A Wearable Wireless Sensor System Using Machine Learning Classification to Detect Arrhythmia

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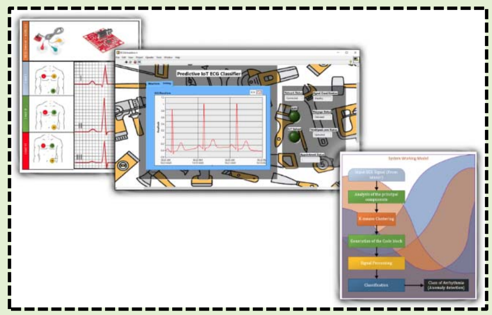

***Abstract*—Health care is becoming a public concern and has given intensifying attention in recent years considering the aspects such as an increase in population, urbanization and globalization. (a). Good quality and effective health care system is although low in cost but its ability to detect abnormalities and anomalies is not compromised. The objective of this research work is to introduce a novel cost-effective technique that allows the measured ECG waveform to get classified with the help of the LabVIEW. Using the combination of the sensor system, first, the input ECG sensor signal is collected and then processed in LabVIEW to get classified. (b). A LabVIEW based simulation is presented in this article which classifies the heart ECG signal to be as healthy, non-healthy and not defined. Moreover, the relevant hardware details are also discussed. The classification system is trained using the machine learning (ML) technique (K-mean clustering). (c). The findings from the work include classification of heart health status, timely detection of anomalies and (various) arrhythmia conditions at their preliminary stages. Further discoveries contain performance evaluation resulting in response time lesser than half a minute and accuracy estimation from the experiment on three patients. (d). The system can be useful for detecting the COVID-19 breathing issues at their early stage and an automatic appointment can be set with the available scheduled heart professional based on the severity of the detected arrhythmia condition. The system allows early access to the hospital support system and can help to reduce the crowds in the medical centers.**

***Index Terms*—Abnormalities, mobile platform, ECG, IoT, LabVIEW, ANN, extraction techniques, HTTP.**

I. Introduction

HEALTH care is important for society and as the population is rising, more and more health care resources are required [1]. Due to *globalization, newborn disease and plastic consumption in industries*, the average life span of individuals has been reduced in several countries. Poisonous and dangerous gases from the air are also creating heart related diseases in humans and animals. The main thing to highly concerned about is that these harmful gases content is increasing in the atmosphere with each passing year [2]. Heart linked diseases are the main cause of death globally. Heart health status is determined in terms of the performance of the cardiac cycle [3]. Cardiac output (CO) is defined to be the blood pumped by the heart in one minute. For a healthy human, the value of the cardiac output is 4 – 8 liters per minute.

In many countries, the most commonly known cause of death is heart failure. Series of heart attacks result in the failure (stopping) of the heart, thereby, leading to the death of the patient [4]. When a heart is about to fail, the patient is unable to breathe properly and after a certain time, the heart stops pumping the blood, thus causing the patient death. Few of the heart disease makes the heart stops after having long term illness [5], [6]. An appropriate diagnosis of the heart is important for avoiding long-standing heart-related sickness. The process of diagnosis consists of having further investigations such as attaining the goings-over from the blood sample, exploration of *electrocardiography (ECG)* signal etc., [7]. Considering the increase in heart diseases, there is a need for a system (device) that can determine the heart problems at their initial diagnostic stage and recommend the expert physician accordingly. Furthermore, with COVID-19 declared as a global pandemic [8], the main focus is to reduce fortuitous patients from medical centers.

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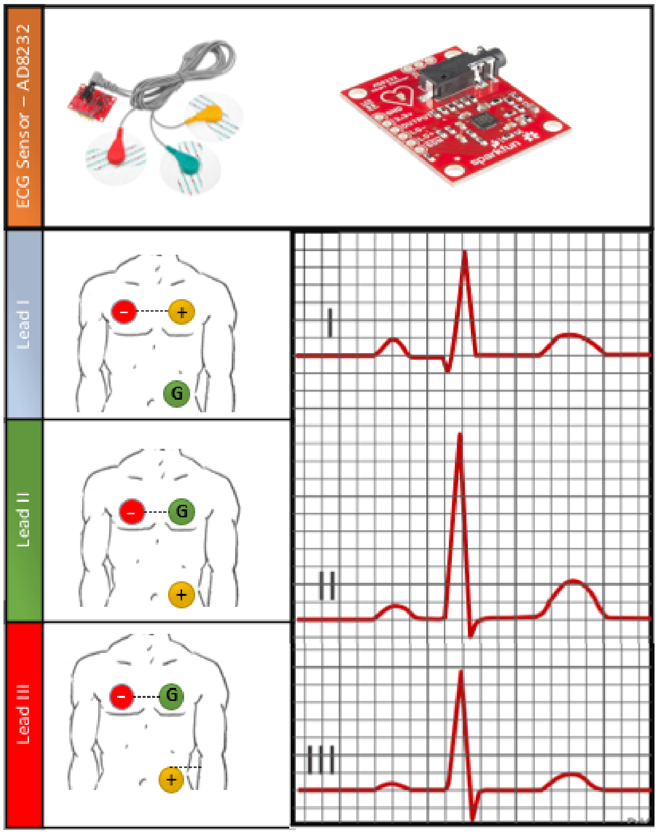


Fig. 1. ECG electrodes configuration.

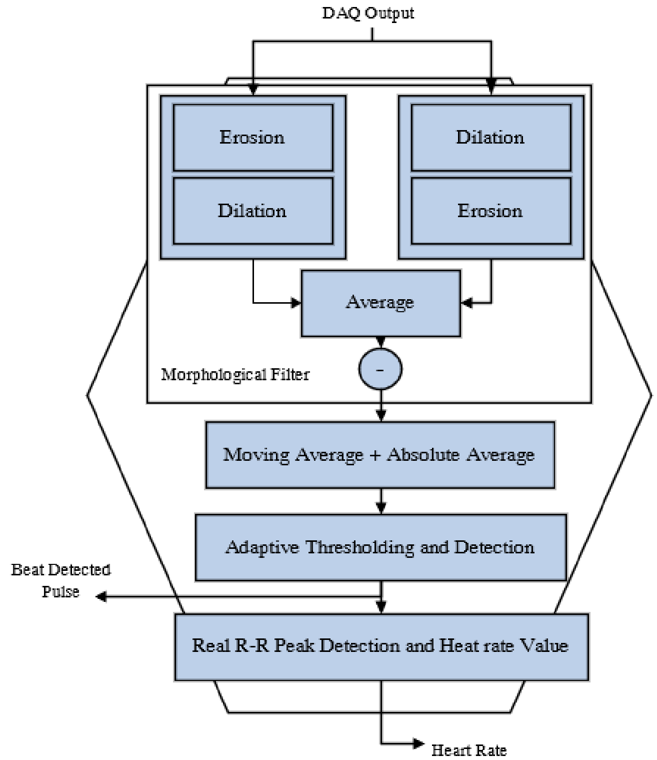


Fig. 2. (Block Diagram) QRS Complex detection.

To determine heart health and to obtain *ECG* signal, a set of electrodes are placed on the patient body in order to determine heart health (See Figure 1 for the possible type of connections and the corresponding waveform, *Lead I, Lead II and Lead III* configurations) [9]. Likewise, *ECG* monitoring is important for the detection of heart-related disease and considering the importance of the emerging platforms and mobile computing, it is much easier to collect data using sensors than before. *ECG sensor* is frequently used for obtaining the heart electrical activity. Various electrical modules are available commercially and due to advanced design tools, electronic sensing modules are becoming efficient, cost-effective and smaller in size. For this work, a smaller ECG module (*AD8232*) with three electrodes is used [10].

In LabVIEW, QRS complex detection is more accurate when a morphological filter is used to remove the noise from the ECG signal [11]. For the ECG signal $y(x)$, the mathematical morphology elementary operators (Opening, Closing, Erosion and Dilation) are:

$$\boldsymbol{Erosion} : y \ominus g(x) = min_{(k)}[y(x-k) + g(k)] \quad (1)$$
$$\boldsymbol{Dilation} : y \oplus g(x) = max_{(k)}[y(x-k) + g(k)] \quad (2)$$
$$\boldsymbol{Opening} : y \diamond g(x) = y \oplus g(\ominus g)(x) \quad (3)$$
$$\boldsymbol{Closing} : y * g(x) = y \oplus g(\ominus g)(x) \quad (4)$$

For the extraction of the peak value, a hybrid morphology operator combines the closing and opening operation as:

$$TB[y(n)] = y(n) - 0.5[y * g(n) + y \diamond g(n)] \quad (5)$$

As ECG signal is a moving signal and has impulse noise, therefore, the filtered signal is required to be smoothened (using a moving average filter) to remove impulse noise. Figure 2 shows the block diagram of the QRS complex detection.

To introduce the classification feature, it is vital to use machine learning techniques. *Machine learning* is the capability of a machine to learn from experience. The human's ability to learn from (past happenings) experience is replicated and programmed in the machines using generic algorithms [12], [13]. *Machine learning (ML) concepts have evolved from computation learning, artificial intelligence (AI) and pattern recognition* [14]. Supervised learning and unsupervised learning are vital terms in machine learning. In supervised learning, a model is provided and has to be followed while in unsupervised learning, a model is required to be trained [15]. *Machine learning* is mainly used in regression, density estimation, classification, topic modeling, clustering and dimensionality reduction [16], [17]. The fundamental aim of machine learning is to create and train a system that learns from data and grow its ability to behave with experience [18], [19]. Moreover, Extraction techniques, ECG databases, Artificial neural network (ANN) classifier helps in predicting the heart disease from ECG waveform.

Using the Internet of things (IoT) technology, connected devices take data from the sensor network (SN) and convey it to the server via the internet [20]. A system operator can monitor and control the connected devices over the network. The data can be updated from a remote location and in this smart connected environment, the system machinist can interrelate effectively with the data [21]. The objective of this research work consists of analyzing the ECG heart signal and classify it into a class of *healthy, unhealthy and not defined*. Analyzing the ECG signal and classifying it is important as medical centers occupancy can be managed efficiently considering the COVID-19 social distancing and lockdown policies (motivation). Classification aims to allow the automatic appointment to be set in a timely manner. In this research work, a novel predictive IoT supported approach is used in context with anomaly detection (contribution). For the *not defined and unhealthy* scenario, an appointment is automatically set by the LabVIEW program with the available doctor.

II. Literature Review

Fan et. al states that owing to the availability of information technology (IT) and health care systems, people are interested in getting their health monitored at homes [22]. *Mario et.al* describes a few of the properties of the ECG waveform and states that to attain operative information from the ECG waveform, it is vital to analyze and observe the peaks and interval points on the ECG waveform signal [23].

According to *Christov et.al*, in one complete cycle, the useful informative points are named as Q point, R point, S point and P point [24]. Each segment point (Q, P, S, R, U and T), interval (RR, PR, QT, ST, QRS) and segments (ST, PR) has value in units of distance, amplitude and interval which varies from patient to patient. *Ramasamy* in his research reveals that each patient has a unique ECG heartbeat pattern and properties similar to the fingerprint [25]. *Machine learning (ML)* plays an imperative role in the formation of a trained classifier for classifying ECG signal into a set of classes. Considering that each person has a unique ECG bimodal, it is also problematic to classify the ECG into fixed classes from a machine learning approach [26]. Furthermore, it is also conceivable that the same disease can show dissimilar symptoms in different patients. In such cases, it would be hard to predict remedy using data-driven and data trained system (challenges). A decent feasible solution is to practice with the pattern classification techniques to categorize the patient illness.

Rahman Protik et al. in their research work suggests that the ECG signal can be classified based on the QRS complex [27]. Each cardiac output cycle contains points (Q, S, U, R, T, P) and the distance between consecutive point is useful for obtaining the patient health information. The way wireless technology is intertwining our lives has altered our habits of making interaction with devices [28]. *Alhalabi et al.* propose that the data obtained from the health care sensor network can be useful for improving the health of the patient [29]. According to *Jian Liu and Xinxin Tan*, to analyze the ECG waveform, it is vital to extract the information values such as average QRS interval, average RR interval and average QQ interval [30]. After analyzing the ECG waveform, it is appropriate to apply a *machine learning* technique to categorize the ECG signal into a customary class [31]. *Weiler et al.* compared (using ANOVA analysis) the measurement results from the Wearable Heart rate(HR) to that of the ECG devices available in the market and realizes the percentage difference is up to 5%[32].

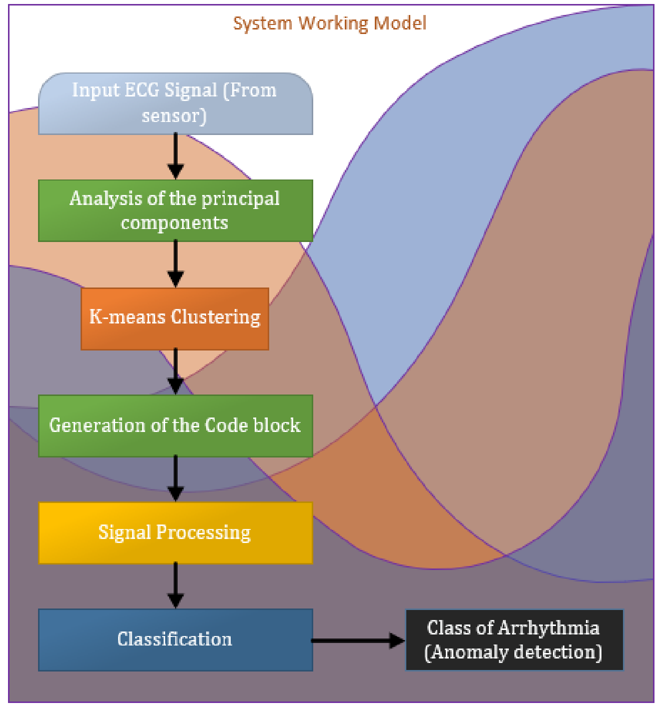


Fig. 3. Machine learning arrhythmia detection -6ystem working model.

Anwar et al proposed a technique using hybrid features to classify arrhythmia but the system is not proposed in the form of hardware and lacks the ability to have a wireless feature[33]. Some of the advancements have been discussed in the work [34] but no hardware relevant details are discussed to support the implementation of the system. Van Zaen *et al.* [35] in their research shows that the cardiac arrhythmia detection from ECG sensor reading using convolutional neural network (CNN) but the discussed technique accuracy over test data is 86.23 %. All these comparative studies hint that there is a need for an efficient wireless system which has higher efficiency and outstanding performance to provide early communication with server for rapid diagnostic result.

In this research work, using LabVIEW VI, the ECG waveform is monitored and various parameters (timing intervals) are extracted to classify the waveform. The classification is performed using a machine learning algorithm (K-mean clustering).

III. Methodology

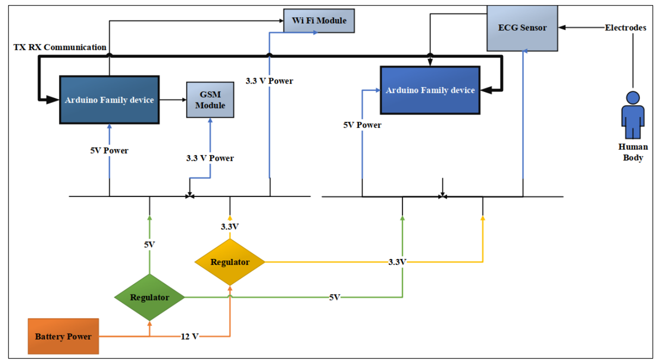
A. Model of the System

To extract suitable information from the ECG signal, noise is required to be removed from the ECG signal. For the early diagnosis of the arrhythmia and to predict an anomaly, it is imperial to use a noise-free ECG signal for accurate results [36]. The system working model is shown in Fig.3.

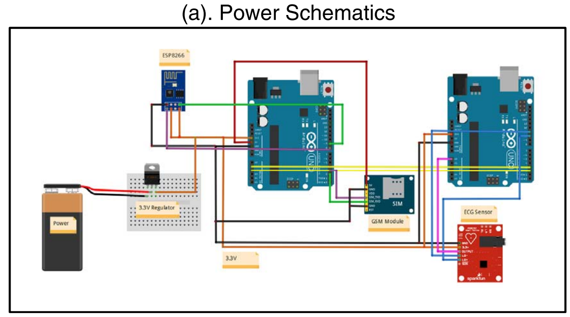
B. Anatomy of the System

The ECG signal time period is of the order of 10^{-2} or lower and to process such a faster signal, powerful computing resources are required. Arduino Uno (AT mega 328p) is used as a medium to allow communication between the sensors

Fig. 4. Different [Example of] heart health class (*Healthy, unhealthy and not defined*).



(a). Power Schematics



(b). System Fritzing Diagram

Fig. 5. Schema Diagram (a). Block diagram demonstrating the working of the system with power regulators marking (b). Schematic diagram of the System using Fritzing software.

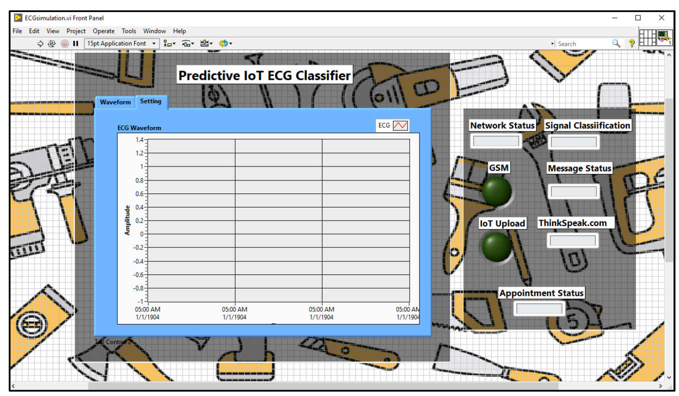


Fig. 6. ECG detection (LabVIEW VI).

and the PC (Arduino Uno is a data acquisition (DAQ) device in this research). Data acquisition device (DAQ) devices contain an analog to digital (ADC) converter and perform signal conditioning. These devices convert the (real-world data) sensor data value into equivalent digital values (binary or machine opcode) and are connected with the computer using PC COM Port (USB Port). One of the effective ECG sensors which are utilized in this research is AD8232 because of its compatibility and available support with the LabVIEW and Arduino platform.

One important goal is to use the IoT technology which is implemented using the ESP8266 Wi-Fi chip [37]. By uploading the data on thinkspeak.com, the patient health status can be visualized by the physician. To avoid the problem of slow uploading, the data is uploaded in the form of a waveform having a value between 0 – 10 based on the patient condition. For cellular communication, Sim900A is selected due to its compatibility with the LabVIEW platform and Arduino Uno, the module requires 5V external power and an onboard Rx (receiving) and Tx (transmitting) communication to send an alert message to the physician (doctor). A wired connection using the USB com port is required to be built to connect the Arduino device with a PC (computer) for monitoring, while the appointment process is automatic.

C. Data Collection and Data Analysis

By classifying the patient heartbeat into relevant class, the crowding of patients at the hospital can be avoided, this approach can indeed be useful for maintaining the social distancing scheme at the medical centers following the Covid-19 lockdowns. In this research work, patients are categorized into classes: *healthy, unhealthy, and not defined*. The "*healthy*" class contains the patient whose heartbeat is normal, while the "*unhealthy*" class patients are the ones in which anomaly is detected. In the *"undefined"* class patients, there are chances of arrhythmia and they need to visit the physician for further diagnosis (See Fig.4 for reference from physionet.org data) [38]. Using the proposed hardware, patients can visualize their heartbeats and an automatic appointment can be set with the expert physician in case of arrhythmia detection. The cellular alert confirms the automatic appointment in the form of an SMS (short message service) message to the patient.

The block diagram (created in (a)Microsoft Visio and (b)Fritzing) representation of the system hardware is shown in Fig.5. The circuit has voltage regulators to generate dc output power at 5V and 3.3V. The wide-ranging circuit comprises of components including: two Arduino units, two voltage regulators (one regulates the voltage at 5V and another being

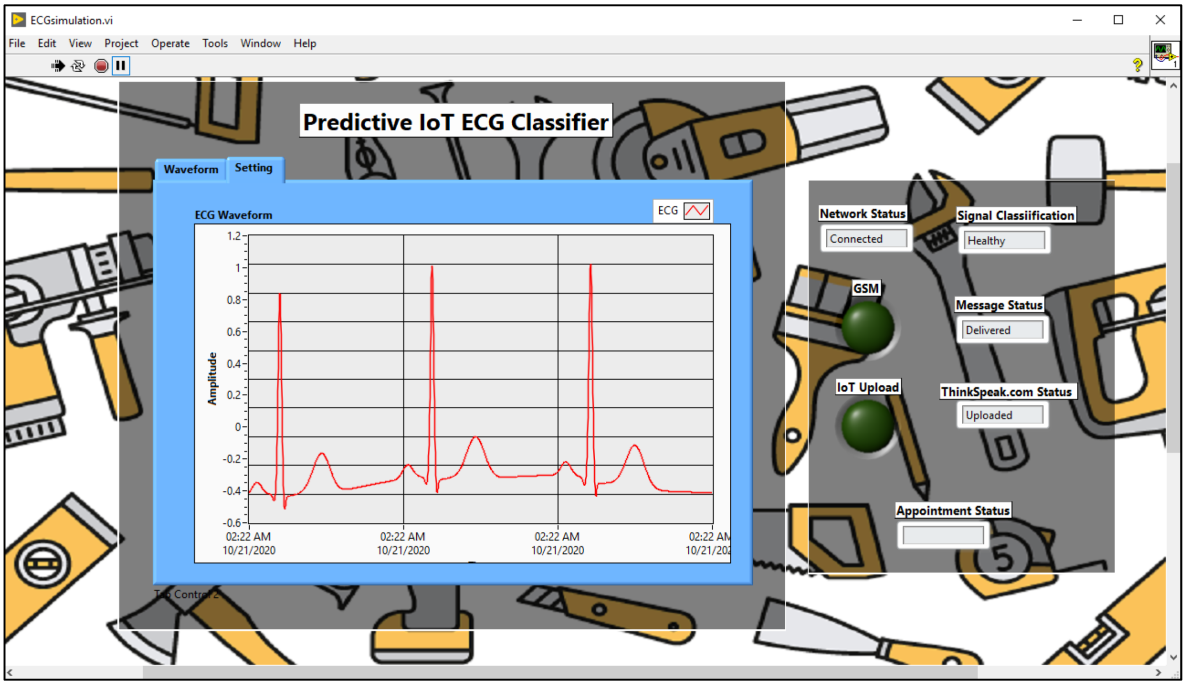


Fig. 7. Simulation of "healthy" patient.

at 3.3V), one ESP8266 (wi-fi) chip, one GSM module and one ECG sensor.

D. LabVIEW Design

(Two units of) Arduino family boards are used. One Arduino is used as a DAQ device and is connected directly with the PC COM port (Seen in Fig.5(b)). The other Arduino family board is attached to the sensors and actuators. To program the LabVIEW environment, the LabVIEW maker Hub library is used. Fig.6 shows the LabVIEW Virtual instrument (VI) file program for the detection of the patient ECG waveform. The data from the sensor is being displayed in the form of the moving curve in the waveform tab.

There are few palettes at the right half of the interface screen in Fig.6 which gives the information about the heart condition and other hardware connectivity. If the network status (internet) is connected, then the Network status tab will display the 'connected' word. For the "signal classification" field, the heart health class will be displayed in it.

The GSM button is created in the form of the press LED and on pressing this, an SMS message will be sent to the patient registered mobile number. If the patient data is being uploaded to thinkspeak.com, then the "ThinkSpeak.com status" field will display "upload" and once the data is fully uploaded, the "upload" word will be changed to the "uploaded". If the patient condition is unhealthy and not defined, then an automatic appointment will be set and the name of the corresponding doctor will be displayed.

IV. Results

A. Simulations

LabVIEW platform is used for creating the simulations. A healthy patient waveform is shown in Fig.7. As the patient condition is *"healthy"*, therefore, no appointment is set by the LabVIEW program, however, the data is uploaded to thinkSpeak.com for the medical record. One of the examples (of the *not-defined case*) of LabVIEW categorizing the patient data as *"not defined"* is shown in Figure 8. As an anomaly is detected, an appointment has been set with "Dr. Mehdi".

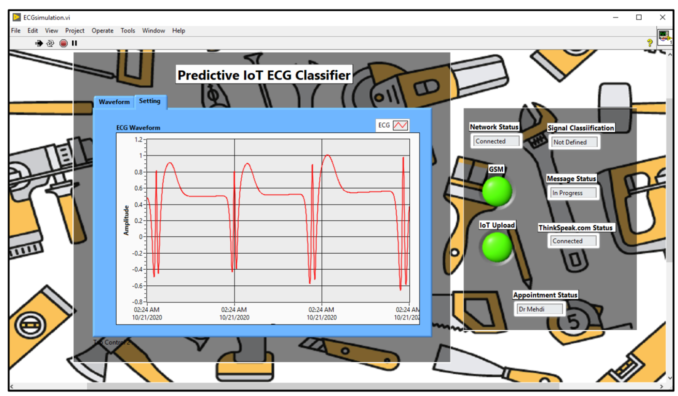


Fig. 8. Simulation of "Unhealthy" patient or "Not Defined" condition.

B. Analysis of Collected Data

The data is collected by performing experiments on three patients (labelled as M1, M2 and M3). While experimenting, the average heartbeat of each patient has logged in an excel file. A normal person heartbeat stays between 60 to 100 beats per minute. Patient M1 age is 45 years, patient M2 age is 25 years and patient M3 age is 35 years. Fig.9 shows the daily average heart rate value of the patient in the form of a bar chart over 14 days with possible error from other measuring devices measurements.

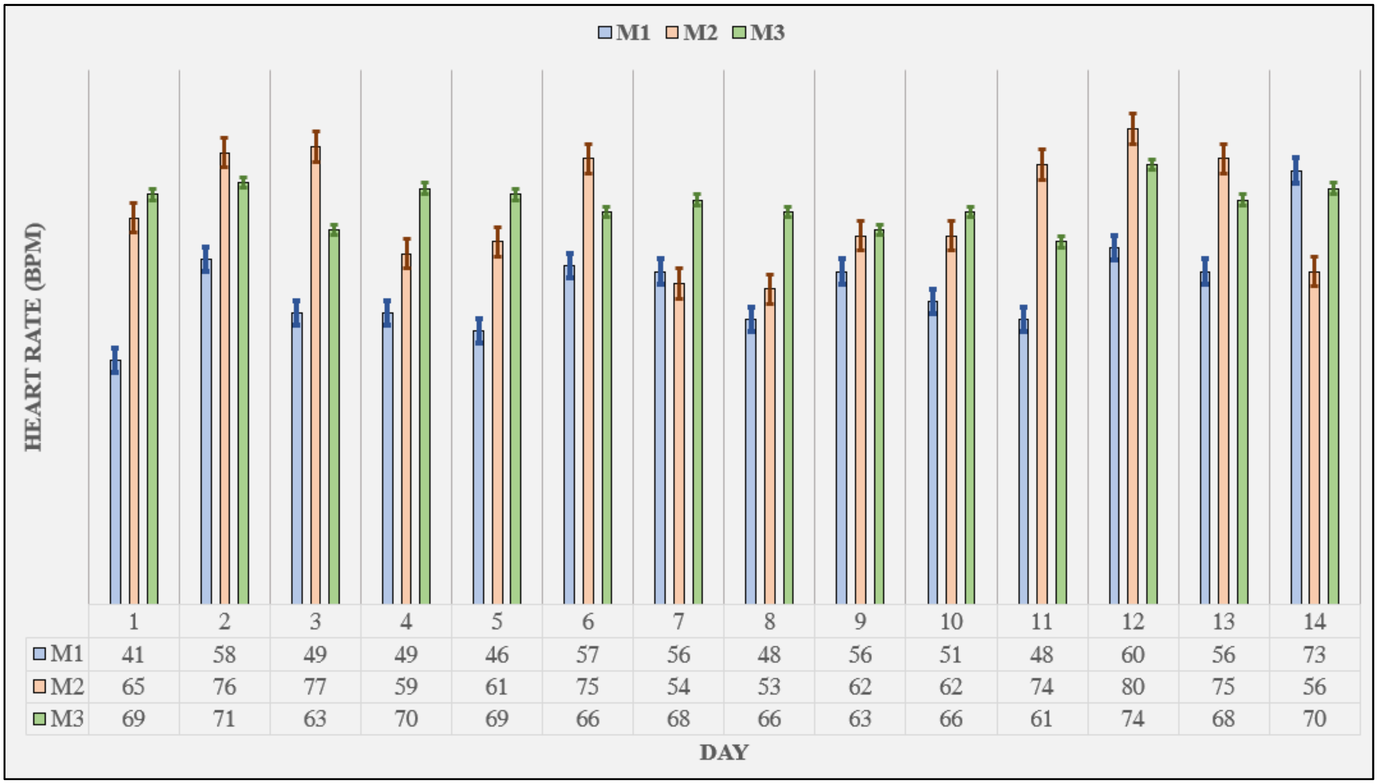


Fig. 9. (Obtained statistics) from the three patients' data.

C. Performance Evaluation

The frequency of the Arduino family processor (Arduino Uno) is 16 MHz and it took $\frac{1}{16\times10^6}$s to execute one operation. For the current system, the response time is the time taken by the sensor system to set an automatic appointment and this time is represented by T_r. The response time is the sum of time required for accessing the health status (T_M), time to get doctor assigned (T_{AD}), time to send patient data to the hospital (T_{A+}) and time to deliver the alert to the user (T_{A-}). The minimum time required to alert the user using a GSM message is around 10s, therefore, the overall time is:

$$T_r = T_M + T_{AD} + T_{A+} + T_{A-}$$

Arduino device performs around 10^8 operations (executions) to measure the health status and the same processing is done at the hospital side to set an appointment. Assuming normal values for message sending via Short message service (SMS) and internet to be 10s and 5s, the numerical value of the response time is:

$$T_r = 10^8 \times \frac{1}{16\text{MHz}} + 10^8 \times \frac{1}{16\text{ MHz}} + 5\text{s} + 10\text{s} = 27.5\text{s}$$

In case of an unhealthy condition, an automatic appointment can be set in less than half a minute (27.5s).

V. Conclusion

Following the Covid-19 safety measures, health care is getting public recognition and considering the sudden rise in population, e-governments focus is on setting a multibillion-dollar health care industry for public safety and welfare. A good health care device includes a smart sensing mechanism for the early recognition of the disease. Furthermore, a quality health care system includes smart design, smart sensors, smart prompts and smart alerts for timely assisting the first aid situation. Owing to industrialization, urbanization and population growth, there is a need for a smart health care system that can help in cutting the cost of health expenditures. On-time provision of first aid to the patient can save lives and reduces the risk of illness getting serious.

The objective of this research work is to use the DAQ device with ECG sensors to detect human heart health and predict arrhythmia, anomaly and illness. The heart health status is classified using the ML approach into: healthy, unhealthy and not defined class. In the LabVIEW programmable interface, ECG sensor data is graphically displayed and the graphical user interface (GUI) is provided with the capability to ensure the decision making about the health status and if the patient condition is found to be ill, then a consultation session will be arranged with the available physician in an early manner. The sensor data is also uploaded on thinkspeak.com using the IoT approach. Due to the slow uploading problem and the missing of certain points, an average rated value from 0 – 10 is uploaded on the server representing an ECG cycle.

The benefits of this system include efficient decision making and timely communication with the hospital (server-side) to save the patient life. Moreover, the overcrowding of unplanned patient can be prevented. At first, the hardware is designed, programmed, created and made to work with the LabVIEW platform, then an experiment is performed on three patients and data is collected to evaluate the performance of the system. The overall response time of the system is less than half a minute. The system works using the data extraction, ML and classifier techniques and can be proved convenient for improving the cardiology department performance.

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