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Classification of Abnormalities in ECG using Machine Learning

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Abstract:

Continuous health tracking using implantable and portable medical devices with cellular networks is envisioned as a transformative healthcare solution. Rapid advances and in electronics and sensors provides low power remote monitoring medical devices and machine learning methods to classify the abnormalities in the monitoring parameter. However, primary issues faced by the remote monitoring devices are storage memory battery and optimal processor load. This paper presents an internet of things based health parameter monitoring system for Ambulatory electrocardiogram (ECG) recorders, which are increasingly in use by people suffering from cardiac abnormalities. However, the ECG signal acquired by the ambulatory recorder is influenced by motion artifacts induced by any Body Movement Activity (BMA). In the proposed methodology, the Heart Rate Variability method combined with Modified Support Vector Machine (MSVM) based Machine Learning algorithm are used to analyze the abnormality of the acquired ECG signal. The ECG signals are simulated from the standard database and the proposed methodology is applied to the ECG signals. The results shows the proposed methodology able to extract the data from ECG to identify the

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abnormality using HRV parameters and continuous remote monitoring.

***Keywords**: Modified Support Vector Machine, Internet of Things, Heart Rate Variability, ECG signal, remote monitoring.*

I. INTRODUCTION

In healthcare and wellness monitoring industry, Internet of Things (IoT) plays a major role in effective health data collection and sharing paradigms for customized health monitoring system. IoT driven health care monitoring systems, provide remote monitoring of the patients, individuals and elderly people, for cardio vascular disease, diabetes, Low / High blood pressure, Body temperature, fall detection. The system also improves the quality care of monitoring and ease the physicians to monitor the patient's vital signs continuously [14].

Cardiovascular diseases are leading cause of death globally and it is one among the diseases which required a continuous monitoring for early detection. This 90% of the disease is preventable and the earlier detection of this disease leads to better treatment for the patient [14]. Cardiac arrhythmias (CAs) are highly predictive indicators of cardiovascular diseases and of potential associated deaths. The classification of arrhythmic beat provides some valuable details on human cardiac disorders. In the past and recent research, morphological analysis with electrocardiogram (ECG) as a base was used to determine arrhythmias with the help of more computational elements [17].

In the prediction of cardiovascular disease (CVD) events in both young and old populations, ECG abnormality plays an important role. As the ECG abnormality is an intermittent symptom, the beat of arrhythmia will not occur in a short period of time. This causes the hospital's ECG diagnosis to really be limited [6]. Three types of ECG solutions are feasible, which are as follows: 1) those that can store data to be diagnosed offline after completion of data collection; 2) those that use network connection to provide real-time diagnosis and 3) those that perform real-time diagnosis within the system itself [5].

Several research studies have documented remote ECG monitoring with wireless technology integration with mobile devices / Portable Device Assistance (PDAs). Wireless technologies include Bluetooth, WiFi, Radio Frequency Identification (RFID) and ZigBee modules to enhance a patient's health. The use of wireless technology makes it possible to create a remote monitoring system targeted at the mass market. Due to wide spread internet connections, the IoT infrastructure available in rural and urban area offers an excellent opportunity to enhance and broaden smart and connected health applications that concentrate on individuals. IoT based ECG monitoring may play an important role in improving the availability and quality of health care [7].

To detect the abnormalities in the ECG waveform various manual methods implemented by

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the physicians. Due to advancement in the electronic and computing devices, various computational methods are used and implemented in the computing devices for classification of the abnormalities in the ECG waveforms. In recent years, machine learning and deep learning has been applied to ECG signals in on board processing for monitoring and classification purpose. In medical devices, sending the raw or unprocessed data to cloud is not preferred because, it will be affected by data transfer limit and latency in transmission. So, processing the data on sensor is preferred [3].

Most wearable sensors need to sustain power consumption at or below milliwatts (mW) to keep the battery life fair. Due to data accumulation in the accumulator and the movement of data from and to the memory for processing will drain the battery (because of hundreds of mW will be used) as it is needed for interfacing the deep learning model. Therefore, a machine learning algorithm, without too much data storage can handle real-time processing in applications [3].

II. LITERATURE SUREY

Portable and wearable ECG device that can be placed behind the ear to detect the Pulse Transit Time (PPT) developed by Qingxue Zhang et.al, used machine learning framework to predict the heart beat from ECG signal besides the noise produced by motion artifacts. Xiaochen Tang et.al showed patient dependent rotated linear-kernel support vector machine classifier to identify Arrhythmias and executed the algorithm as an on-sensor machine learning solution. The wearable device, which they developed used to sense the ECG, PPG signals and 21 features were extracted from two signals for arterial stiffness evaluation using proposed machine learning algorithm. The Joseph J. Oresko et.al, developed a smart phone based realt time ECG monitoring device and implemented machine learning feedforward multilayer perceptron (MLP) artificial neural network (ANN) to classify the abnormality of the ECG signal. Sandeep Raj et.al developed remote cardiac activity monitoring system. The system is incorporated with the support vector machine algorithm to classify the ECG signals. Ahmed Faeq Hussein et.al showed the Heart rate Variability (HRV) method to identify the abnormality in the ECG signal. In their proposed method, HRV algorithm runs on ECG node system and the classified data are stored in the cloud. Mohamed Elgendi et.al developed a device to detect the stress of driver using ECG signal and machine learning.

In this paper, we present a wireless critical parameter monitoring system that measures ECG signal. We apply the machine algorithm using MATLAB and Heart Rate Variability (HRV) methods to detect abnormality in the ECG signal. Then the ECG and HRV parameters are stored in the cloud through Internet of Things. From the cloud the physician can continuously monitor the health of patient.

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III. PROPOSED METHODOLOGY

The flowchart of the proposed system shown in the Fig. 1. , the system consist of 32 bit microcontroller with WiFi feature which able to monitor the patient's vital signs simultaneously. The ECG signals are acquired, processed and transmitted by the microcontroller. The acquired ECG signal is noise removed and wavelet transform applied to identify the R peak. Using the HRV algorithm, RMSSD value for the measured ECG is calculated. Then, the ECG signal and RMSSD values are transmitted to cloud.

In the virtual server, the vital parameters like ECG signal and RMSSD are stored and the data management are done in the virtual machine itself.

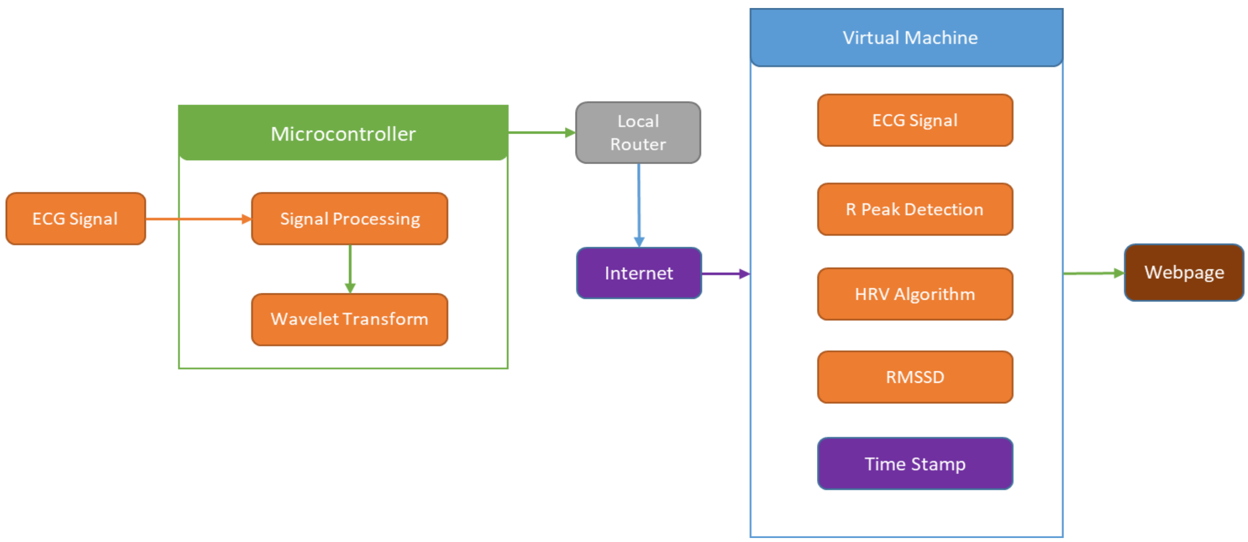

Fig1: Block diagram of proposed methodology

A. R Wave extraction from ECG using wavelet transform

There are two significance for using wavelets as general feature detectors. The wavelet converts signal elements into various frequency bands, allowing the signal to be viewed more sparingly. And the second significance is, a wavelet, which resembles the element you are attempting to detect, can also be found in the wavelet transform. The 'sym4' wavelet is found to be the similar type with QRS complex, which make it to be good choice for the detection of QRS Complex.

In the MATLAB software, the wmpdictionary which is a tool used for the extraction of QRS complex from the ECG wave. The term 'sym4' which is used in wmpdictionary denotes the Daubechies least-asymmetric wavelet in which it had 4 vanishing moments. These vanishing moments are at Level 5.

The full overlap discrete wavelet transform (MODWT) was used to boost the R peaks which are present in ECG signal (waveform). The MODWT, which manages random sample

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sizes, is an undecimated wavelet transform as shown in Fig. 3.

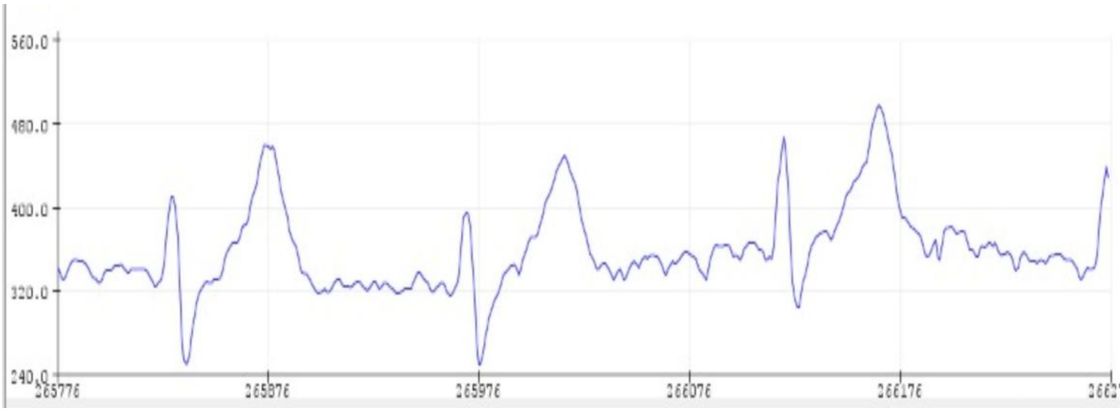

Fig 2: ECG signal simulated from the database

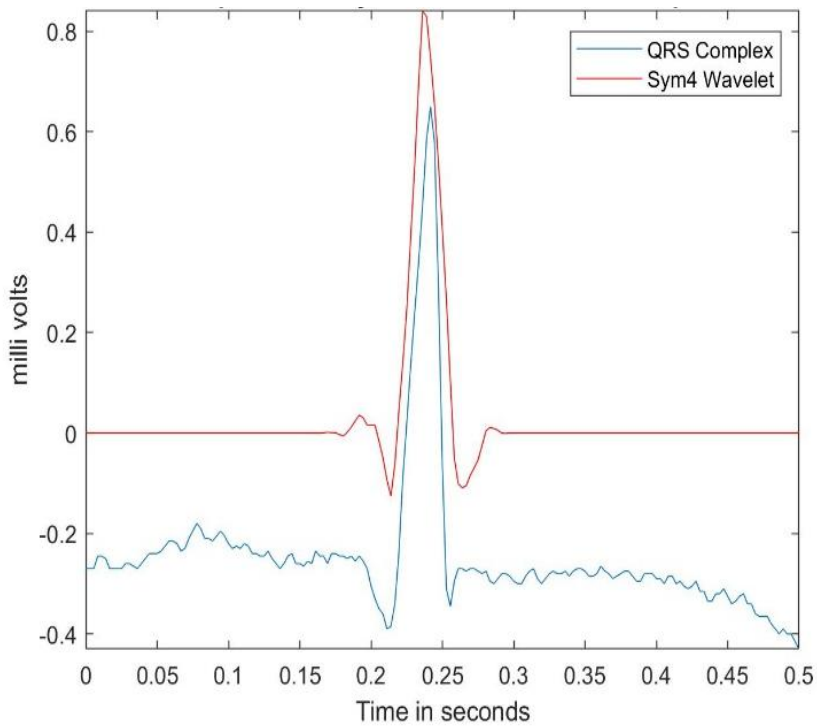

Fig 3: Overlap of Sym4 Wavelet signal on the QRS complex

The number of R peaks is detected using 'findpeaks' function in the MATLAB as shown in the Fig. 4. The number of R waves are summed and the data are given to the HRV algorithm to detect the abnormality of the ECG signal.

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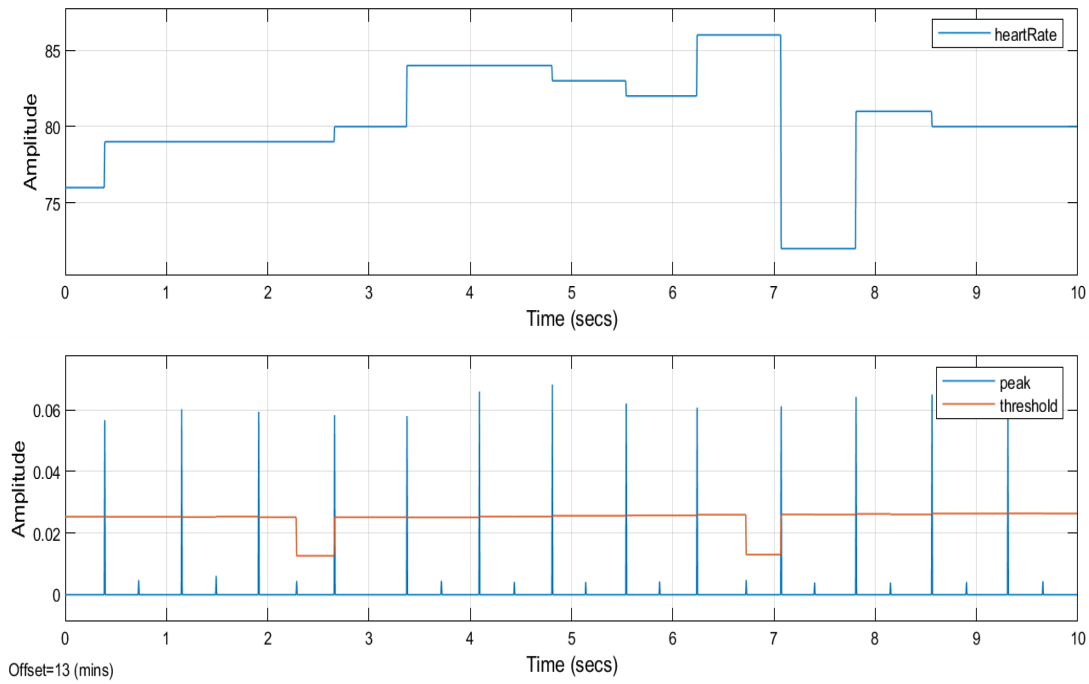

Fig 4: R peaks detection by Wavelet Transform

B. Data Transmission to Cloud Storage

The ECG signals are simulated from the physionet.org database are used in the microcontroller to transmit the ECG processed signals to the cloud storage. In this paper, we used local virtual machine and apache 2 as the server. And then Maria DB as the for the cloud storage. The databases are modified using the phpMyAdmin software to store the ECG signals as per the required format as shown in the Fig 5.

The algorithm developed in the MATLAB are programmed to the microcontroller using autocode generation. In the virtual machine HRV algorithm were developed to identify the RMDSS value of the transmitted ECG signals to classify the abnormality of the heart function. The website user end are developed by php programming using the local virtual machine.

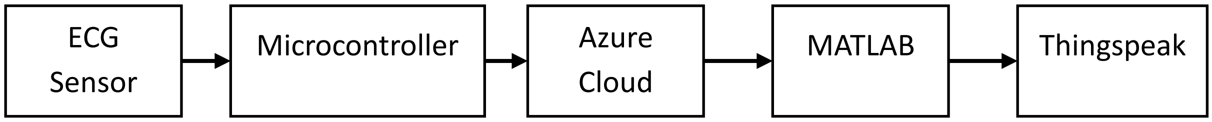

Fig 5: Dataflow from Sensor to Thingspeak Visualization

C. Heart Rate Variability Measurements

The HRV analysis method consist of time and frequency mode analysis. The key

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divisions for the measurement of HRV are either the use of time or frequency. Time-domain methods mean calculating the number of beats within a span of time, on the other hand frequency-domain method measures the sum of low frequency as well as the high frequency beats which exist. In Time domain, the important point to remember is that the field from which the values for measurement are taken is the "R" of the complex [12]. So, “RR interval” may be defined as the distance between the success “R” of the complex in milliseconds. It can also be denoted as “NN interval”, if the rhythm or a heartbeat correspond to the normal one.

The common time domain approach called Root Mean Square of Successive Differences (RMSSD) is the single most widespread way to evaluate HRV. This is the Root Mean Square between each heartbeat of successive differences. Standard Deviation of Normal to Normal (SDNN) and Standard Deviation of the Average of NN intervals (SDANN) are the other methods related to time-domain approach which are used for the calculation of HRV. The standard deviation of all RR intervals (difference between the successive heartbeats, or the QRS complex 'R') is measured as SDNN. It is relatively easy to quantify and provides an accurate measure of HRV and parasympathetic behaviour (important for large-scale computation).To identify the normal ECG range of HRV parameter, the researchers compared the patients HRV parameter values with those of average people. Table 1 defines the normal values of the HRV parameters, which were calculated during normal activities [9].

TABLE 1. HRV parameters ranges

	HRV parameters	Units	Value Range
Time Domain	SDNN	Ms	62-101
	SDNN index	Ms	11-48
	RMSSD	Ms	19-75
	HR	Beats/min	51-105
Frequency Domain	LF	ms^2/Hz	293-1009
	HF	ms^2/Hz	183-3630

D. Machine Learning

The human Electrocardiogram (ECG) signals are classified using two different classifiers namely wavelet time scatter and a modified support vector machine (MSVM). In

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the former method, data will undergo a series of transforms, nonlinearities and averaging which in turn produces the representation with low variance. This method will yield the representation which are not sensitive to the input signal's shift. Due to this, the class discriminability will be left undisturbed.

Here, the data are collected from the three different set of people namely, people or group with disease named cardiac arrhythmia and the second set includes the people with the disease named congestive hear failure and last set include the normal people having regular rhythm in heart (normal sinus rhythm). Here, the 162 recording of ECG had been picked up from the three different databases under the cluster named PhysioNet. The three databases in PhysioNet includes, MIT-BIH Arrhythmia Database, MIT-BIH Normal Sinus Rhythm Database and The BIDMC Congestive Heart Failure Database which will corresponds to the people selected above.

There are 96 ECG recording which are taken from the Arrhythmia database and 30 from the Heart Failure database and 36 from Normal Rhythm database. Here, the aim is to train the model or the classifier to classify the signal corresponding to the normal people and one with the diseases.

For that, the entire datasets have be divided into two parts. One will be used for training and the other will be used for testing. For making it to be a random division, the helper function is used which will divide the datasets randomly without any logics. It will only get the percentage as an input for dividing the datasets.

The output or the result from the helper function will contain two datasets which will contain the same labels as the parent, or the original dataset had. All the elements in the dataset will also have the same labels as before in the class which corresponds to that row of the data matrices. For training the model, the datasets are divided into 70% percent and 30% percent in which the former datasets will be used for training and later will be used for testing.

	B	N	T	VT
B	27	1	0	0
N	0	8	0	0
T	0	0	11	0
VT	0	0	0	0

True Class

Predicted Class

Fig 6: Confusion matrix for Machine learning shown in MATLAB

As shown in the Fig 6., there is approximately 98% accuracy in classifying the signals. From the confusion matrix, we came to know that the signal from Heart Failure dataset has been wrongly classified as Arrhythmia signal. Remaining signal are classified as expected which shows its accuracy.

IV. HARDWARE SETUP

In our patient monitoring system, to measure the ECG signal, we implemented the AD8232 ECG sensor. The sensor placed on the human body using the adherence aluminum electrodes. It has three electrodes which had a position on left and right chest and lower right abdomen.

And as the sensor placed inside the cloths, the environmental parameters like sunlight, wind and lights will not affect the accuracy of the sensor. The hardware setup is shown in the Fig. 7. ECG sensor connected to the 32 bit microcontroller through I2C communication. The address of the sensor and the baud rate are configured in the controller itself.

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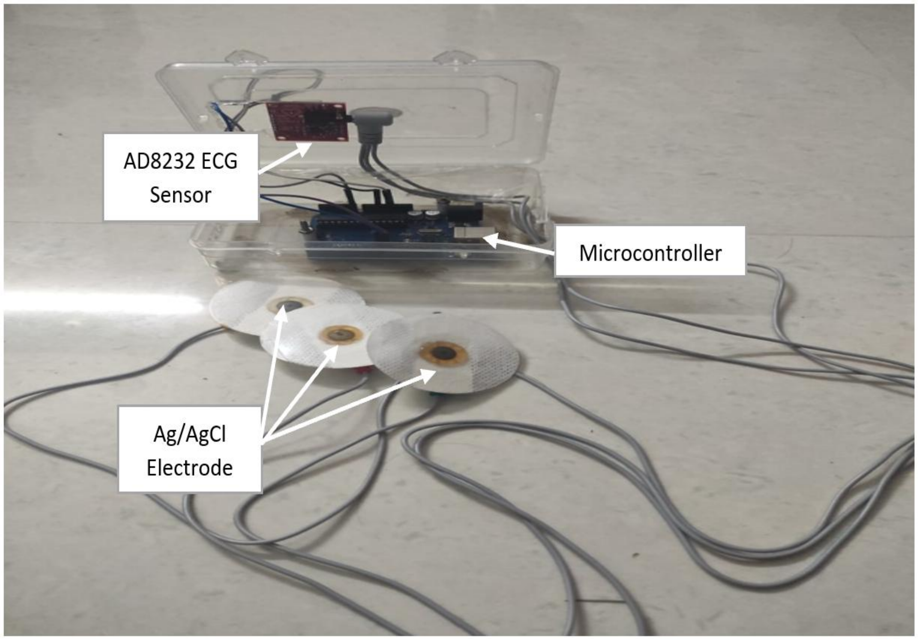

Fig 7: Hardware Setup for ECG Wave Extraction

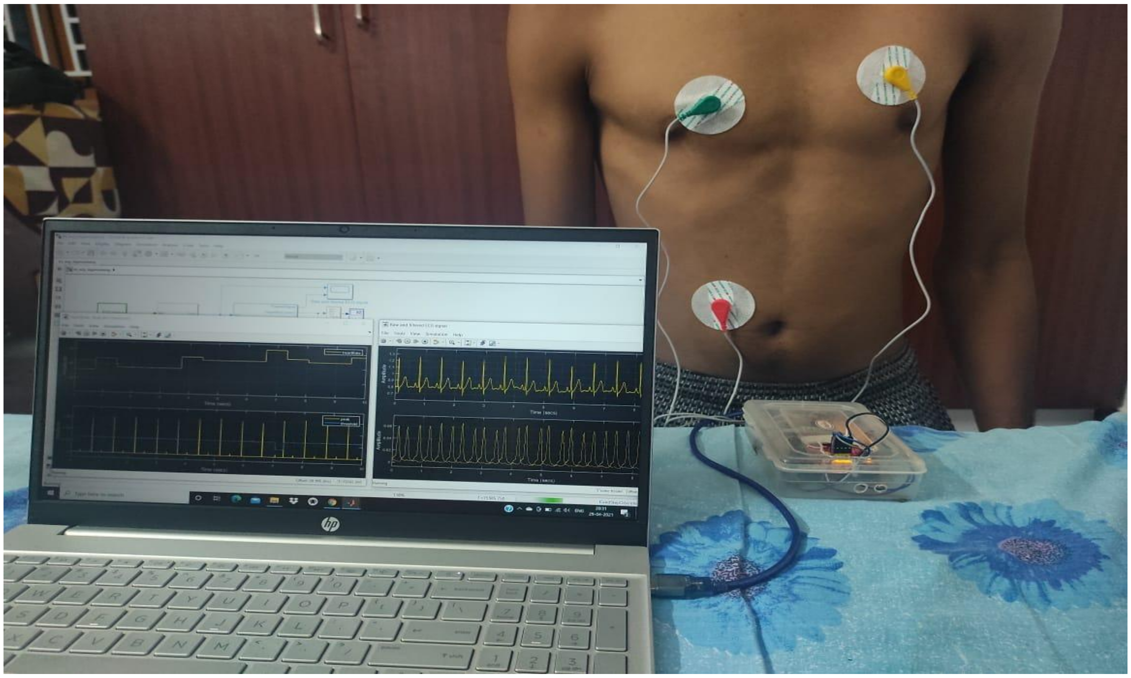

Fig 8: Overall System Setup

After acquisition, the data are then sent to the cloud for further processing which includes RR peak detection, RMSSD calculation and classifying the result. The entire system overview has been showed in Fig. 8. At the first stage, after signal acquisition, the signals are filtered, and the noises are removed in the micro-controller itself. The filtered signals are

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then transferred to the cloud for further classification.

V. RESULTS AND DISCUSSION

The AD8232 ECG sensor sensed the patient's ECG signal and its respective result stored in the Microsoft cloud. For experiment purpose, the sensor is subjected to normal ECG wave and the respective results stored in cloud. It has ECG sensor which is connected to the Microcontroller which then send the data to cloud.

The ECG signal after processing from the wavelet transform and machine learning algorithm, the parameters of HRV are predicted. As shown in the Fig 9., the HRV value of the ECG signal identifies it as normal sinus rhythm signal, because the RMSSD value of the signal is between 19 – 75. The analysis for abnormal signals are represented in Fig. 10 and Fig. 11.

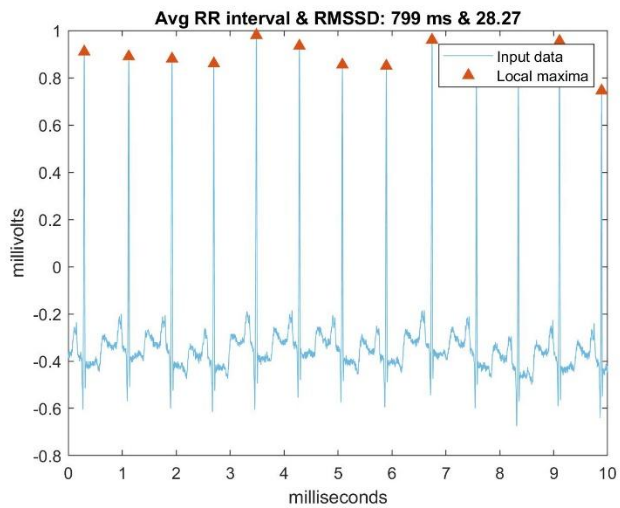

Fig 9: Graph results of HRV parameter detection for Wave Sample 1

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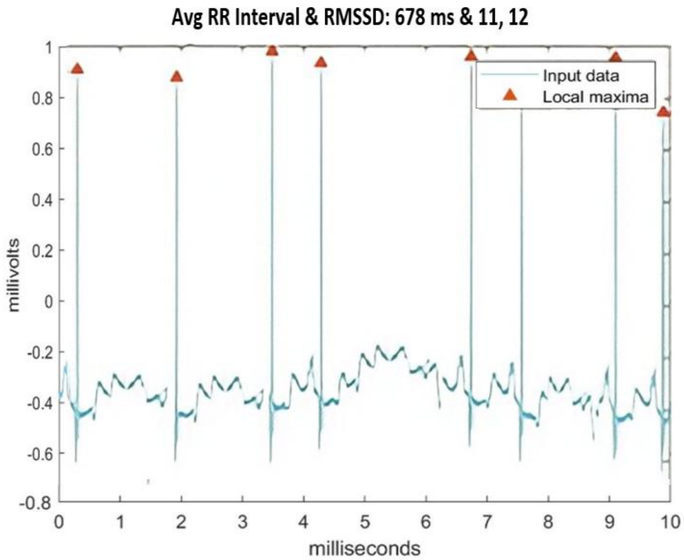

Fig 10: Graph results of HRV parameter detection for Wave Sample 2

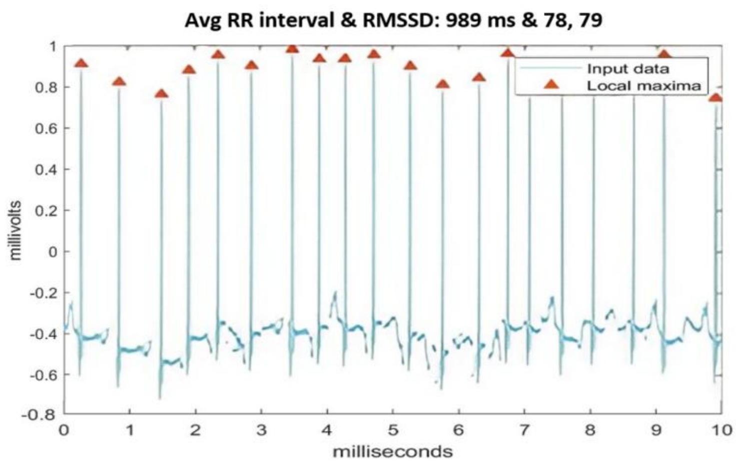

Fig 11: Graph results of HRV parameter detection for Wave Sample 3

The sample outputs calculated from the trained and tested datasets are represented in a table form as shown in the table 2.

TABLE 2. Output Representation for the Tested Datasets

Wave Sample Number	RMSSD Value	Classified Type	Boolean Result [0 – Normal, 1 – Abnormal]

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1	27	Normal	0
2	11	Bradycardia [Low Heart Rhythm]	1
3	78	Tachycardia [High Heart Rhythm]	1

The normal and abnormal conditions are expressed in the Boolean form for easier better understanding. The classifier will also classify the type on which the wave is corresponding. In table 2, the tested waves/signals are represented where the first dataset corresponds to the normal rhythm with the RMSSD value as 27. The next two waves are abnormal caused by slow and fast beating of the heart named as Bradycardia and Tachycardia respectively which is also represented in the above table.

VI. CONCLUSION

This paper presents internet of things based health parameter monitoring system for ECG signal. Machine learning and HRV algorithm shows the feasible outcome in classifying the abnormal ECG from the recorded database. The microcontroller with IoT feature and cloud technology provides faster updates of the patient's parameter. The data will be updated for every 30 ms.

Here for training and testing, the datasets are collected from PhysioNet database. For abnormal waves, the waves correspond to Arrythmia is chosen to show the maximum difference or deviation on the wave and correspondingly the results also generated. The datasets are randomly split into two parts. One for training and another for testing. Due to the usage of custom cloud, the data transmitting occurs in 30ms.

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