandable for the users is what makes it novel and unique than other research projects.

8.1 User Interface

As there are a number of parameters,users interfaces are kept very simple. The main vertical menu shows all the sensors and upon tapping launches the corresponding pages. The page shows the values from a desired date in tabular and graphical form. When the display page is launched, it shows the latest measurement of the sensor without selecting any dates. This is useful for the patient to know their last values of the corresponding measurement. All the readings are actually first sent to the MySignals cloud directly from the main device and the readings are downloaded using MySignals API into the app for display. The BLE sensors (SpO2 and glucometer), can be directly read in the app, without a need to send them to the server. The UI is simple with a list of sensors and tabs at the bottom. The users can see all the sensors in the main screen making it easy to see all the sensors at a glance. A customized display for the main screen would be even better because some of the users may not need all these sensors or may get overwhelmed by a lot of sensors.

8.2 Analyses of Features

8.2.1 Health Status

The users can see the individual values of the body parameters separately, but as there are many parameters, to go to each page and check if their latest values are normal or not will be a cumbersome process. This gave rise to the concept of Overall Health Status which is shown in the main screen of the app. The users are more interested in knowing if their overall health is normal and get notified instantly if there is something serious. To have this facility, the concept of overall status has been implemented which checks if the four important vital parameters temperature, blood pressure, respiration rate, and pulse rate are within the normal ranges or not. The Health Status is green, or red according to the range of these parameters. The algorithm actually checks only four parameters, a better and more reliable approach would be to incorporate more parameters. For example, considering glucose values also for a diabetic patient. The app already has an input page which takes in input that gives more information about the diseases associated with the patient. This page was actually designed in order to have customization in the Main screen and also to include these parameters as well besides the important parameters temperature, pulse rate and respiration rate. Such customization actually increases the reliability of the app, but due to lack of time could not be implemented. Not only for calculating the Heath Status, it can also be used to show the values on the main screen. Besides the important parameters, the display of the values can be customized according to the interests and necessity of the users which will definitely meet customer needs and increase their satisfaction.

8.2.2 Single Parameter

Further, attempts to get more information from the parameters is made by calculating more useful values such as Glucose Variability from glucose level and Heart Rate Variability from an ECG curve. A study summarizes different methods of calculating GV and its link with diabetic macrovascular and microvascular complications, and hypoglycemia (Zhou et al., 2020). There is no fixed standard methods accepted by all to calculate GV. In this project, intra day variation is calculated in the form of Coefficient of Variation.

GV has been considered as a better approach for Glucose control than HbA1c. So, GV can be a very useful tool for doctors to find a better regimen for their patients. Also HRV is an emerging concept which is considered a powerful parameter that can reflect upon overall health status of a person. A higher HRV can be an indicator of higher capacity to stress tolerance and better physical and psychological well-being[68]. There are two methods that have been used in order to calculate HRV. The standard way is to use ECG curve and calculate the variation of the time difference between consecutive heart beats. The other method used makes a non linear regression model to calculate HRV from heart rate (Monfredi et al., 2014 & Kazmi et al., 2016). The latter is not a standard one but it was worth learning and exploring about the method. In case of unavailability of an ECG curve, it can give some guidance if it could be possible to find HRV with other parameters also. HRV calculated and shown in the app (Analyses Screen) is RMSSD value and HRV calculated in Section 6.3.1 is SDRR using ECG curve. Also SDRR has been calculated using non-linear regression. SDRR using regression and ECG curve are 75.73 ms 68.13 ms respectively. They are in a comparable range but this comparison cannot make any conclusion because of many reasons. First reason is HRV from ECG generally uses a very long period of ECG graph (24 hours). In this project it is a graph of 5 secs. This limitations is created by MysSignals measurement also because it creates small graphs of 5 secs to 10 secs even if ECG is continuously measured. Also, the graphs and heart rate are not consistent and accurate. If the measurements were accurate, these short snippets of graph could be analyzed for longer period of time which could give a more reliable conclusion. Second reason is the use of a small portion of the dataset; machine learning could be a better alternative to develop a model which can be more accurate. The dataset from Kaggle is huge which provides test and train datasets, which is ideally for machine learning approaches.

8.2.3 Multiple Parameters

The above two analyses are based on a single variable-glucose level and heart rate or ECG graph. Additionally, the relationship between the parameters can also be used to understand the disease better and make more efficient decisions. For example, instead of just notifying that HR is abnormal, if the related parameters that can cause HR to increase such as temperature or activity (through steps counter sensor) or stress is checked first, it can give more useful information and prevent false alarms.Various relationships between these parameters were studied and simple algorithms were made to find some

[68]https://www.ajphysio.com.au/heart-rate-variability-why-its-important-and-how-to-train-it/ [Accessed 10/05/2021]

robust algorithms specific to some case or scenario. But due to lack of time, no such implementation could be made and as such these studies and algorithms are shifted to Future Work section.

8.3 Analysis of Performance

The performance of the app with respective to the usage of CPU, Memory, Network and Energy has been made for Login, SMS, Display, Graph and BLE sensor measurement. It can be seen from the graph that there is no any abnormal/huge usage of any of these resources during any of these activities. Also, all the resources are minimally used when the app is running without any activities proving that the implementation may not have any unnecessary leakages or activities running in the background that consume resources unnecessarily. Without any activities, the CPU usage is very low (around 5%), battery consumption is way below Light consumption, no Network usage and a Memory usage of around 100 MB. The memory usage could be reduced but, as for android profiling, debugging and profiling option has be to on and this adds to the size of the apk file. The size of apk can also affect the Memory usage[69].If the apk is released without the debugging options, it might help reduce memory usage significantly.

Log in to the app requires the app to load various images in the menu screen, and download data from the server to show in the first screen. This could be the reason why it takes the longest (2-3 secs) to launch. Also, CPU usage is maximum around 22% for about 2-3 seconds. There are peaks of CPU usage in other activities also like while displaying the values but for a very brief period of time. The maximum CPU usage occurs during log in. The maximum Network usage occurs while displaying the values and plotting the graphs because during these activities, the app has to download many values depending upon the date selected and show or plot. During SMS sending, there is a slight increase in Network and no significant increase in any other resources. The reason is it simply checks the fours parameters for latest values which should not take a lot of Network. Memory usage seems to increase only when the date picker is used. The instance where memory has increased is always followed by selection of date(Refer to Figure 51 and 52). BLE does not increase any resource usage but there are some peaks reaching up to Light consumption of battery, the reason of which is unknown.

[69]https://developer.android.com/topic/performance/memory [Accessed 12/05/2021]

8.4 Security

Health data of patients need to be very secured against any unauthorized access. MySignals have documented the following about their security features. (Extracted from MySignals Technical Guide[6])

- Bonding is required when BLE sensors are read by the MySignals main device and the communication is AES-128 encrypted.
- For communication with the cloud, the device uses WPA2 with AES-256 encryption.
- HTTPS is used to transfer data from device to cloud.
- HTTPS is used to download the data from the cloud and show them in the app.

In this project, data are not saved on the mobile device. They are downloaded from the server and presented to the user. Assuming that the user is cautious that they do not leave their mobile accessible to anybody or they are cautious enough about their data being peeked by others when they are using the app, the patient's health parameters are safe. The app and cloud are password protected. HTTPS has been used while accessing the data from server. However, there is an issue with the data of BLE sensors. The BLE sensors are easily read using any types of apps that can read the GATT profile of a BLE device. So, there are chances that someone can read and extract the values of the sensors without the knowledge of the patients. MySignals claim that BLE sensors need pairing between the devices before communication, but their BLE sensors show all the information without pairing. This might be the limitations of the sensor itself. There are many types of pairing methods a BLE can use [70]. It looks like the pairing method used in MySignals is "Just Works" in which there is no need to share any keys to pair and this is vulnerable to many attacks such as passive eavesdropping or MITM (Man in the Middle).

8.5 Other Features

It accurately sends SMS to the numbers inputted for SMS if it finds an abnormal health status. It regularly checks every two minutes (for ease of testing, in real cases it will be different) the latest important parameters and sends SMS if any of these values are abnormal. A more robust approach would be to analyze and include all parameters that can cause serious emergencies and send SMS based on deeper analysis rather than just checking if the values are normal or abnormal.

[70]https://forum.digikey.com/t/a-basic-introduction-to-ble-4-x-security/12501 [Accessed 21/05/2021]

Steps counter sensor on mobile phones have been used to find the number of steps walked. The mechanism used in the project to find number of steps uses the in-built step counter and simply records its values.The steps are registered not only while walking but also if the phone is swayed in the hand or moved from one place to other without walking. A comparison between the steps walked and steps recorded in the app has been made in Table 8, which shows that the steps measured slowly tend to become more than the steps walked. The sensor works based on the motion of mobile phone. So the extra steps may be the false interpretation when phone is moved without walking. At the end of 1000 steps, the sensor readings are 1020 and 1001, which are close to 1000 steps walked. As steps can increase while using the mobile phone also, if there was a mechanism to turn it off while the app is running, it could reduce the chance of measuring the false steps. And when a person starts activities, it could be turned on again.

The app is primarily designed for the chronic disease patients but can be used by others as well. Other scenarios mentioned above are when health workers have to consider the case of drug interaction, in emergency situation and for education purposes. There are many supporting sensors also which can measure different parameters. Let's assume a situation in which a person is suffering from many diseases and medication administered for one disease can affect the other diseases. So in this situation both diseases can be monitored, the effects can be understood and a more effective and balanced treatment regimen can be decided. The second scenario mentions of an emergency situation. If an emergency situation occurs in a remote place from where nearby hospitals are hours away, this system can help the patients by checking their parameters and doctors sitting in another corner giving them advice or medications through the local health care workers. Third is the possible use of the whole system in school as an educational tool. The students can learn a lot of health parameters through the direct use of health sensors. They can learn about different communication protocols, APIs, hardware sensors, cloud and mobile app. It will be a lot of fun for them to learn health technologies by immersing in the whole process rather than just through theoretical concepts. Further implementations need to be done to more suit each of these scenarios.

There could be a few more considerations which can help the app to be more practical. Let's understand this with a few examples. A person "X" is regularly monitoring his parameters using this system. The system shows that his health is absolutely fine, there are not any abnormal values. The person may get an impression that he is absolutely fine and he may skip regular doctor visits also. So, people using this system should be made aware that regular health checkups are still necessary and the system is just complementary to it. For such system to stand alone, there is a long way to go. A second case may be with the persons who have abnormal values compared to the standard but still are normal for them . For example, another person "Y" is also using the system regularly. The system always shows her heart rate 50 bpm which is clearly low compared to standard 60 bpm but can be absolutely normal for many people. As the system shows it as a warning, she may try to get in contact with the doctors frequently, being worried of her condition. Such false alarms and unnecessary visits can be reduced by a model for user where the parameters for a particular person can be observed for a certain period and the normal values can be found. Besides, awareness among the patients can also help.

9 Future Work

The project collects many different bio-parameters in an app and displays them for the users in a simple and comprehensible way. It does not simply show the values of the parameters but takes it further to present the values in a way the users do not have to analyze them but understand them just at a glimpse.

The project can be further extended in a number of ways.

- Diagnostic tool: As there are a number of bio signals available, using the relationship between various parameters it may be possible to make diagnosis of diseases. If an abnormal value is seen then instead of just notifying about that particular value, a check can be made if it is related to other parameters. It will help to find the root cause or the main parameter because of which the other parameters might have been disturbed. This is, however, possible if the sensors measuring the parameters are accurate or approved by the concerned organizations. One of the major limitations of this project is that the sensors used do not give consistent and correct readings.

- Graphs: The graphs implemented now allows the users to choose between the parameters to plot. But rather than plotting any random parameters, it would prove more beneficial if a parameter chosen can automatically choose the related parameters and show them on the plot. This will enhance understanding of the users as they can see which parameters are related to each other and what effect can one parameter have on the other. Eventually the users will be aware of the root cause of the abnormal values and can work towards achieving the required goal.

- Outbreak Detection Mechanism: Various studies have shown that there is a relationship between diabetes and infections (Trivedi, 2003;Botsis et al.,2007;Lauritzen et al., 2011; Botsis & Hartvigsen, 2010;Coucheron et al., 2019). Woldaregay has designed an outbreak detection system which can successfully detect an infection outbreak during its incubation period. The author has been able to detect an infection in its incubation period before it spreads widely (Woldaregay, 2016).This is based on the fact that diabetics have an increased blood sugar when an infection occurs. So, if an area has many patients with increased sugar, then it is likely to be infected with some virus or bacteria. This knowledge has been exploited and and a system has been designed such that it collects the data from various places at different times, make spatio-temporal analysis of the collected information and predicts if an area might be infected. This implementation detects infection based solely on the increase of blood sugar level, while in reality an increase in sugar might be due to various other factors as well, like *Holiday Effect*. The author mentions blood pressure, white blood cell counts and temperature are also directly related to infection. So if these parameters are available along with blood sugar values, the false detection of outbreak can be stopped. This project can be integrated into Woldaregay's project in order to have a more realistic outbreak detection mechanism as this project can provide with temperature and blood pressure readings required to check if an infection has occurred.

- User's Model: The values of the vital parameters can differ from person to person. The values can be inside the standard normal values but can be different for different persons. Everyone can have their own normal values. Various machine learning techniques can be applied to model a user governing all the available parameters. Once the model is prepared, the same can be used to find the deviations instead of using the standard normal values. This will be more accurate in finding any abnormalities than making a comparison with the same standard values for everyone.

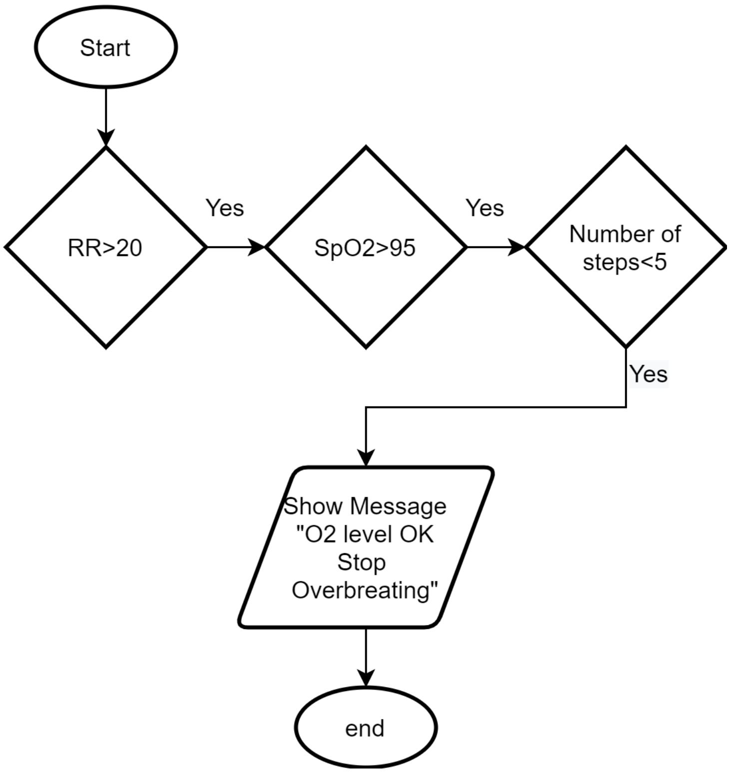
- User-Customized App: As there are many different vital parameters, all the users may not be interested in all the parameters. For example, if a user has a heart problem, then he may only want the app to show the parameters related to heart and the most vital ones, rather than all the parameters like GSR, spirometry, etc. Even though these parameters will be measured and stored in the cloud and analyzed in the background but they may not be in the menu items of the app. Such customization will actually serve better user interface and lead to more customer satisfaction.

- Educational Tool: As the project uses a lot of sensors, it can be used as an educational tool to teach about these sensors. The students will have the opportunity to learn about the essential sensors which are used for monitoring purposes. Besides, they can try to learn how these sensors work and how the signals can be captured and sent to the server. They will learn the API for BLE sensors and also the ones when communicating with the server.

- App for iOS and Windows phone: Xamarin framework was chosen for this project because the framework provides us with the necessary platform to develop an app for Android, iOS and Windows phone at a time. The code can be shared among all three platforms. There can be, however, some platform specific implementation too which is not shareable. Only the Android app has been tested for this project so, app can be developed using the same code for iOS and Windows too in future.

- Suggestive Tool for other Diseases: Besides chronic diseases, it can be used for many other diseases as well-to detect and make suggestions. Below points show relations between various parameters which can be useful for analyzing the patient's conditions. They have been studied and some algorithms have been made from them.
  - SpO2 and Hyperventilation: Gilbert discusses relation between hyperventilation and blood oxygenation (Gilbert, 2012) . SpO2 value has been used to show the hyperventilating patients that there is no need to take in more oxygen. An algorithm has been made, if there is hyperventilation detected, it checks the SpO2 values and suggest that there is no need to hyperventilate. But if both values are abnormal then it indicates a warning on the display (Algorithm 3).

Algorithm 3 Hyperventilation

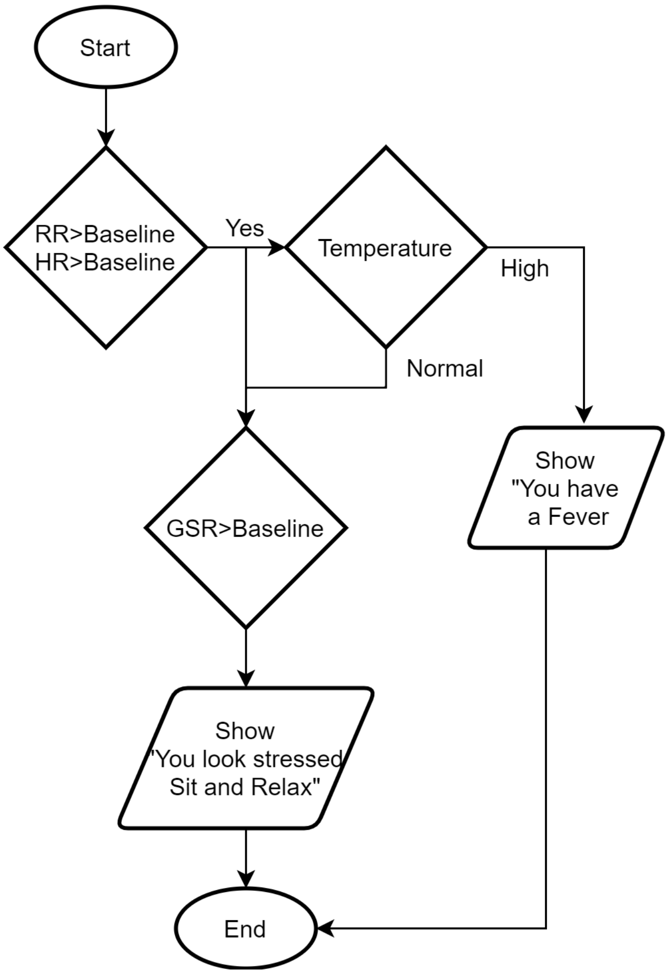


  - HRV and Hypoglycemia: HRV is linked with hypoglycemia (Pertseva et al., 2018;Bekkink et al., 2019). They have shown that hypoglycemic events lead to decrease in RMSSD(Root Mean Square of the Successive Differences). So decrease in RMSSD value over a period of time can be used to predict that patient may suffer from hypoglycemia.

- HRV, HR and Stress: A relationship between mental stress and HR, HRV has been studied (Taelman et al., 2009). The study shows that short term HRV (determined by pNN50) decreases with increase in stress. pNN50 is NN50 divided by total number of NN intervals. NN50 is the number count of successive heartbeat interval exceeding 50 ms.[71]
- GSR and Blood Pressure: A study has tried to find if the patient is under stress with the help of GSR and Blood Pressure (Fernandes et al., 2014). Mere GSR cannot predict stress because GSR increases during exercise also. An increased GSR but same BP may indicate stress. The same idea can be implemented which can more accurately detect stress than GSR alone.
- Respiration Rate and Stress: A relation was found that RR increases with stress (Vlemincx et al., 2011). They have used attention and arithmetic tasks to induce stress. Their focus is on respiratory variability that it needs to be considered when assessing effects of emotion on respiration rather than merely analyzing respiration rate.
- Temperature, Respiration Rate and Heart Rate: Kirschen et al. show how temperature, HR and RR are linked to each other (Kirschen et al., 2020). When temperature rises, there is a corresponding increase in HR and RR. This relationship can been used to have a more clear picture of the health status. For example, if there is an increase in HR or RR without increase in temperature then it may be due to stress but otherwise it may be due to fever. Also pedometer can be used in the analysis. If there is rise in HR and RR with increase in number of steps then it is normal otherwise it may be due to stress (Algorithm 4). Baseline here indicates the normal range for a particular person not standard values.

[71] https://help.elitehrv.com/article/344-hrv-metrics-pnn50 [Accessed 19/05/2021]

Algorithm 4 Stress



10 Conclusion

Health monitoring improves overall health of a patient. It has become an utmost necessity for the chronic patients. Chronic patients and old people are rapidly increasing and thus a robust health monitoring system has become quintessential. There are many apps and system which can monitor patients but they are mostly specific to a particular disease. A system which incorporates many different sensors and can thus provide more health information about the patients besides the disease of interest is not found. The extra information can help to make more effective treatment decisions and become aware of the other parameters also, which in fact can contribute to an improved health in the long term.

The inclusion of many different parameters has given rise to a few more concepts. First is, how the parameters are be presented so that it is easy for the user to grasp and understand. This has been achieved by keeping the user interface very simple. A menu lists out all the sensors and launches the corresponding pages. All the sensors and features are visible in the main screen and the tabbed page; this must make it easy for the users to see the inclusion of many sensors, graphs, inputs, BLE sensors, and analyses. The implementation of Health Status and the use of colors for normal and abnormal values must make it easy for the users to understand their health at a glance and grasp their values without difficulty.

Second is the facility to plot graphs between any two parameters. This was made for the users to understand how one value can affect the other and can help to have an insight to the cause of the disease. Ultimately, it can bring about behavior change. For example, a diabetic patient can plot weight and blood glucose and understand how their weight is affecting their diabetes. Now, it can plot only two parameters. It can be improved to plot 3 or more parameters and the inter-related parameters when plotted can give meaningful information.

Third is the analyses of the parameters. There are two parameters that have been analyzed. One is the glucose level and the other is ECG graph. Through glucose values, Glucose Variability is calculated. GV is taken as a better measure than HbA1c to decide a treatment regimen. Also, it has been linked with many different complications and hyperglycemia. There are many different ways of calculation of GV. In this project, intra day variation has been calculated using Coefficient of Variation. Now, it only shows the values of GV but further implementation can be done which can give some advice to the users based on the value and type of GV that is calculated. Similarly Heart Rate Variability is another measure which is a very useful parameter that can tell about the ability to cope with stress and overall health. There are frequency domain and time domain calculations of HRV. Time domain calculations RMSSD(Root Mean Square of the Successive Differences) and SDRR(Standard Deviation of the RR intervals) have been made. It is difficult to find any standard normal values for HRV. HRV has been calculated using the ECG curve and also using an exponential relation between heart rate and HRV. A non-linear regression analysis was used to fit the curve and predict HRV based on HR. This is not a standard method and was an experiment to find HRV with some alternative methods also. Only a snippet of ECG curve has been used to calculate HRV, this needs to be improved in further implementation by using graph of a longer period of time because the standard way of calculating HRV uses a 24 hour period.

All the health parameters are extracted from the server and displayed.However, BLE sensors SpO2 and glucometer can be directly read also. The requirement of the project was to make make it as automatic as possible, but the app does not read the value automatically. There is a need to tap once for the BLE sensors to send the values. This can be improved and made fully automatic in future implementations..

Other features include SMS and steps counter. SMS is sent if the system finds any abnormal parameters from among the four important values blood pressure, temperature, respiration rate and pulse rate. It makes check after certain time interval and does the necessary function. Steps counter has been implemented which simply registers the count of the in-built step counter of the device.

The project has implemented an app that integrates many different parameters and show them in an easy-to-understand way. The interface is kept simple so that it can be used for a long time by the chronic patients specifically for the diabetics and blood pressure patients. The use of different colors, Health Status in the front screen can help them comprehend their health status at a glance. GV and HRV were implemented keeping these patients in mind. The use of graph to plot the desired parameters can give them more insights to their health conditions.

The project has been successful in designing and implementing an app that can be very useful to the chronic patients, in emergency situations, for patients with two or more diseases which can affect each other, and for educational purpose for students. The project can be extended in multiple ways, and also by including more behavior changing principles, a robust application can be developed to suit the needs of different types of patients.

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Appendix 1

Python Program to receive Notifications from BLE Devices

```
from bluepy import btle
import binascii
import time

class MyDelegate(btle.DefaultDelegate):
    def ___init___(self):
        btle.DefaultDelegate.___init___(self)
    def handleNotification(self, cHandle, data):
        print("A notification was received:", binascii.b2a_hex(data))

p = btle.Peripheral("00:A0:50:04:18:2b")#spo2 sensor MAC ID
p.setDelegate( MyDelegate() )
# Code to turn notifications on
svc = p.getServiceByUUID("49535343-fe7d-4ae5-8fa9-9fafd205e455")
ch = svc.getCharacteristics()[0]
print(ch.valHandle)
#turns on notification
p.writeCharacteristic(ch.valHandle+1, b"\x01\x00",withResponse=True)
time.sleep(12.0)#wait for the value to be stabilized
p.waitForNotifications(1.0) #waits for one notification
```