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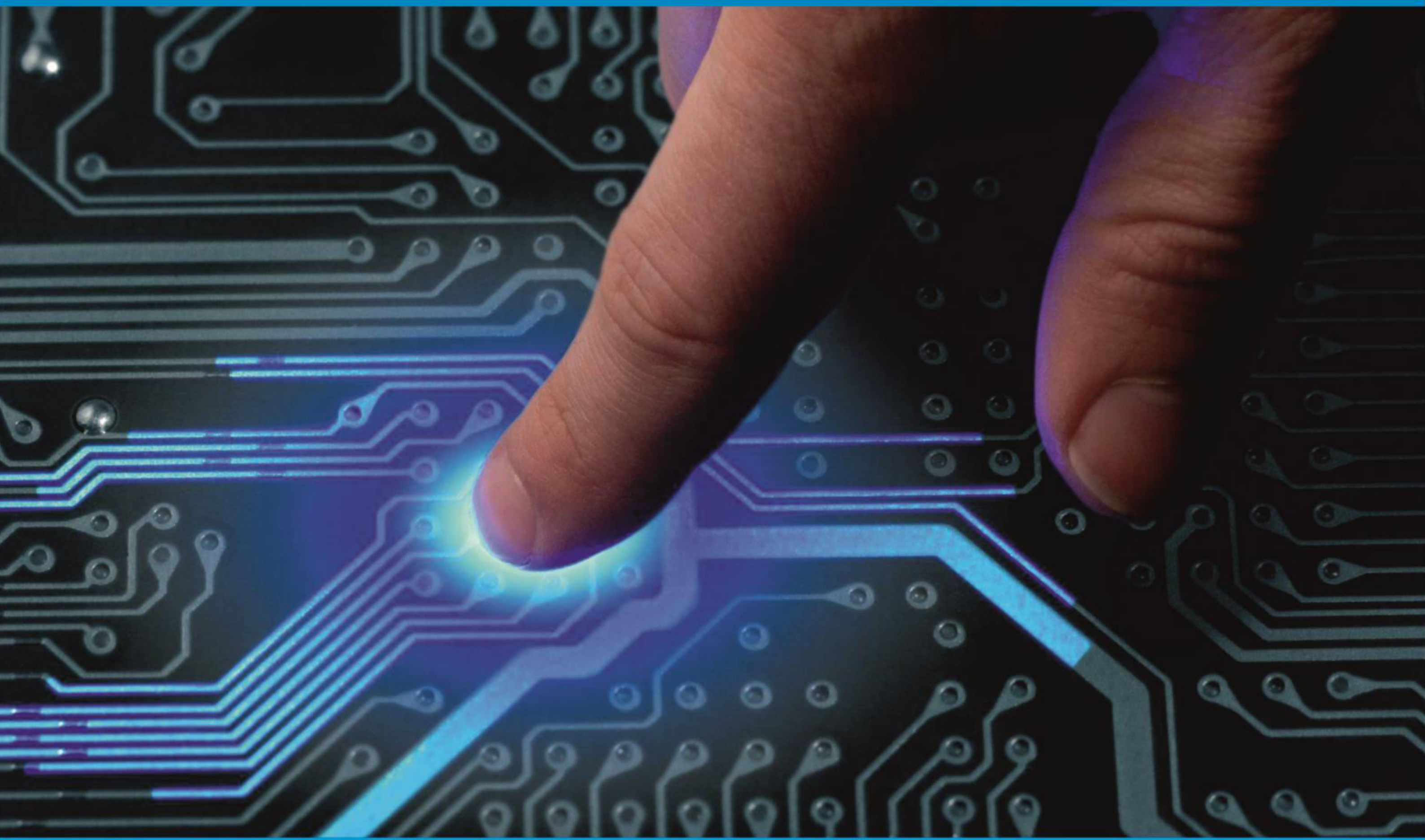

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Earlier Cardiac Arrest Detector System using IOT

Priyadharshan R[1], Thillai Manickam G[2], Vishnu Prasad K[3], Vasanth P[4], Gayathri A[5]

UG Students, Dept. of C.S.E., Sri Eshwar College of Engineering, Coimbatore, India[1,2,3,4]

Assistant Professor, Dept. of C.S.E., Sri Eshwar College of Engineering, Coimbatore, India[5]

ABSTRACT: Cardiac arrest is a sudden loss of blood flow resulting from the failure of the heart to effectively pump. In-hospital cardiac arrest (IHCA) is a major burden to public health, which affects patient safety. 80% of patients with cardiac arrest show signs of deterioration in the 8 hours before cardiac arrest. Cardiopulmonary resuscitation (CPR) is originally developed for victims of sudden cardiac or respiratory arrest. Doing CPR keeps blood circulating until trained to jump-start the heart back into a normal rhythm. This technique came into being after the invention of closed-chest cardiac massage in 1960. It is an emergency procedure that combines chest compressions often with artificial ventilation in an effort to manually preserve intact brain function until further measures are taken to restore spontaneous blood circulation and breathing in a person who is in cardiac arrest. It is standard practice to attempt CPR on any patient in the hospital who has a cardiac arrest, regardless of the underlying illness. Therefore, it is very important to detect CA patients.

We design a novel approach to detect CA for emergency patients. Our goal is to develop an early warning system (EWS) to avoid using CPR for patients. We propose some methods to develop the EWS and relatively high performance for the SCA detection on electrocardiogram (ECG) signal

KEYWORDS*:*Internet of Things; Machine learning; Cardiac arrest; Electro Cardiogram.

I. INTRODUCTION

Cardiac arrest is the abrupt loss of heart function in a person who may or may not have been diagnosed with heart disease. It can come on suddenly, or in the wake of other symptoms. Cardiac arrest is often fatal, if appropriate steps aren't taken immediately. Each year in the United States, more than 350,000 cardiac arrests occur outside of a hospital setting. No. The term "heart attack" is often mistakenly used to describe cardiac arrest. While a heart attack may cause cardiac arrest, the two terms don't mean the same thing.

The Internet of Things (IoT) refers to a system of interrelated, internet-connected objects that are able to collect and transfer data over a wireless network without human intervention. Today, businesses are motivated by IoT and the prospects of increasing revenue, reducing operating costs, and improving efficiencies. Businesses also are driven by a need for regulatory compliance. Regardless of the reasons, IoT device deployments provide the data and insights necessary to streamline workflows, visualize usage patterns, automate processes, meet compliance requirements, and compete more effectively in a changing business environment.[1]

Machine learning is a branch of artificial intelligence (AI) focused on building applications that learn from data and improve their accuracy over time without being programmed to do so. In data science, an algorithm is a sequence of statistical processing steps. In machine learning, algorithms are 'trained' to find patterns and features in massive amounts of data in order to make decisions and predictions based on new data. The better the algorithm, the more accurate the decisions and predictions will become as it processes more data.

II. RELATED WORK

2.1. Comprehensive Health Care Systems. "Patientlike" focused on helping patients answer the question: "Given my status, what is the best outcome I can hope to achieve, and how do I get there?" They answered patient questions in several forms like having patients with similar conditions connect to each other and share their experiences [3]. But they did not mention data security and the usability of the system. Another related system is called "Daily Strength". It is a social network centerer on support groups, where users provide one another with emotional support by discussing

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their struggles and successes with each other. The site contains online communities that deal with different medical conditions or life challenges [4]. It is very similar to "patientlike" in the sense that both of them are free platforms that involve patients and doctors interacting. Two major discrepancies between them are that "Daily Strength" does not involve research institutes and does not have a mobile application. Also, both systems are not IoT-based system. In another work, a robust model was developed that included multiple pulse parameters, EEG, and skin conductance sensors into a shirt [5]. Another system was developed for connecting facial expressions and voice recognition with EEG patterns [6]. Other researchers proved that EEG alone exhibits characteristics for different emotions [7]. Facial recognition software has been compared with heart rate variability in order to better understand patterns associated with various emotions [8]. It has also been proven that certain pulse patterns are associated with physical stress and not from emotional stress [9]. But, their systems are mobile and they did not use IoT as a platform for their system. Another comprehensive health care system is called "Omnio" which is an all-in-one application for Medical Resources [10]. It provides, among its services, clinical resources, diagnostic resources, disease guides, and drug information. Everyday Health [11] is a company which owns websites and produces content relating to health and wellness. It has higher ratings and publishes many health articles that can be very helpful for patients. In addition, it has a smart search that provides users with easy access their materials.

2.2. Connected eHealth Mobile Applications. Even though all the systems mentioned above provide health services, they do not provide any smart devices that can be used to monitor user's daily activities and alert them when needed. There are many heart monitors that provide users with their ECG signals so they can keep track of their condition but none of which who alert the users upon emergencies. A Smart Elderly Home Monitoring System (SEHMS) designed and developed on an Android-based smartphone with an accelerometer; it could detect a fall of the user [12]. It provides a smartphone user interface to display health information gathered from the system. The main advantage of SEHMS is that it has the remote monitoring facility for elderly who and chronically hostile patients. But it cannot warn the user in case of emergency. Remote Mobile Health Monitoring (RMHM) is a system that provides monitoring of a user's health parameters such as his or her heart rate, which is measured by wearable sensors [13]. It allows care givers and loving one to monitor the users to facilitate remote diagnosis. the system does not have the capability of monitoring in real time. The idea of predicting heart attacks remains a challenge and that is the focus of our research. Every research group specifies its own approach on how they plan to achieve its objective. We decided to use a combination of body temperature and ECG to predict heart abnormalities. Other systems have different approaches with different hardware implementations. None of them were discussed about power consumption rate during data collection. Our system uses a low power Bluetooth module to collect a longitudinal data wirelessly using a smartphone. In [14,15], authors presented a comparison between different data mining techniques for heart attack prediction. They present just prediction algorithms rather than a complete system with a data collection device and a computing platform. The best techniques that are most commonly used for predicting heart problems are: Decision Tree, Naive Bayes, Neural Network, and K-mean. Our research not only includes a complete system with an IoT device and a computing platform, but also uses one of those data mining techniques (Decision Tree) to predict heart problems. This makes our system unique in the sense that we created a low power smart IoT system and used a data mining technique in our prediction algorithm. Upon testing our prediction algorithm, we obtained results with a high accuracy for all our healthy and unhealthy test subjects. We illustrate the difference between our system and the other related works. To address the drawbacks of the above-mentioned research and systems, in this paper, we propose a smart IoT based heart rate monitoring system. Our system is designed to address directly some of the drawbacks of the existing systems and potentially yield good prediction results. The most important aspect of our system is the warning that allows the user to prevent an injury before it actually happens. To the best of our knowledge, our system is the first smart IoT-based health assistance which uses a subject-specific Body Area Sensor signals for predicting heart related injuries.

2.3. Measure your blood oxygen level with a revolutionary new sensor and app. Take an ECG anytime, anywhere. See your fitness metrics at a glance with the enhanced Always-On Retina display. With Apple Watch Series 6 on your wrist, a healthier, more active, more connected life is within reach. Your blood oxygen level is a key indicator of your overall wellness. It can help you understand how well your body is absorbing oxygen, and the amount of oxygen delivered to your body. The remarkable new sensor and app in Apple Watch Series 6 allow you to take on-demand readings of your blood oxygen as well as background readings, day and night. The new blood oxygen sensor is made up of four LED clusters and four photodiodes. Incorporated into the completely redesigned back crystal, this new sensor works in concert with the Blood Oxygen app to determine your blood oxygen level.

2.4. Galaxy Watch3 uses red LED and infrared rays to estimate your SpO2 levels, or the amount of oxygen in your bloodstream. Because this oxygen saturation is directly linked to physical performance, you can use Galaxy Watch3 to push your routine to the next level.

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III. PROPOSED ALGORITHM

Pan and Tompkins QRS detection algorithm, described in Verilog HDL (Hardware Design Language). The generated source has been simulated for validation, synthesized and tested on a Xilinx FPGA (Field Programmable Gate Array) board using the European ST-T database. To the best of the authors' knowledge this is the first attempt for the hardware implementation of the Pan and Tompkins QRS detection algorithm, in reconfigurable FPGA boards.

QRS Detection Algorithms

Several QRS detection algorithms have been proposed in the literature [22], [23]. Algorithms [4], [5] and [6] are based on the amplitude and the first derivative. In [4] a point is classified as QRS candidate when three consecutive points of the first derivative exceed a positive threshold (ascending slope) followed within the next 100ms by two consecutive points which exceed a negative threshold (descending slope). Fardeen and Neuman [5] developed a QRS detection scheme where a threshold is calculated as a fraction of the peak value of the ECG. Gustafson [6] suggested that a point is a QRS peak candidate when the first derivative and the three next derivative values exceeds a threshold and the next two sample points have positive slope amplitude products

Pan & Tompkins QRS detection Algorithm

The Pan–Tompkins algorithm applies a series of filters to highlight the frequency content of this rapid heart depolarization and removes the background noise. Then, it squares the signal to amplify the QRS contribute. Finally, it applies adaptive thresholds to detect the peaks of the filtered signal. The methodology followed is that the ECG is passed through a low-pass and a high-pass filter in order to remove noise from the signal. Then the filtered signal is passed through derivative, squaring and window integration phases. Finally, a thresholding technique is applied and the R-peaks are detected.

One of the most popular QRS detection algorithms, included in virtually all biomedical signal processing textbooks. An overview of the algorithm follows. The signal passes through filtering, derivation, squaring, and integration phases before thresholds are set and QRS complexes are detected. In the first step the algorithm passes the signal through a low pass and a high pass filter in order to reduce the influence of the muscle noise, the power line interference, the baseline wander and the T-wave interference. The low-pass filter is described by the formula:

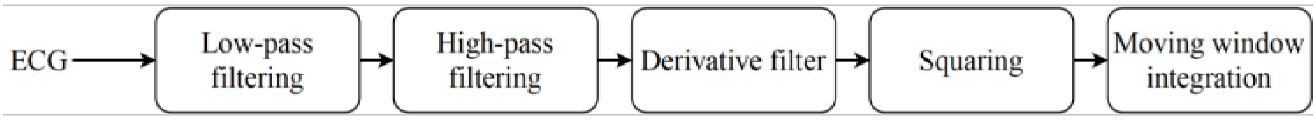

Fig 1. Flow Diagram

Low-Pass Filter. The difference equation of the filter is

y (nT) = 2y (nT – T) − y (nT − 2T) + x (nT) − 2x (nT − 6T) + x (nT − 12T)

Its delay is 6 sampling points.

High-Pass Filter. The difference equation is

y nT = 32x nT − 16T − y nT − T + x nT − x nT − 32T

The delay is 15 sampling points. 3.1.3. Differentiation. The difference equation is

y (nT) = (1/8) [−x nT − 2T) – 2x (nT − T) + 2x (nT + T) + x (nT + 2T)]

Squaring. The squaring process amplifies the slope of the frequency response. The difference equation is

y nT = x (nT)^2.

Integration. The value is summed through a moving window with the width of 24 points (66.7 ms). The difference equation is

y(nT) = (1/N) x (nT – (N – 1) T) + x (nT – (N – 2) T) + ··· + x (nT)

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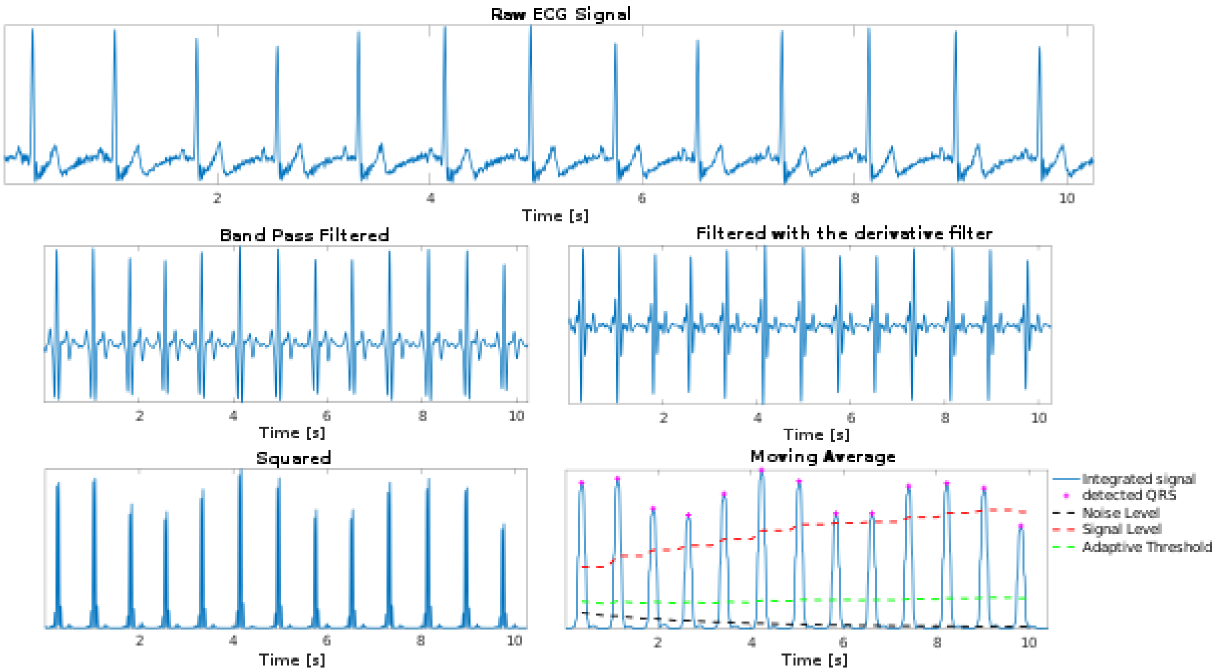

Fig 2. ECG Signal & QRS Wave

IV. EXPERIMENTAL RESULTS

The hardware things should be worn by the patient and adequate power should be provided for the hardware. The patient should know the place/part where the device should be worn on the body. The device should be started and the data will be generated and analogue readings can be viewed in Arduino IDE. In Arduino IDE the plotter will be showing the PQRST wave form (i.e., ECG readings). If the patient has some idea in human healthcare can assume whether he is heart is functioning good.

From the analogue plotter, the readings should be exported and should be converted into digital readings. There is an application called “TERA TERM”, which will be used to convert Analog to Digital and can be retrieved as .CSV file

When readings are taken, the tera term application should run simultaneously. This is because readings should be taken in the same time.

Pan & Tompkins algorithm code should give in the MATLAB compiler. The CSV file should be uploaded and the code should be executed. After execution, the QRS complex will be retrieved and that QRS complex will be sent to android app. From there the analysis takes place.

In android application, it acts like more or less SOS app. If the value goes beyond the normal level and retains for some time, then the app will notify the nearby hospital or the patient’s relation.

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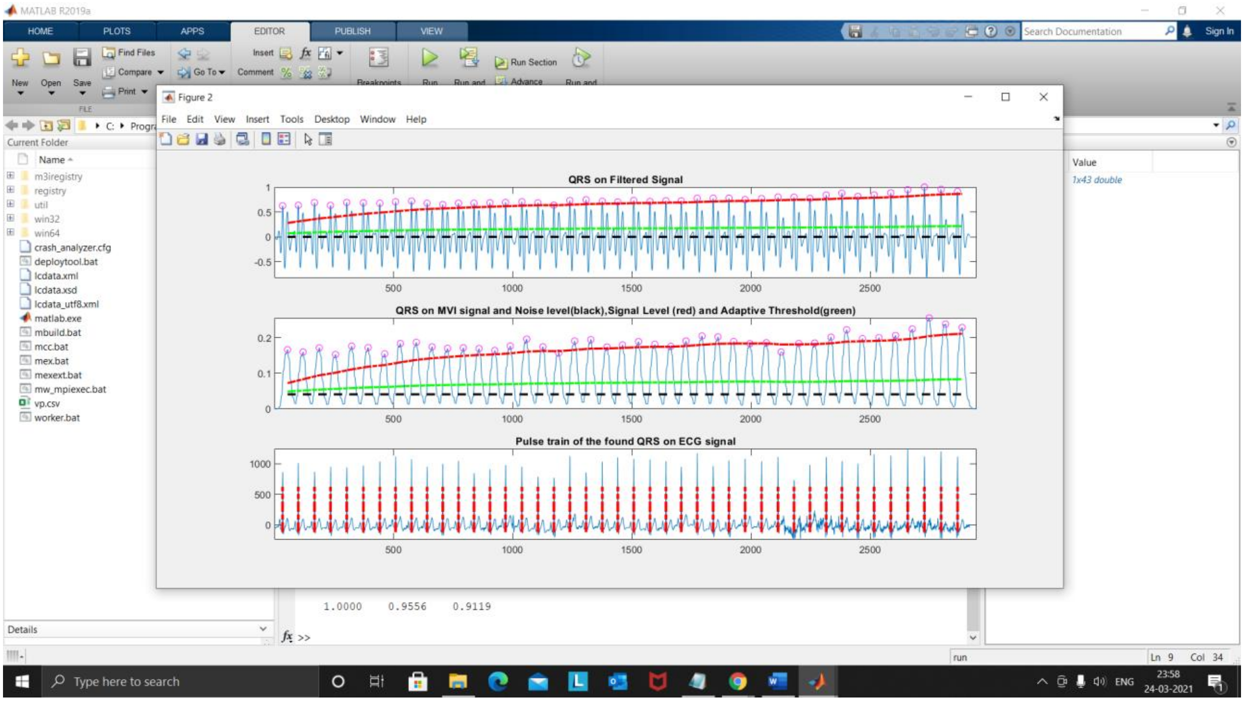

Fig 3. Pulse train Detection on ECG Signal

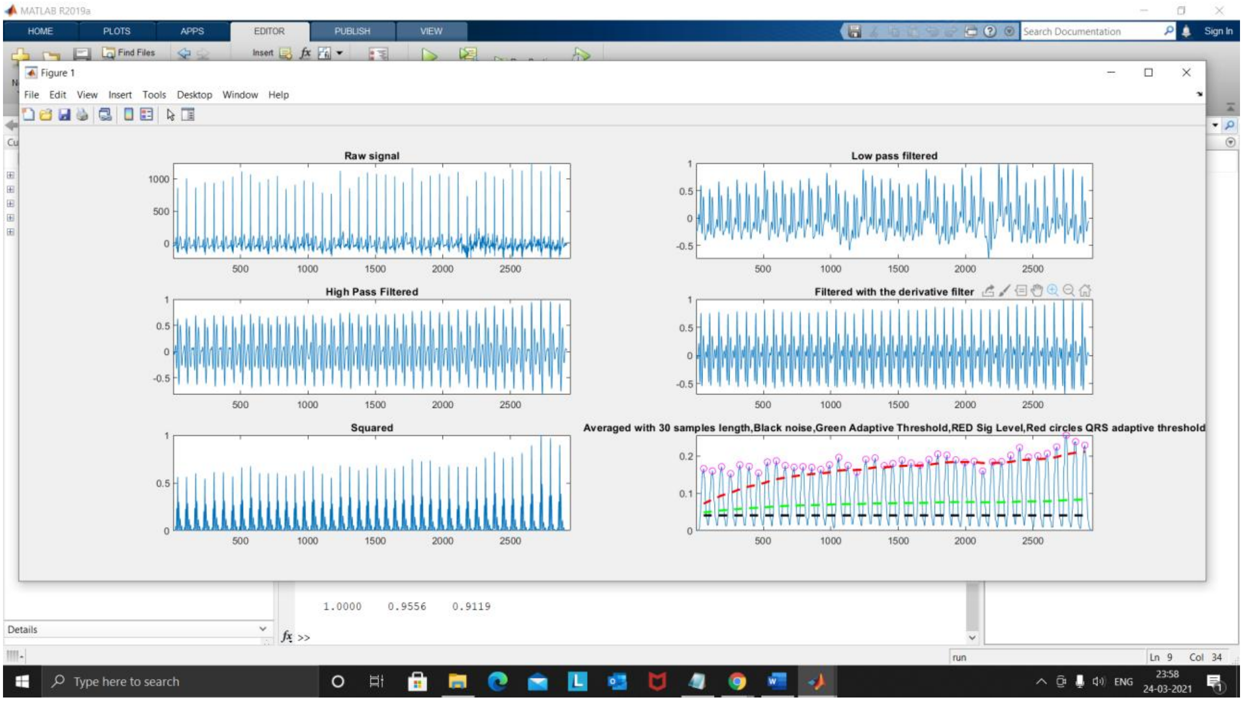

Fig 4. QRS Detection

V. CONCLUSION

To evaluate our proposed system, we developed a prototype application and investigated its performance. We evaluated the prototype with extensive experiments. In this section, we explain how the data is analysed and performance is measured for healthy and unhealthy subjects.

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