Smart Remote Patient Monitoring for Congestive Heart Disease.

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A progress report submitted for Postgraduate Project B

in partial fulfilment of the requirements for the degree of

Master of Information and Communications Technology.

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April 2021

Abstract

The rise of internet has enabled new opportunities for latest technologies and has allowed IT solutions to be implemented in various areas. An online telehealth solution which is totally automated has a high scope, however there are not many products available on the market that offer these features, this opens numerous opportunities for designing and implementing a full-fledged telehealth solution. This solution will use different sensors that will communicate with an edge divice which will be connected to the cloud, it will enable the user to see their health metrics via a mobile app. It also will use some already existing machine learning techniques to detect several chronic health conditions and anomalies.

1. Introduction

The internet has caused many traditional businesses and industries to go online, and the coronavirus pandemic has further accelerated the process (PricewaterhouseCoopers n.d.). As the COVID-19 pandemic has affected around 144 million people worldwide with causing over 3 million fatalities as of April 2021 (Worldometer 2021), one industry which needs to go online is the healthcare industry. This will enable the remote monitoring of the patients without them visiting the hospital. This project will create a platform on which multiple chronic conditions can be monitored. It will use a 3 layered architecture which will include IoT sensors which will collect patient data, IoT edge devices that will process the data, do machine learning edge inference, and provide monitoring of the data for the users on their mobile devices. the cloud will be used to do the machine learning training, storing some of the edge data based on predefined rules and further analytics. We will use congestive heart failure as a use case to demonstrate this architecture.

2. Objective

In a traditional healthcare setup, every stakeholder faces several challenges, especially the patients with chronic health conditions, as they must visit the hospital multiple times a week and must do the sign in procedure each time they visit. This takes ample of time and energy of the patient. Even if the patients visit multiple times a week there is no solution to continuously monitor their condition. Our solution will take all these challenges under consideration. And implement fully automated system considering all the stakeholders.

- The system will collect the patient's health related data with the use of body sensors.
- It will use edge devices to collect the data from the sensors.
- Time series sensor data will be stored in a database within the edge device.
- The user's health metrics will be accessed through an app on the mobile device.
- Rule based analytics will be done to the edge data.
- Machine learning will be used for complex data analysis with edge Inference.

- Feedback with the help of notification will be given to the user.
- Detected anomalies will be sent to the doctor.
- The machine learning model will be trained in the cloud.
- The same architecture could be used for detection and monitoring of multiple chronic diseases however we will use congestive heart failure as a use case for demonstration purposes.

The system will be built and tested in 500 days after which the base architecture can be used to deploy multiple machine learning algorithms as per requirements of the disease being monitored. As the system will use the AWS cloud services it can be expanded to millions of users in a short amount of time.

3. Related works

With heart failure, the physicians are being challenged with the ever-changing scientific evidence of the condition, new drugs and increasing complexity of the Heart Failure management (Choi et al., 2020) However, there are some already researched solutions that can be looked upon.

- **Edge Intelligence for Connected In-home Healthcare-** The solution by (Zhao, Haddadi and Barnaghi, 17AD) provides a base architecture that contains couple of sensors to track user's heath related activities. All this data can be collected and analyzed. Identification of heath related incidents within the data can be done, with various predictive analysis algorithms. The cloud is used for training the machine learning models, however with the risk of security of data in transit, user data will be kept local by just doing edge inference at the edge. This architecture can be seen in **Figure 1**.

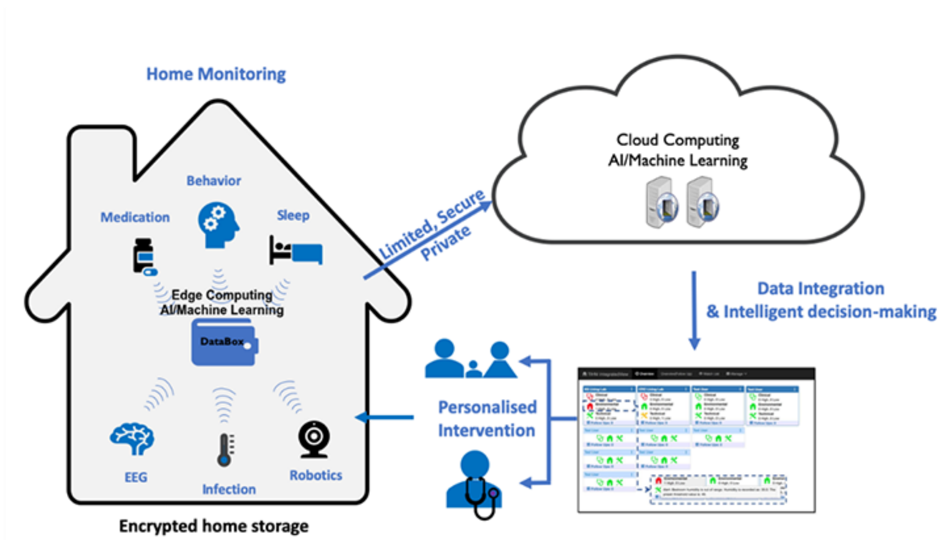


Figure 1: Edge Intelligence for Connected In-home Healthcare.

- **A Smart Service Platform for Cost Efficient Cardiac Health Monitoring-** This solution by (login.ezproxy.uws.edu.au, n.d), provides a concept for monitoring and analyzing various heart related diseases such as Coronary Artery Disease, Congestive Heart Failure, and atrial fibrillation. It makes the use of IoT sensors and artificial intelligence to achieve this. As shown in **Figure 2**, the patient's data is collected in the data accusation phase, this data is stored in the database. then it is analyzed in deep learning phase and alerts can be generated on basis of the machine leaning results which can be give as a feedback to the patient with the help of notifications.

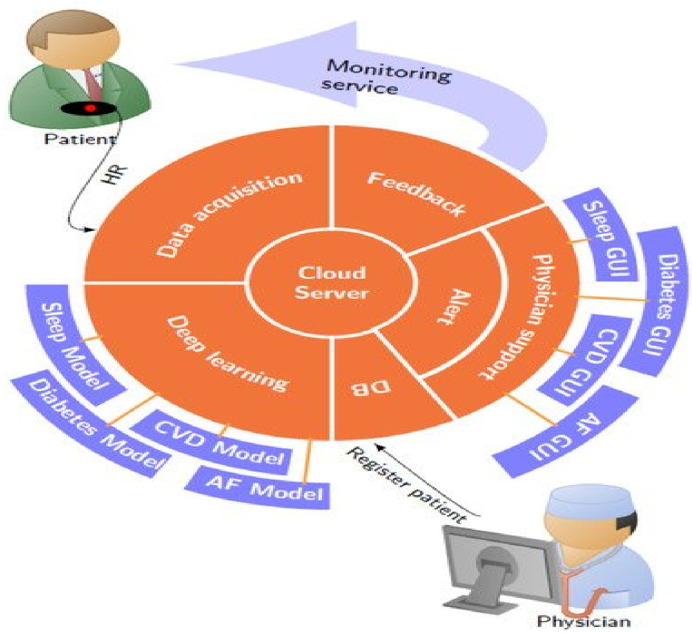


Figure 2: Smart Service Platform for Cost Efficient Cardiac Health Monitoring.

Medical sensors available in the market to collect data regarding congestive heart failure.

Purpose of the product	**Sensor name**	**Features**	**Size**	**Connectivity**	**price**	**API Toolkit**	**API platform**
Checking ecg	Withing's bpm core	Provides medically accurate results on your phone,	15.7 cm x 19.5 cm	Wi-Fi	540 AUD	Withing's SDK	IOS/Android
	HealthyPi v4	Can collect ecg, spo2 and body temperature by on a raspberry pie	26 cm × 17 cm × 6.5 cm	Wi-Fi, Bluetooth	250 AUD	Rest API	IOS/Android
Blood pressure monitoring	Withing's bpm core	Provides medically accurate results on your phone,	15.7 cm x 19.5 cm	Wi-Fi	540 AUD	Withing's SDK	IOS/Android

	Withing’s bpm connect	Provides immediate feedback on the device, has a secure data storage and a rechargeable battery.	5.99 cm x 5.49 cm x 15.49 cm	Wi-Fi	180 AUD	Withing’s SDK	IOS/Android
Heart rate	Withing’s bpm core	Provides medically accurate results on your phone,	15.7 cm/6. x 19.5 cm	Wi-Fi	540 AUD	Withing’s SDK	IOS/Android
	Withing’s bpm connect	Provides immediate feedback on the device, has a secure data storage and a rechargeable battery.	5.99 cm x 5.49 cm x 15.49 cm	Wi-Fi	180 AUD	Withing’s SDK	IOS/Android
body weight	Withing’s Body+	It is a scale which can measure highly accurate body weight and also body fat, water percentage, bone/muscle mass.	32.7cm x 32.7cm x 2.3 cm	Wi-Fi	170 AUD	Withing’s SDK	IOS/Android
Blood glucose	Dexcom g6	It sends the glucose readings to your smart devices every 5 minutes, it is water resistant and is easy to insert.	1.8in x 1.2in x 0.6in	Bluetooth	350 AUD	Dexcom API	IOS/Android
	Zimmer and Peacock's glucose sensors (pH, lactate, potassium, hydrogen peroxide)	Continuously Monitors blood glucose levels	-	Bluetooth	$220	Digi-Key's APIs	IOS/Android
Temperature body/environment.	Withing’s thermo	It has 16 infrared sensors which ensure that the obtained result is accurate. For measuring body temperature.	11.6 cm x 3.3 cm	Wi-Fi	180 AUD	Withing’s SDK	IOS/Android
	HealthyPi v4	Can collect ecg, spo2 and body temperature by on a raspberry pie	26 cm × 17 cm × 6.5 cm	Wi-Fi, bluetooth	250 AUD	Rest API	IOS/Android

	Sonoff SNZB-02	Can monitor indoor temperature and humidity	2 in x 1.8 in x 0.7 in	Zigbee	16 AUD	Sonoff API	IOS/Android

Table 1: Medical sensors available in the market to collect data regarding congestive heart failure.

There are several sensors present in the market to measure all kinds of heart related parameters however we need the sensors which have an API, which will enable us to link the sensors up with our edge device. For this some of the sensors that collect the major heart related parameters are mentioned in **Table 1**. appropriate sensors from this table will be chosen for our implementation.

Artificial intelligence solutions available online that can detect heart related anomalies.

AI Solutions	Algorithms used	Measuring parameters	Available Code
Heart failure diagnosis	Classification and Regression Trees for Machine Learning	electrocardiogram	("Ubiquitous-Computing-Lab/AI-CDSS-Cardiovascular-Silo")
Time Series Anomaly Detection	LSTM Autoencoders	electrocardiogram	("Time Series Anomaly Detection Using LSTM Autoencoders with PyTorch in Python")
rnn-based-af-detection	LSTM Autoencoders	atrial fibrillation	(Shenfield)
Detection of CHF	Unsupervised machine learning	electrocardiogram	("Detection of Congestive Heart Failure Using ECG")
ecg-mit-bih	Unsupervised machine learning	electrocardiogram	("Physhik/Ecg-Mit-Bih")
Smart heart health monitoring based on heart rate signals.	Neural networks	Heart rate	(Ramshur)

Table 2: Artificial intelligence solutions available online that can detect heart related anomalies.

The **Table 2** mentions some artificial intelligence solutions already available on the internet which are used for the detection of anomalies related to heart disease. We will select one of the algorithms for implementing it on our system.

4. Methodology

The designed solution will take all the challenges mentioned above under consideration to provide a seamless remote healthcare solution. It will collect the patient's health data via sensors, the edge divice will store this data and perform rule-based analytics and machine learning inference on the data. The cloud will be used for training the machine learning model. The users will be able to monitor their health data with the use of the mobile app. The designed system shown in **Figure 3**. It uses the architecture by (Zhao, Haddadi and Barnaghi, 17AD) as the base architecture. It also uses some ideas from (login.ezproxy.uws.edu.au, n.d.).

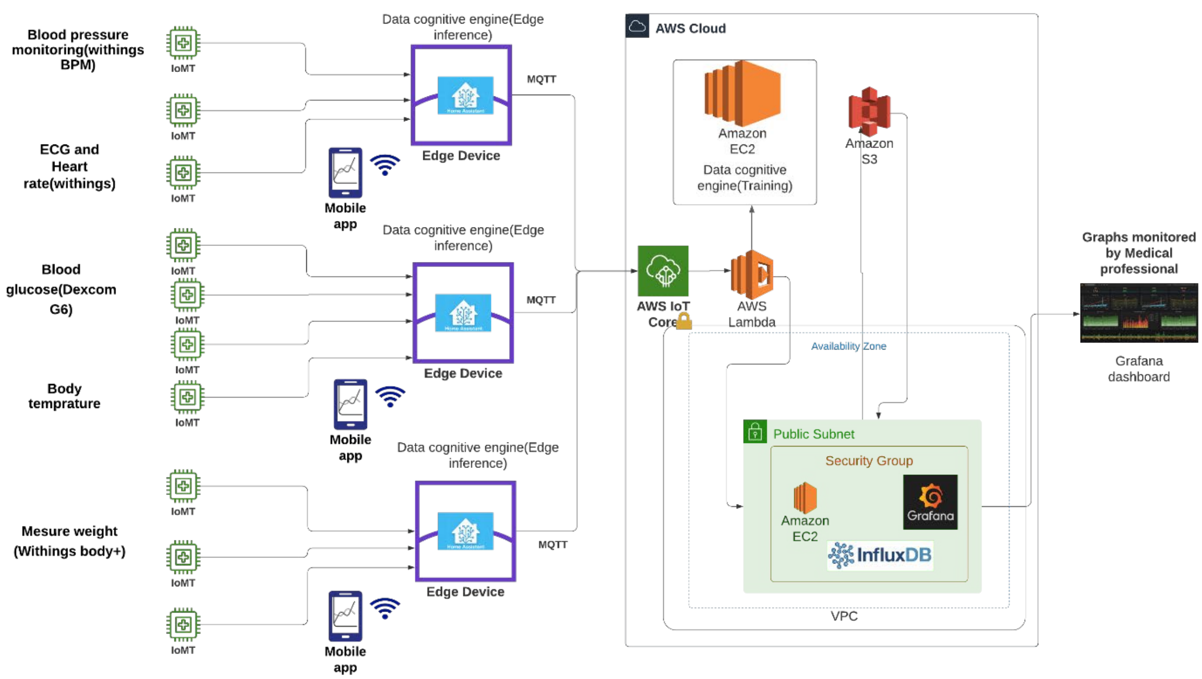


Figure 3: Smart Remote Patient Monitoring for Congestive Heart Disease Architecture.

IoMT sensors- these are the sensors that collect user's heart health related parameters, the ones which could be used with our solution are mentioned in **Table 1**. From these sensors we are using the Withing's BPM core and Sonoff SNZB-02 shown in **Figure 4**.

Figure 4: IoMT sensors.

Edge device- we are using a Raspberry pie as an edge device with home assistant deployed over it. Home assistant shown in **Figure 5**, is an open source solution for integrating a number of IoT sensors from different manufracturers with a single device. This will collect all the sensor data and store it in its internal database by which simple visualization of the data can be done.

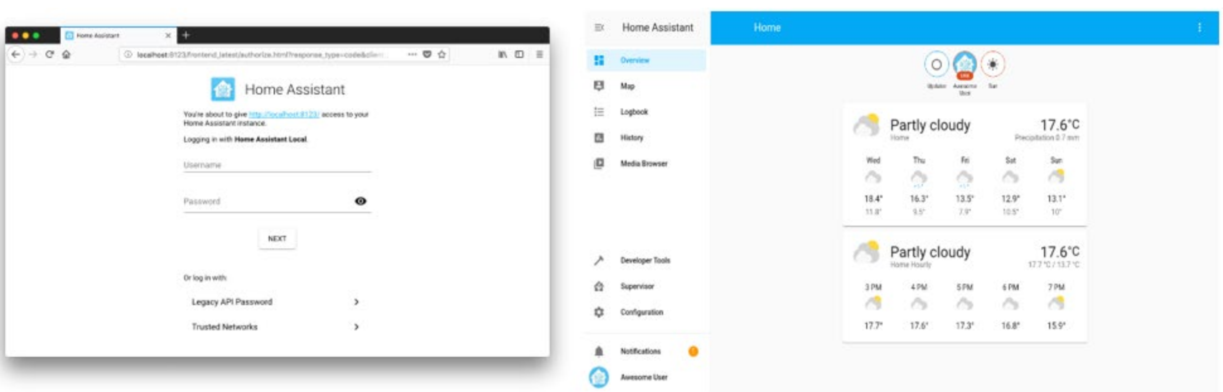


Figure 5: Edge device.

Event based rules- event based rules can be set in home assistant, with home assistant automations. An example for this is shown in **Figure 6.** rules can be set according to our requirements so when a value goes beyond a set threshold it will trigger the notification to be sent.

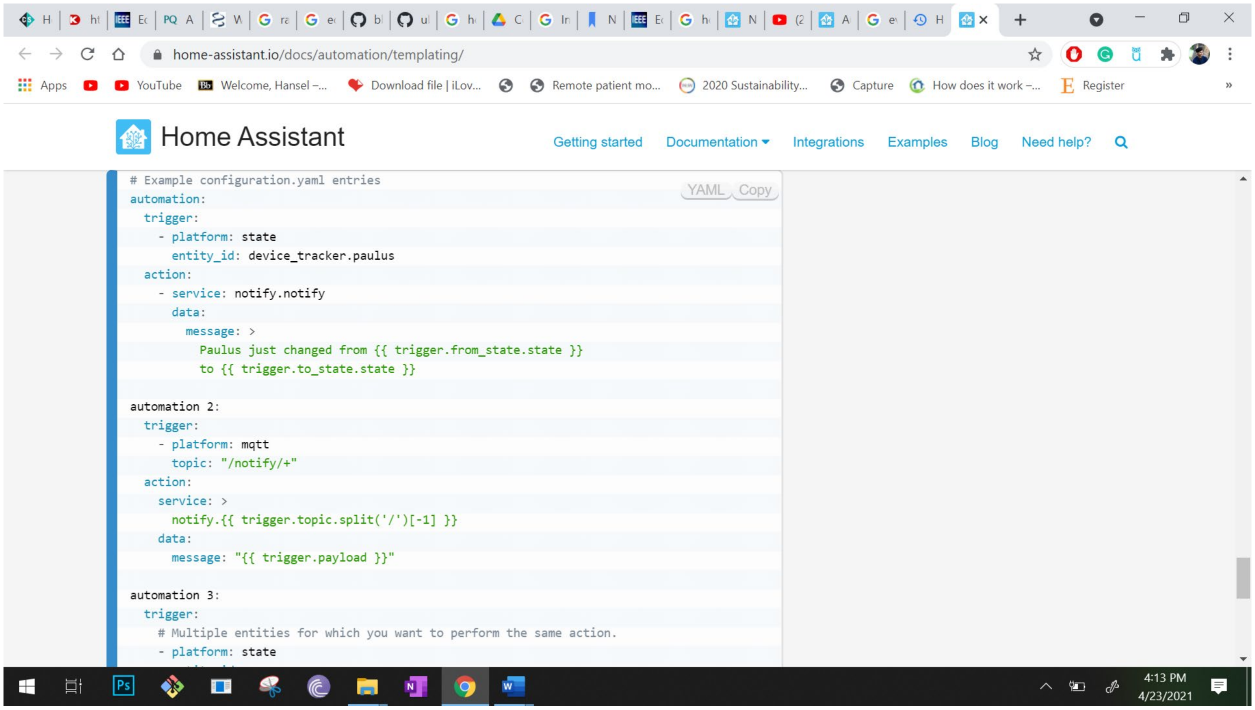


Figure 6: Event based rules.

Artificial Intelligence solution- several Artificial intelligence techniques that use heart disease parameters are mentioned in **Table 2**. we will use Time Series Anomaly Detection which uses LSTM Autoencoders, as this works with time series ECG data it will work best for our solution. It detects 5 types of data as shown in **Figure 7** and tells if the data is normal or has anomalies in it. The training of the model is shown in **Figure 8**, but for our solution the training of the model will be done in the cloud, as it is resource intensive and hence cannot be done on the edge device. The testing of the model with some sample data is done in **Figure 9**. in our solution this will be done in the edge section.

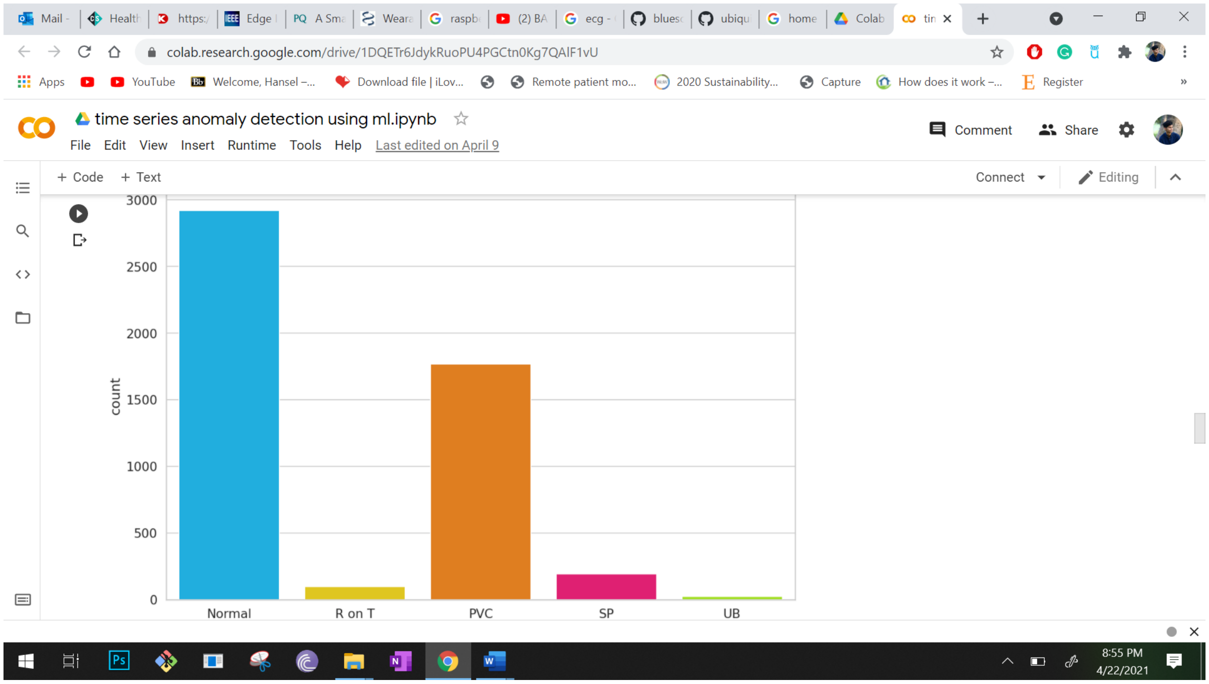


Figure 7: Five types of data detection.

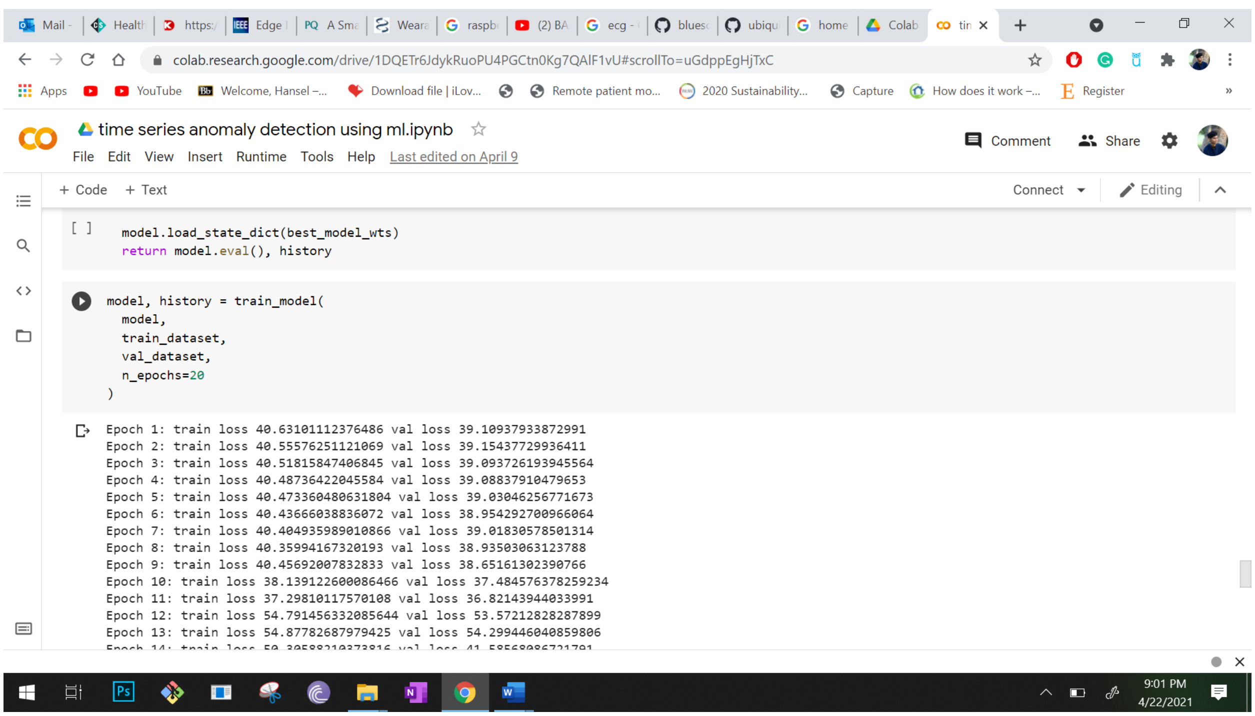


Figure 8: Training the AI.

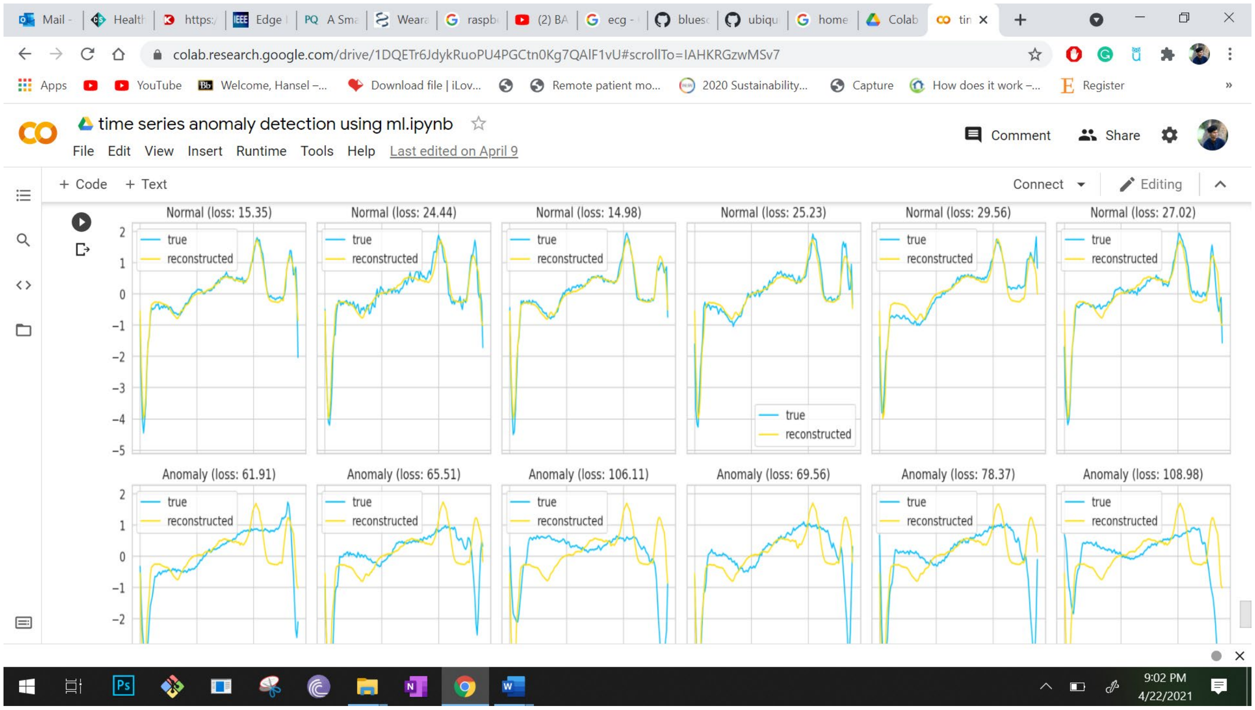


Figure 9: Testing the AI.

Mobile app- as shown in **Figure 10**. the mobile app enables the patients to monitor their health metrics on their phones. It can show basic graphs of the patient's health data that is collected by the sensors. The mobile app will receive a notification whenever the value set in the rule goes beyond the set threshold or whenever an anomaly is detected. Notifier integration in home assistant will be used to achieve this which is mentioned in **Figure 11**.

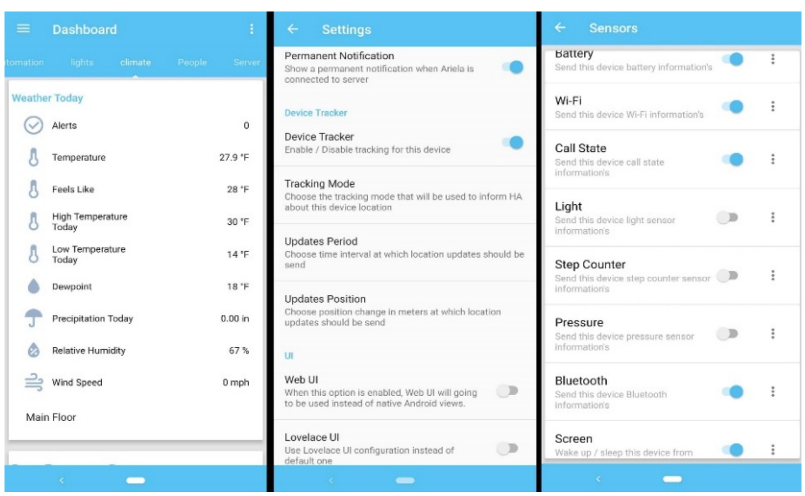


Figure 10: Mobile app.

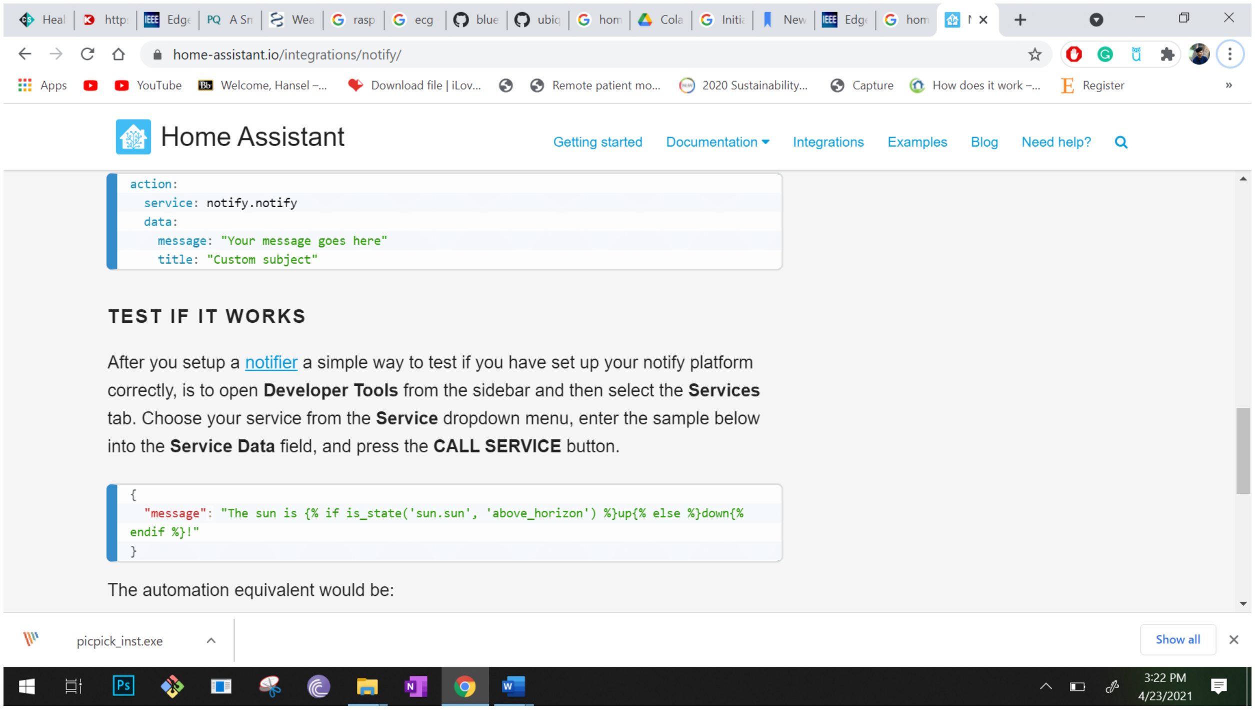
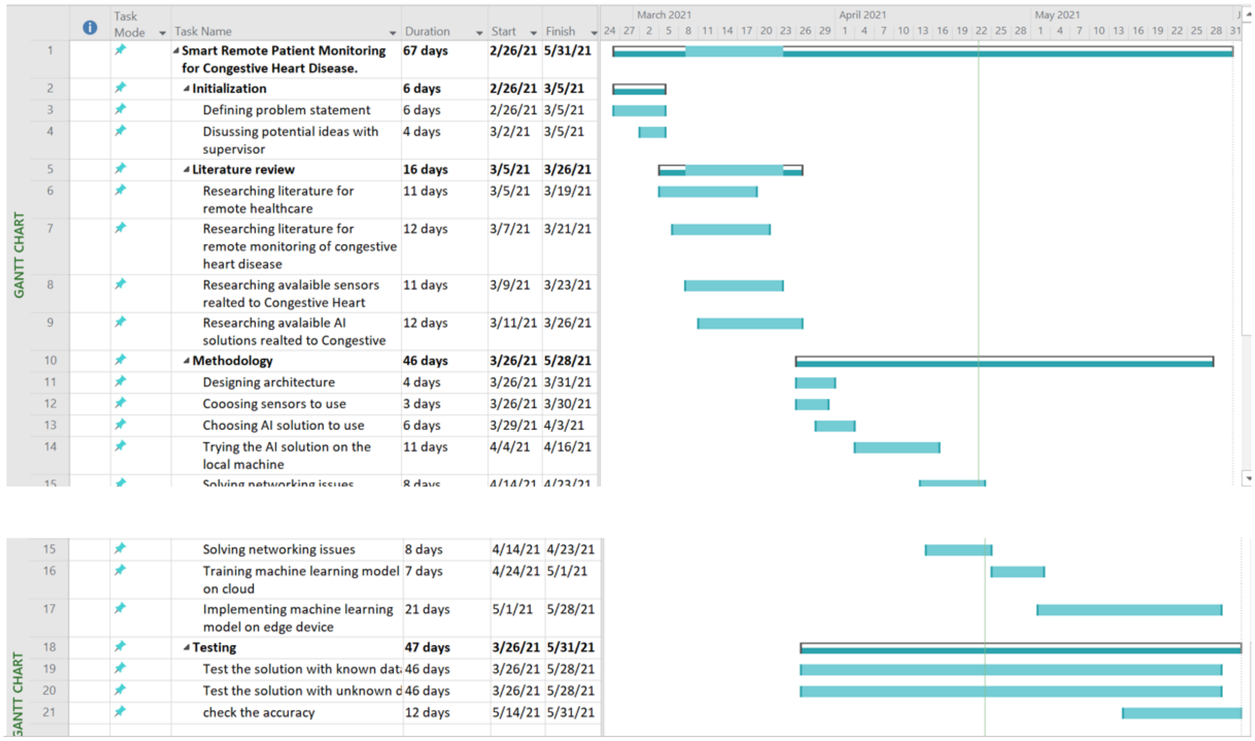


Figure 11: Mobile notification.

5. Program of work

The Gantt chart in **Figure 12**, shows the workflow of the project and has different phases. initialization that includes finding problem statement. Literature review includes researching various existing solutions to gather ideas it also includes researching about available sensors and AI solutions. The methodology includes the implementation of the project and the testing will happen while finishing each implementation stage.



	Task Mode	Task Name	Duration	Start	Finish
1		Smart Remote Patient Monitoring for Congestive Heart Disease.	67 days	2/26/21	5/31/21
2		Initialization	6 days	2/26/21	3/5/21
3		Defining problem statement	6 days	2/26/21	3/5/21
4		Disussing potential ideas with supervisor	4 days	3/2/21	3/5/21
5		Literature review	16 days	3/5/21	3/26/21
6		Researching literature for remote healthcare	11 days	3/5/21	3/19/21
7		Researching literature for remote monitoring of congestive heart disease	12 days	3/7/21	3/21/21
8		Researching avalaible sensors realted to Congestive Heart	11 days	3/9/21	3/23/21
9		Researching avalaible AI solutions realted to Congestive	12 days	3/11/21	3/26/21
10		Methodology	46 days	3/26/21	5/28/21
11		Designing architecture	4 days	3/26/21	3/31/21
12		Cooosing sensors to use	3 days	3/26/21	3/30/21
13		Choosing AI solution to use	6 days	3/29/21	4/3/21
14		Trying the AI solution on the local machine	11 days	4/4/21	4/16/21
15		Solving networking issues	8 days	4/14/21	4/23/21
16		Training machine learning model on cloud	7 days	4/24/21	5/1/21
17		Implementing machine learning model on edge device	21 days	5/1/21	5/28/21
18		Testing	47 days	3/26/21	5/31/21
19		Test the solution with known dat	46 days	3/26/21	5/28/21
20		Test the solution with unknown d	46 days	3/26/21	5/28/21
21		check the accuracy	12 days	5/14/21	5/31/21

Figure 12: Gantt chart.

6. Conclusion

As the covid-19 pandemic is spreading through the world, there is an urgent need for a remote health monitoring system. Considering the current situations and other traditional healthcare problems, we have proposed a fully automated remote healthcare solution which uses IoT sensors and edge devices to collect data and to do edge inference. The AWS cloud will be used for training the machine learning models and storing the data.

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