

ULTRA-LOW POWER DESIGN OF WEARABLE CARDIAC ARRHYTHMIA DETECTION

Submitted in partial fulfillment of the requirements for the award of Bachelor of
Technology Degree in Biomedical Engineering

By

SONICA SREE K (Reg No. 37240071)



**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

**Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE
JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119**

MARCH 2021



SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)

Accredited with "A" grade by NAAC | 12B Status by UGC | Approved by AICTE
Jeppiar Nagar, Rajiv Gandhi Salai, Chennai – 600 1190
www.sathyabama.ac.in

DEPARTMENT OF BIOMEDICAL ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **SONICA SREE K (37240071)** who carried out the project entitled "**Ultra-low power design of wearable cardiac arrhythmia detection**" under our supervision from **October 2020 to March 2021**.

Dr. J. Bethanne Janney, ME., Ph.D.,
Guide and Supervisor

Dr. T. SUDHAKAR, M.Sc., Ph.D.,
Head of the Department

Submitted for Viva voce Examination held on _____

Internal Examiner

External Examiner

DECLARATION

I, **Sonica sree K (37240071)** hereby declare that the Project Report entitled “**Ultra-low power design of wearable cardiac arrhythmia detection**” done by me under the guidance of **Dr. J. Bethanneey Janney**, Department of Biomedical Engineering is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

DATE:

PLACE: CHENNAI

2.

A handwritten signature in black ink that reads "K. Sonica Sree". The signature is written in a cursive style and is placed on a light gray rectangular background.

SIGNATURE OF THE CANDIDATES

ACKNOWLEDGEMENT

We are pleased to acknowledge our sincere thanks to **Board of Management of SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. We are grateful to them.

We convey our thanks to **Dr.J.Premkumar** M.Sc., Ph.D., and **Dr. T. Sudhakar** M.Sc., Ph.D., **Head of the Department, Dept. of Biomedical Engineering** for providing us necessary support and details at the right time during the progressive reviews.

We would like to express our sincere and deep sense of gratitude to our Project Guide **Dr. J. Bethanney Janney**, ME., Ph.D., **Department of Biomedical Engineering** for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of our project work.

We wish to express our thanks to all **Teaching and Non-teaching** staff members of the **Department of Biomedical Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

Heart diseases are becoming a big issue for the last few decades and there are many people die because of certain health problems. Therefore, heart disease cannot be taken lightly. By analyzing and monitoring the ECG signal at the initial stage this disease can be prevented. As the result of ageing population and a progressively greedy will give better healthcare, new medical devices have arisen. Some focus on prevention, others in treating. The prototype developed here focus within the acquisition of the heart's electrical activity with an easy circuit embedded in an Arduino microcontroller, with the chance of early detection of heart diseases. An effective and affordable solution was proposed and can made dozens of trials were performed with the device. These pointed to a high rate of detection of R, S and T-peaks (~100%, 78, 3% and 72, 5%, respectively) with an accurate pulse rate measure. Despite of the great results obtained, this device, for now, must not be used for other purposes than monitoring.

TABLE OF CONTENT

CHAPTER NO	TITLE	PAGE NO
	ABSTRACT	i
	LIST OF FIGURES	iv
	LIST OF TABLES	v
	LIST OF ABBREVIATION	v
1	INTRODUCTION	1
	1.1 OUTLINE OF THE PROJECT	1
	1.2 CARDIAC CYCLE	2
	1.3 ELECTRICAL ACTIVITY	2
2	LITERATURE REVIEW	4
3	AIM AND SCOPE	15
	3.1 AIM	15
	3.2 SCOPE	15
	3.3 EXISTING SYSTEM	16
	3.4 PROPOSED SYSTEM	16
4	MATERIAL AND METHOD	17
	4.1 HARDWARE USED	17
	4.1.1 ARDUINO UNO	17
	4.1.1.1 GENERAL PIN FUNCTIONS	18
	4.1.1.2 SPECIAL PIN FUNCTIONS	18
	4.1.2 AD8232 ECG SENSOR	19
	4.1.2.1 PIN DEFINITIONS AND DESCRIPTIONS	20
	4.1.3 LOW PASS FILTER	21
	4.1.3 ELECTRODES POSITIONING	23

	4.1.3.1 ECG FEATURES AND ANOMALIES DETECTION	24
	4.1.4 DEVELOPMENT AND DESIGN	26
	4.1.4.1 ACQUISITION	26
	4.1.4.2 FILTRATION	26
	4.2 SOFTWARE USED	27
	4.2.1 ARDUINO IDE	27
5	RESULTS AND DISCUSSION	30
	5.1 RESULTS	30
	5.2 DISCUSSION	33
6	SUMMARY AND CONCLUSION	35
	6.1 SUMMARY	35
	6.2 CONCLUSION	35
	REFERENCES	36
	APENDICES	42

LIST OF FIGURES

FIG NO	TITLE	PAGE NO
1.1	CARDIAC CYCLE EVENTS	3
4.1	ARDUINO BOARD	17
4.2	AD8232 ECG SENSOR	20
4.3	OP07 IC	22
4.4	OP07 IC PINOUT	22
4.5	0.1 MICROFARAD CAPACITOR	22
4.6	82 K RESISTOR	23
4.7	AUDIO JACK TO 3 ELECTRODES SNAP CONNECTORS	24
4.8	P WAVE MORPHOLOGY	24
4.9	SCHEMATIC REPRESENTATION OF A STANDARD ECG	25
4.10	ARDUINO IDE	29
5.1	PROPOSED HARDWARE MODEL	30
5.2	OUTPUT OBTAINED ON ARDUINO IDE	31
5.3	ZOOMED IMAGE OF OUTPUT OBTAINED ON ARDUINO IDE	32
5.4	FILTERED SIGNAL OBTAINED ON ARDUINO IDE	33

LIST OF TABLE

TABLE NO	NAME OF THE TABLE	PAGE NO
1.1	STANDARD VALUES OF NORMAL ECG SIGNAL	4
4.1	PIN DEFINITIONS AND DESCRIPTIONS	20
5.1	AVERAGE OUTPUT READINGS OBTAINED ON 5 DIFFERENT PERSONS	34

LIST OF ABBREVIATIONS

ABBREVIATIONS	EXPANSION
ECG	ELECTROCARDIOGRAM
IDE	INTEGRATED DEVELOPMENT ENVIRONMENT
IOT	INTERNET OF THINGS
HR	HEART RATE
ADC	ANALOG TO DIGITAL CONVERTER
RLD	RIGHT LEG DRIVE
USB	UNIVERSAL SERIAL BUS
PVM	PARALLEL VIRTUAL MACHINE
LED	LIGHT EMITTING DIODE

CHAPTER 1

INTRODUCTION

1.1 OUTLINE OF THE PROJECT

Big efforts to provide good healthcare at affordable prices have become a central issue in the last decades. Along with the wide technological developments, it has been possible to create the more efficient devices with new available features. Wearables are the classes of devices with an exponential growth in the last years, if problems with battery life get overpassed. This electrocardiograph joins with Arduino features with an analog circuit and acquires and filters a very weak signal obtained from the chest. A set of algorithms are then proposed to detect the arrhythmias, heart muscle necrosis, hypertrophic ventricles, variations in the heart rate depending on the position of the person. A set of trials were carried out to evaluate the sensibility and reliability of the obtained measurements. Despite we were only able to test our device in healthy people (thus, no pathologic recordings were obtained), different and representative results were obtained among all the candidates. The results obtained the simplicity of the circuit ,great improvements are expected to be achieved in a reducing the time scale. Observing the world tendency, in a near future, it is expected to see ECG (wearable) devices at home, automatically detecting many pathologies without an clinician.

1.2 CARDIAC CYCLE

The cardiac cycle is controlled by the sinoatrial node via electrical stimulation. The node consists of a group of very peculiar cells with the ability to spontaneously produce an electrical impulse that propagates through a network of specialized fibers (atrioventricular node, His bundle, Purkinje fibers), regulating heart muscle's contraction. Because, it is responsible for the setting of heart's rhythm. SA node is often called as natural pacemaker.

1.3 ELECTRICAL ACTIVITY

This electrical exercise of the coronary heart is the organic fundament at the back of the electrocardiogram (ECG) register. In fact, every function of the ECG is related to some phase of the cardiac cycle. At the commencing of the cardiac cycle, both the atria and ventricles are comfy (diastole), and the blood is flowing into the proper and left atria from venae cave and the 4 pulmonary veins, respectively. Since both the tricuspid and mitral valves are opened and blood flows unimpeded from the atria to the ventricles. Following atrial depolarization, represented with the aid of the P wave of the ECG, the atrial muscle tissues contract from the most efficient component of the atria toward the atrioventricular septum, pumping the blood into the ventricles via the open atrioventricular valves. At the start of atrial systole, the ventricles are usually crammed with approximately 70-80% of their capacity, in the course of the atrial systole the ventricles are absolutely filled. Atrial systole lasts about 100ms and ends before the ventricular systole. Ventricular systole follows the depolarization of the ventricles and is represented by means of the QRS complex in the ECG. Initially, the stress generated in the ventricles is not ample to eject the blood from the heart, the blood flows back and closes the atrioventricular valves, it's the isovolumetric contraction phase given that blood's volume remains constant. When the contraction of the ventricular muscle counterbalances the pressures in the pulmonary trunk and aorta, the ejection section of the ventricular systole starts offevolved and

the blood is pumped from the heart. Ventricular relaxation, or diastole, follows repolarization of the ventricles and is represented by means of the T-wave of the ECG.

Table 1.1: Standard values of normal ECG signal

SR.NO	PARAMETER	VALUES
1	RR interval	600-1200(ms)
2	QRS complex	80-120(ms)
3	R amplitude	1.60(mv)

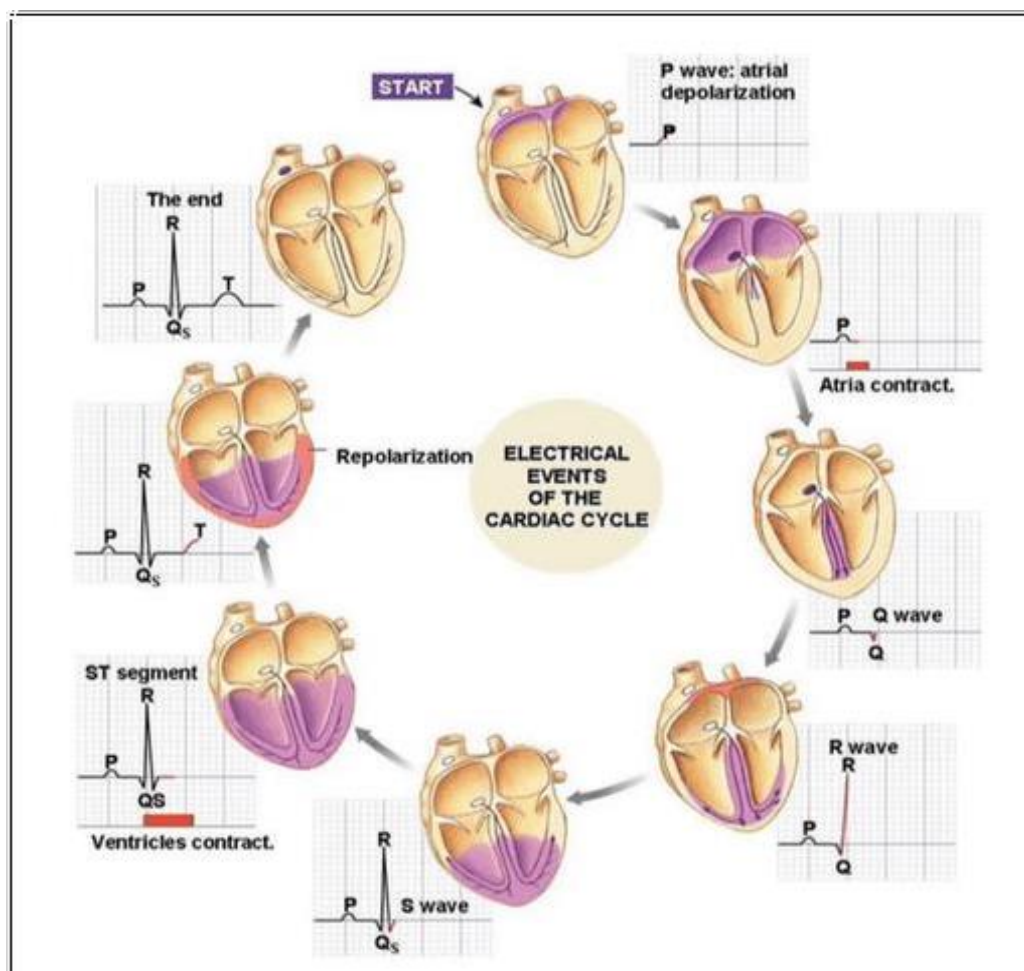


Fig: 1.1 Cardiac cycle events

CHAPTER 2

LITERATURE REVIEW

Afadar et.al (2020),reported that Heart arrhythmia disease is a heart condition in which the electrical pulses that control the heartbeat become abnormal and leads to an irregular rhythm of heartbeat. we propose a device that monitors and diagnose the heart arrhythmia, using electrocardiogram signal, machine learning, and Raspberry_Pi microcontroller. The proposed methodology has two stages, the first stage is to trained the Artificial Neural Network (ANN) model using available databases. After feature evoke, the sample pool is used to trained the ANN model using various machine learning tools to obtain the sharper accuracy. The second stage is to transmit the model within our microcontroller and start forecast real stream ECG signal coming from the sensor. The microcontroller export the signal and the unexpected results to the mobile application and stores it on the cloud for easy access by the end user or the physician.

Andrey Kuzmin et.al (2017) mentioned that describes a solution for mobile coronary heart monitoring. In section of hardware the authors targeted on engineering troubles of increasing the variety of ECG leads and growing the sampling rate. It doubtlessly approves to expand the effectiveness and accuracy of localization and to reduce the have an impact on of pacemaker pulses on the ECG sign recording respectively. Implementation of hardware and software parts is described. The technique and software program tool for wavelet-based evaluation of ECG alerts are proposed for arrhythmia detection task. Experimental results show that proposed wavelet-based method of ECG evaluation can observe signs of arrhythmia. Results of wi-fi channel speed test confirm that the chosen hardware meets the necessities of wi-fi protocol bandwidth. Proposed solutions are suitable for transportable coronary heart monitoring systems.

Apsana et.al (2017), Fetal ECG monitoring provides important information about the condition of the fetus and it helps during labour. In utmost cases, a harsh fetal arrhythmia can cause collapse and leads to sudden cardiac death. Throughout pregnancy period fetal health must be delicately monitored to detect the early fetal cardiac diseases, and for providing treatment immediately when possible. At present reference based approaches are used to extract fetal ECG from the mother's abdomen ECG. But this ECG contains antique due to the muscle contraction, breathing, and noises. This makes even harder to extract the ECG. The research going to wrench fetal ECG using the method BSS. The autonomous component analysis (ICA) algorithm is used to initialization and surplus the fetal ECG. Peak detection algorithm is used to state-machine logic is used to extract the features from the fetal ECG. The classification is done by using Naïve Bayesian classifier. Majority of the data used for this examination were extracted from the Physionet database. Attestation of the propose extraction and detection methodology has been done on publicly available datasets.

Ashish Kumar et.al (2018) Reported that Bradycardia can be modulated the usage of the cardiac pacemaker, an implantable clinical machine which units and balances the patient's cardiac health. The machine has been broadly used to become aware of and screen the patient's heart rate. The fact collected therefore hence has the easiest authenticity assurance and is handy for in addition electric stimulation. The device is available in its new digital form, which is extra efficient and correct in performance with the delivered benefit of low price energy consumption platform. It has a joint algorithm based totally on biorthogonal wavelet transform and run-length encoding (RLE) is proposed for QRS complicated detection of the ECG sign and compressing the detected ECG data.

Buhao Guo et.al (2018) reported that Electrocardiogram (ECG) classification is an essential system in detecting the arrhythmia, and neural network models have been extensively used in this field. However, these fashions are frequently disrupted by using heartbeat noise and are negatively affected by skewed data. To tackle these problems, a novel heartbeat awareness technique is presented. The aim of this find out about is to practice a main aspect evaluation (PCANet) for function extraction based on a noisy ECG signal. To enhance the classification speed, a linear aid vector laptop (SVM) used to applied. The consequences exhibit that our approach has high attention accuracy in the classification of skewed and noisy heartbeats, indicating that our method is a sensible ECG awareness method with suitable noise robustness and skewed statistics applicability.

Couceiro et.al (2017) mentioned that Atrial Fibrillation (AF) is the most common arrhythmia and it is estimated to affect 33.5 million human beings worldwide. AF is associated with an expanded chance of mortality and morbidity, such as heart failure and stroke and affects broadly speaking older humans and individuals with other conditions (e.g. heart failure and coronary artery disease). In order to forestall such lifestyles threatening and existence fine decreasing stipulations it is crucial to grant higher algorithms, succesful of being built-in in lower priced personalized health systems. The new algorithm for AF detection, which is primarily based on the analysis of the three physiological traits of Irregularity of heart fee and Absence of P-waves and Presence of fibrillatory waves. Basedon these characteristics a number of elements have been extracted from 12-lead electrocardiograms (ECG) and selected in accordance to their discrimination ability. The classification between AF and non-AF episodes used to be performed using a Support Vector Machine (SVM) classification model. Our outcomes show that the identification of the fibrillatory patterns, the use of the proposed features, extracted from the evaluation of 12-lead ECG improves the performance of thealgorithm to a sensitivity and specificity, when compared to our previous single-channel approach, in the equal database.

David Menotti et.al (2016) stated that electrocardiogram (ECG) measures the electric activity of the heart and has been widely used for detecting heart diseases due to its simplicity and non-invasive nature. By inspecting the electrical signal of every heartbeat, i.e., the aggregate of motion impulse waveforms produced by using exclusive specialized cardiac tissues located in the heart, it is possible to realize some of its abnormalities. In the last decades, various works had been developed to produce computerized ECG-based heartbeat classification methods. In this work, we survey the current trendy methods of ECG-based computerized abnormalities heartbeat classification by way of providing the ECG signal preprocessing, the heartbeat segmentation techniques, the function description techniques and the gaining knowledge of algorithms used. we talk about limitations and drawbacks of the techniques in the literature providing concluding remarks and future challenges, and additionally we propose an comparison process workflow to information authors in future works.

Dash et.al (2016), reported that categorized of data including Electrocardiogram (ECG) is considerably affected with unstable class distribution. Efforts have been made to known from the imbalanced data to improve the enforcement of the classifier. As the result of ECG arrhythmia detection of normal(N) beat .We observe that various five arrhythmia beats based on balanced input to the classifier for training . The ECG signals are taken from MIT-BIH arrhythmia database. A three layer feedforward Backpropagation neural network(FFBNN) is used for the classification. The input for training the network is perfectly well matched, taking the same number of patterns from the each class. After rearing the trained netwo rk is used for classifying fully different dataset. We achieved adequate accuracy, sensitivity, & specificity of 99.24%, 94.90% & 99.57% respectively.

David et.al (2016) started that a fairly accurate, automated algorithm would facilitate competitively priced screening for asymptomatic atrial fibrillation. This find out about analyzed a new algorithm and compared it to present techniques. The incremental gain of every step in refinement of the algorithm used to be measured, and the algorithm used to be compared to different techniques the usage of the Physionet atrial fibrillation and normal sinus rhythm databases. When examining segments of 21 RR intervals or less, the algorithm had a appreciably higher region underneath the receiver working attribute curve (AUC) than the different algorithms tested .The described algorithm indicates magnificent promise for automatic screening for atrial fibrillation by decreasing false positives requiring guide review, whilst retaining excessive sensitivity.

Ehsan Ullah et.al (2016) pronounced that T-wave alternans refer to variant in amplitude, segment or wave shape in alternating T waves in ECG signals and has been linked with the SCD and ventricular arrhythmia. TWA detection is still undertaking as in many cases amplitude of TWA is well below vital method noises. Empirical mode decomposition (EMD) is a empirical signal processing technique employed as noise elimination tool for nonlinear and non-stationary TWA signals. Least rectangular works in time area and higher for the non-stationary TWA indicators that gives the method an facet over the different techniques that count on stationary nature of the signals. Least rectangular with higher order polynomial curve becoming has been recently explored as a promising TWA estimation method for threat stratification of SCD.

Esther Pueyo et al (2016) started that instabilities in ventricular repolarization have been documented to be tightly linked to arrhythmia vulnerability. Translation of the records contained in the repolarization section of the electrocardiogram (ECG) into valuable scientific decision-making tools stays challenging. This work aims at offering an overview of the closing advances in the thought and quantification of ECG-derived indices that describe repolarization properties and whose ameliorations are associated with threatening arrhythmogenic conditions. A evaluation of the state of the art is provided, spanning from the electrophysiological foundation of ventricular repolarization to its characterization on the surface ECG through a set of temporal and spatial threatmarkers.

Gupta et al (2018) reported that the examine of Electrocardiogram (ECG) signal is very inconvenient due to its non-stationary nature. ECG signal is the composite of P-wave, QRS-wave and T-wave. R-peaks recognize is very important for classifying the heart diseases in QRS-wave. R-peaks detection is not easy work. Due to the involvement of various types of impact of sound and large length of data sets. Discrete wavelet transform (DWT) is considered for preprocessing step. Hilbert transform has been used for spectral estimation for the step of extracting features. Finally, principal component analysis (PCA) is embraced for reducing feature bearing. R-peaks have been detected from reduced features on the basis of calculating the variance of principal components (PCs). The detection sensibility (SE), positive presage (PP), F-measure (F-m) and mean squared error (MSE) are appraise for estimate the performance of the proposed technique.

Kalita et.al (2020) reported that early detection of the heart disease by using Computer Aided Diagnosis system (CAD) which can reduce the mortality rate among the cardiac patients. Arrhythmia is also a heart disease when the uniform pumping mechanism of heart becomes non-uniform and this will make very little change in the Electro Cardiogram (ECG) signal. But with the help of normal eyesight it is very difficult to diagnose the irregular heart function from the ECG signal early stage. we have presented an highly efficient method for detection of Arrhythmia disease based on ECG signal. For the reason we have obtain the ECG signal data from MIT-BIH. Then we have to do preprocessing method to remove the noise from the signal. Then we have to detect the peaks from the ECG signal and QRS Complex. After that feature extraction method and process is done by using the wavelet transform technique. After that we use Artificial neural network to find out the input data is normal or abnormal. Our system gives 99.5% accuracy rate in Support Vector Machine (SVM) base and 99% accuracy rate in Artificial Neural Network (ANN) based system to diagnose the Arrhythmia disease from the given ECG signal.

Muhammad Majid et.al (2018) mentioned that arrhythmia is considered a life-threatening ailment inflicting serious health issues in patients, when left untreated. An early analysis of arrhythmias would be useful in saving lives. This study is carried out to classify patients into one of the sixteen subclasses, among which one classification represents absence of disease and the different fifteen training represent electrocardiogram archives of a number of subtypes of arrhythmias. It is carried out on the dataset taken from the University of California at Irvine Machine Learning Data Repository. The dataset consists of a massive quantity of feature dimensions which are decreased the usage of wrapper based totally feature determination technique. For the multiclass classification, support vector machine (SVM) based totally methods which include one-against-one (OAO), one-against-all (OAA), and error-correction code (ECC) are employed to observe the presence and absence of arrhythmias.

Priyanka Kakriaet.al (2015) reported that Online telemedicine systems are useful due to the possibility of timely and efficient healthcare services. These structures are based totally on superior wireless and wearable sensor technologies. The speedy boom in technology has remarkably more suitable the scope of faraway fitness monitoring systems .A real-time coronary heart monitoring gadget is developed thinking about the cost, ease of application, accuracy, and records security. The machine is conceptualized to furnish an interface between the physician and the patients for two-way communication. The major reason of this find out about is to facilitate the far off cardiac patients in getting modern day healthcare services which may no longer be possible in any other case to low doctor-to-patient ratio. The developed monitoring gadget isthen evaluated for 40 folks the use of wearable sensors while preserving an Android device. The performance evaluation shows that the proposed system is dependable and beneficial due to high speed. The analyses confirmed that the proposed gadget is convenient and reliable and ensures statistics safety at low cost. In addition, the developed system is geared up to generate warning messages to the doctor and affected person under integral circumstances.

Shalin Savaliaet.al (2016) suggested that electrocardiogram (ECG) performs an vital position in the scientific field, as it documents coronary heart signal over time and is used to find out numerous cardiovascular diseases. If a documented ECG sign has a positive irregularity in its predefined features, this is known arrhythmia, the types of which encompass tachycardia, bradycardia, supraventricular arrhythmias, and ventricular, etc. This has encouraged us to do research that consists ofdistinguishing between various arrhythmias by using the usage of deep neural network algorithms such as multi-layer perceptron (MLP) and convolution neural network (CNN). The TensorFlow library that was established by Google for deep learning and computing device getting to know is used in python to accumulate the algorithms proposed here. The ECG databases available at PhysioBank.com

and kaggle.com had been used for training, testing, and validation of the MLP and CNN algorithms.

Syed Muhammad Anwar et.al (2018) reported that automated detection and classification of life-threatening arrhythmia plays an important section in dealing with more than a few cardiac conditions. Discrete wavelet transform (DWT) is utilized on every coronary heart beat to achieve the morphological features. It presents higher time and frequency decision of the electrocardiogram (ECG) signal, which helps in decoding important records of a quasiperiodic ECG using variable window sizes. RR interval records is used as a dynamic feature. The nonlinear dynamics of RR interval are captured the use of Teager strength operator, which improves the arrhythmia classification. Moreover, to put off redundancy, DWT subbands are subjected to dimensionality discount the use of impartial element analysis, and a whole of twelve coefficients are selected as morphological features. These hybrid aspects are combined and fed to a neural community to classify arrhythmia.

Sadaf Khan et.al (2016) mentioned that at some stage in data acquisition and transmission of biomedical alerts like electrocardiography (ECG), one of a kind sorts of artifacts are embedded in the signal. Since an ECG is a low amplitude sign these artifacts notably degrade the signal first class and the sign turns into noisy. The sources of artifacts are electricity line interference (PLI), high frequency interference electromyography (EMG) and base line wanders (BLW). Different digital filters are used in order to decrease these artifacts. ECG sign is a non-stationary signal, it is tough to find constant filters for the removal of interference from the ECG signal. In order to overcome these troubles adaptive filters are used as they are nicely perfect for the nonstationary environment. It has been observed that the overall performance of new algorithm is choicest to the current ones in terms of SNR and convergence rate then again it is greater complicated than the other algorithms.

Yufaxiaet.al (2018) said that an automated wearable electrocardiogram (ECG) classification and monitoring gadget with stacked denoising autoencoder (SDAE). We use a wearable system with wireless sensors to obtain the ECG data, and send these ECG facts to a laptop with Bluetooth 4.2. Then, these ECG data are categorised with the aid of the automated cardiac arrhythmia classification system. First, the ECG function representation is discovered by using the SDAE with sparsity constraint. In the fine-tuning phase, an energetic learning is added to improve the performance. In the energetic learning phase, we use the approach that depends on the deep neural networks posterior chances to companion confidence measures to choose the most informative samples. Breaking-ties and modified breaking-ties strategies are used to select the most informative samples.

Yol et.al (2019),review that Raspberry Pi 3B+ based on Electrocardiogram (ECG) device has been purposed for real-time determine of cardiac arrhythmia. ECG signals that were taken by utilize AD8232 heart rate sensor have been displayed with developed software using Python in real-time monitoring. By using R-peak detection algorithm, we resolved beats per minute (bpm) and arrhythmia type that is related with bpm. These results have been censoring into the user interface that has been created with Python. The arrhythmia detection success rate of this study is determined as 97.9%.

ZhaohanXionget.al (2017) said that Electrocardiograms (ECG) provide a non-invasive strategy for medical diagnosis in sufferers with cardiac problems, specially atrial fibrillation (AF). Robust, computerized AF detection in clinics stayschallenging. Deep learning has emerged as an high-quality device for coping with complicated information analysis with minimal pre- and post-processing. A 16-layer 1D Convolutional Neural Network (CNN) was designed to classify the ECGs together with AF. One of the key advances of the proposed CNN was that ignore connections were employed

to decorate the rate of statistics transfer throughout the community by using connecting layers previously in the community with layers later in the network. Skip connections led to a enormous increase in the function mastering competencies of the CNN as properly as rushing up the coaching time. For comparisons, we also have carried out recurrent neural networks (RNN) and spectrogram learning. We have confirmed a novel CNN withbypass connections to function efficient, automatic ECG sign classification that ought to doubtlessly resource strong patient analysis in actual time.

CHAPTER 3

AIM AND SCOPE

3.1 AIM

In this project, we propose real-time cardiac monitoring and analysis, and discusses the main design challenges of this new generation of medical devices(Clark, et al.,2018). In particular, it highlights first the unsustainable energy cost incurred by the straightforward wireless streaming of raw data to external analysis.

The acquisition of the heart's electrical activity with a simple electrical circuit embedded in an Arduino microcontroller, with the possibility of early heart diseases detection.

There are several kinds of arrhythmia, and some of these are unsafe which may also lead to cardiac arrest and surprising demise if not detected and monitored in time.

3.2 SCOPE

In the Arduino, we implement the algorithms for R, S and T-wave detection. After trying both derivative and threshold based algorithms we went for the latter due to the better results, for the T-wave detection we experimented several empirical conditions. In a modern person, in the absence of artifacts, our algorithm detects practically of the R-peaks. The results, however are not so good in S and T-wave detection, in three 2 minute tests we missed 21, 7% of the S-wave and 27 % of the T-wave(S and T-wave misses appear to be uncorrelated).ECG varies from person to person, in one of our tests there were also some false detection of Q-wave peaks as S-wave(Joseph, et al.,2018).

We had already recognized some systematic mistakes in our S-wave detection algorithms and suppose that with more time we would be able to perform in S-wave detection as exact as in R-wave.

3.3 EXISTING SYSTEM

- By embedding more onboard intelligence and exploiting specific knowledge, it is possible to perform real-time compressive sensing, filtering and classification of heartbeats (Clark, et al.,2018).
- The design of a truly effective embedded cardiac monitor has to overcome diverse challenges.

3.4 PROPOSED SYSTEM

- Low-overhead mechanisms are introduced to synchronize code execution and enable single-instruction multiple-data operations, resulting in a decrease of the energy consumption.
- Electrode and electrode connectors are used to connect the electrodes with the pcb board and AD8332 sensors are used to measure the electrical activity of the heart which is also connect with the pcb board.
- From the ECG waveform we can detect the different types of arrhythmia (Lekuthai, et al.,2016).

CHAPTER 4

MATERIALS AND METHODS

4.1 HARDWARE USED

4.1.1 ARDUINO UNO

The Arduino UNO is an open-source microcontroller board based totally on the Microchip ATmega328 microcontroller and developed by using Arduino-cc. The board is outfitted with sets of digital and analog input/output (I/O) pins that may additionally be interfaced to a number of growth boards (shields) and different circuits. The board has 14 digital I/O pins (six capable of PWM output), 6 analog I/O pins, and is programmable with the Arduino IDE(Integrated Development Environment), through a type B USB cable It can be powered via the USB cable or by an exterior 9-volt battery, although it accepts voltages between 7 and 20 volts.

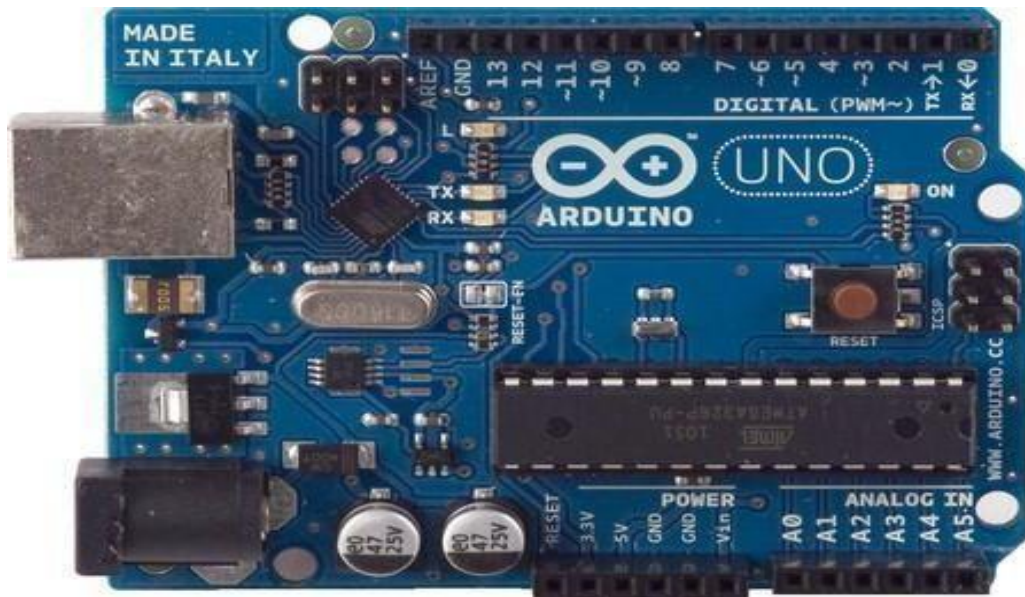


Fig: 4.1 Arduino board

4.1.1.1 General pin functions

- LED: There is a built-in LED pushed by way of digital pin 13. When the pin is excessive value, the LED is on, when the pin is low, it is off.
- VIN: The input voltage to the Arduino board when it is the use of an exterior power source (as antagonistic to 5 volts from the USB connection or different regulated power source). You can supply voltage through this pin, or, if providing voltage by way of the strength jack, get entry to it through this pin.
- 5V: This pin delivers a regulated 5V from the regulator on the board. The board can be furnished with the electricity both from the DC electricity jack (7 - 20V), the USB connector (5V), or the VIN pin of the board (7-20V). Supplying voltage through the 5V or 3.3V pins bypasses the regulator, and can harm the board.
- 3V3: A 3.3volt supply generated by way of the on-board regulator. Maximum present day draw is 50 mA.
- GND: Ground pins.
- IOREF: This pin on the Arduino board offers the voltage plug with which the microcontroller operates. A appropriate configured guard can study the IOREF pin voltage and pick the suitable energy source, or allow voltage translators on the outputs to work with the 5V or 3.3V.

4.1.1.2 Special pin functions

One another of the fourteen digital pins and six analog pins on the Uno can be used as an input or output, underneath software program manipulate. They operate at 5 volts. Each pin can furnish or get hold of 20 mA as the recommended running situation and has an inner pull-up resistor (disconnected by way of default) of 20-50K ohm. A most of 40mA should no longer be exceeded on any I/O pin to keep away from everlasting injury to the microcontroller. The Uno has 6 analog inputs, labeled A0 via A5; every affords 10 bits of decision (i.e. 1024 exceptional values). By failure to appear, they measure from ground to 5 volts, although it is feasible to opportunity of choosing the upper end of the vary the usage of the AREF pin and the analog function.

4.1.2 AD3282 ECG SENSOR

The sensor is an integrated signal conditioning block for ECG and different biosignal measurement applications.

It is designed to extract, amplify, and filter small biopotential alters in the presence of noisy conditions, such as those created with the aid of motion or faraway electrode placement.

This format lets in for an ultralow strength analog-to-digital converter (ADC) or an embedded microcontroller to gather the output signal easily. The AD8232 can put in force a two-pole high-pass filter for casting off motion antiquity and the electrode half-cell dormant.

This filter is tightly coupled with the instrumentation structure of the amplifier to enable both large reap and high-pass filtering in a single stage, thereby saving space and cost.

An uncommitted operational amplifier permit the AD8232 to create a three-pole low-pass filter to stimulate off greater noise. The user can pick out the frequency cutoff of all filters to go well with exceptional kinds of applications.

To improve common-mode rejection of the line frequencies in the machine and different undesired interferences, the AD8232 consists of an amplifier for pushed lead applications, such as right leg pressure (RLD).

The AD8232 consist of a quick restoration feature that reduces the length of otherwise lengthy settling tails of the high-pass filters.

After an abrupt sign alternate that rails the amplifier (such as a leads off condition), the AD8232 routinely adjusts to a greater filter cutoff.

This characteristic allows the AD8232 to recover quickly, and therefore, to take legitimate measurements quickly after connecting the electrodes to the

subject. Performance for the A grade models is detailed from 0°C to 70°C and the fashions are operational from -40°C to +85°C. Performance for the W grade fashions is certain over the automotive temperature vary range from -40°C to +105°C.

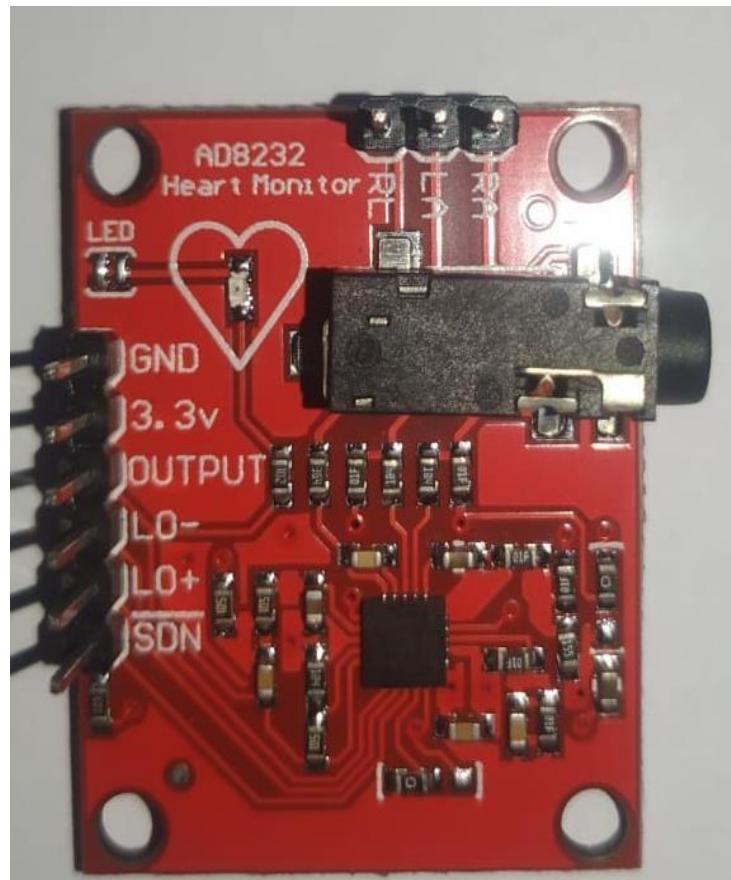


Fig 4.2: AD8232 ECG sensor

4.1.2.1 Pin Definitions and Descriptions

Table 4.1 Pin definitions and descriptions

Pin no.	Mnemonic	Description
1	GND	Power Supply Ground.

2	3.3v	3.3v Power Supply
3	OUTPUT	Output signal
4	LO-	Leads Off Comparator Output. In an dc leads off detection mode, LOD- is high when the electrode to -IN is disconnected, and it is low when connected. In an ac leads off detection mode, LOD- is always low.
5	LO+	Leads Off Comparator Output. In an dc leads off detection mode, LOD+ is high when the +IN electrode is disconnected, and it is low when connected. In an ac leads off detection mode, LOD+ is high when either the -IN or +IN electrode is disconnected, and it is low when both electrodes are connected.
6	SDN	Shutdown Control Input. Drive SDN low to enter the low power shutdown mode.

4.1.3 LOW PASS FILTER

A simple passive RC Low Pass Filter or LPF, can be easily made by connecting together in series a Resistor with series of Capacitor. In this type of filter arrangement the input signal (V_{IN}) is applied to the series combination (both the Resistor and Capacitor together) but the output signal (V_{OUT}) is taken across the capacitor only. the reactance of a capacitor varies inversely with frequency, while the value of the resistor remains constant as the frequency changes. At low frequencies the capacitive reactance, (X_C) of the capacitor will be very large compared to the resistive value of the resistor, R.

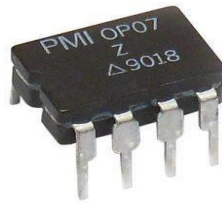


Fig 4.3: OP07 IC

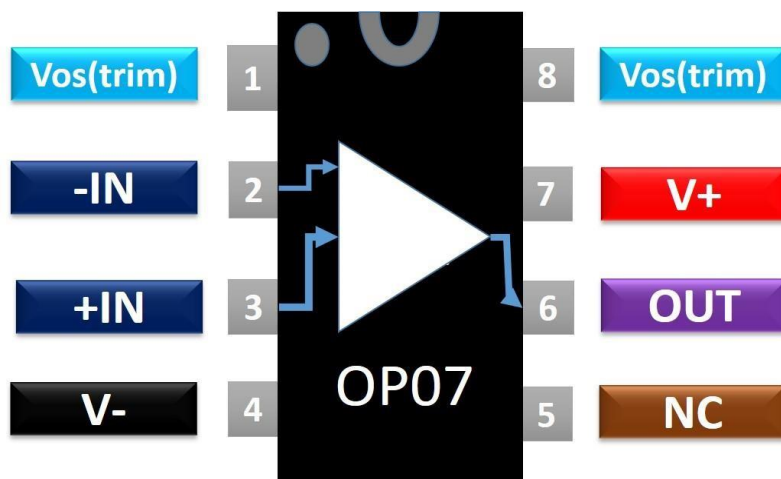


Fig 4.4: OP07 IC pinout

This means that the voltage potential, V_C across the capacitor will be much larger than the voltage drop, V_R developed across the resistor. At high frequencies the reverse is true with V_C being small and V_R being large due to the change in the capacitive reactance value.



Fig 4.5: 0.1 microfarad capacitor



Fig 4.6: 82 K Resistor

4.1.4 Electrodes positioning

An ECG offers three principal sorts of information. First through measuring the time intervals, it is viable to determine how lengthy the electrical wave takes to pass by thru the heart. This indicates if the electrical pastime is normal, slow, speedy or irregular. Second, by using measuring the amount of electrical recreation passing through the heart, it may be feasible to find out if components of the heart are too massive or overworked. Third, it gives the heart rate.

The dimension is accomplished the usage of three electrodes positioned on the skin in the following locations.

1. Right arm on front of forearm or on right facet of chest.
2. Left arm on front of forearm or on the left facet of chest.
3. Right leg on center thigh or decrease right abdomen.



Fig 4.7: Audio jack to 3 electrode snap connectors

4.1.4.1 ECG features and anomalies detection

P wave – Represents atrial depolarization all through atrial systole, with a traditional duration smaller than 120ms. An increased or lowered P-wave can point out hypo or hyperkalemia, respectively. Right and left atrial hypertrophy can also be detected by means of gazing P-wave morphology.

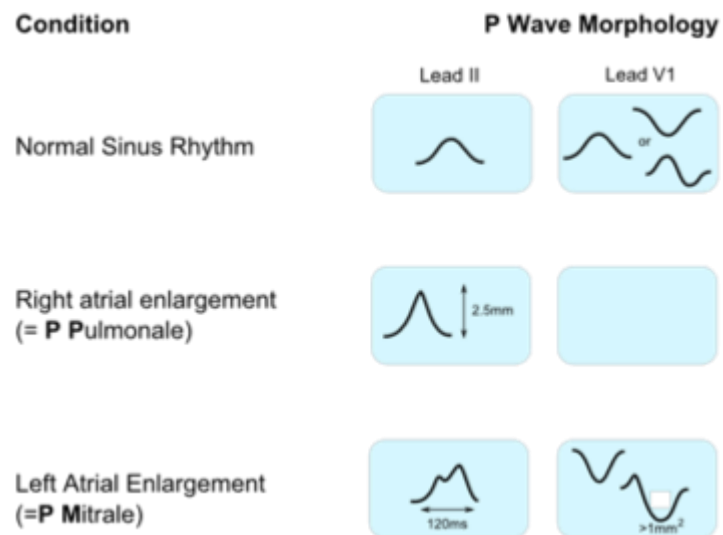


Fig 4.8: P Wave morphology

QRS complex – Indicates ventricular depolarization and contraction for the duration of ventricular systole, with a standard period usual between 60 and 100ms. Prolonged period shows hyperkalemia or bundle branch block and multiplied amplitude shows cardiac hypertrophy, which is a common situation in athletes. Other anomalies reveal the presence of infarction. The time between RR-peaks may additionally be used to compute the coronary heart rate.

ST-segment – Refers to the hole between the S-wave and the T-wave, represents the time between ventricular depolarization and repolarization and has a standard period between 80 and 120ms.

Flat, down sloping, or depressed ST-segments may also point out coronary ischemia. ST-elevation is the classical indicator for myocardial infarction. T-wave – Represents ventricular repolarization. T-wave inversion can be an indicator for countless heart disorders. U-wave – Represents repolarization of the Purkinje fibers. It is now not usually visible on an ECG because it is a very small wave in evaluation to the others.

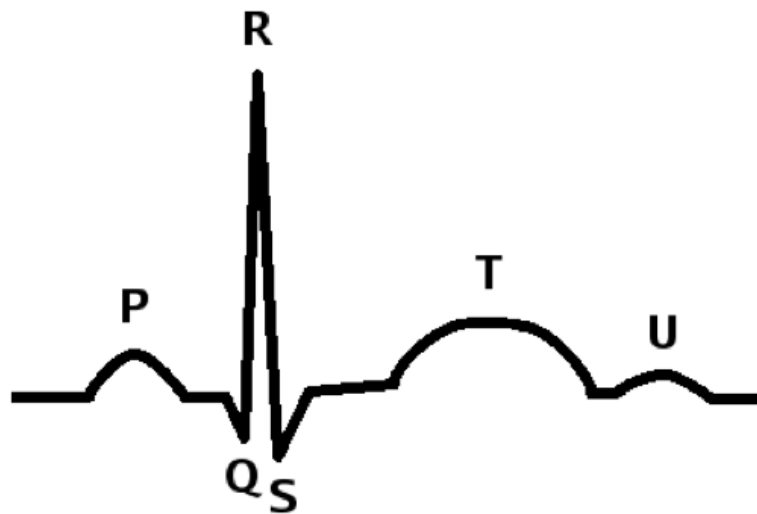


Fig 4.9: Schematic representation of a standard ECG

4.1.4 DEVELOPMENT AND DESIGN

The circuit used to measure heart's electric recreation can be divided into various blocks. Signal acquisition, filtration were the two primary methods used to extract a very susceptible signal from one's chest. All the connections had been performed in a breadboard and then an Arduino UNO was once chosen to obtain all the digital processing.

4.1.4.1 Acquisition

The circuit proposed in this paper used to be based totally on a widespread circuit of ECG acquisition. The input electrodes are related directly to the ampop's effective terminals. Therefore, it used to be viable to make bigger a very vulnerable sign besides worrying the physique voltage. To do so, ECG specific electrodes have been used to detect the sign and transmit it thru a set of 3 coaxial cables created to better insulate the circuit from external electromagnetic interferences. Along with this, any other huge gain of these cables is the electromagnetic fields carrying the signal exist solely in the space between the internal and outer conductors. This lets in coaxial cable runs to be hooked up next to different steel objects. The position of every electrode substantially influences the polarity and the structure of the electric powered coronary heart activity registered. Different positions empower one to find out about special precise ECG curve parameters (Joseph, et al.,2018). This is why in a medical environment, it's expected to perform these assessments with more than three electrodes.

4.1.4.2 Filtration

The human physique is a top conductor acting as an antenna which selections up electromagnetic radiation current in the environment. The most frequent electromagnetic radiation, that was vital to deal with, was once the one coming from the electricity line, which has a essential frequency round 50Hz. To decrease its preponderance, both ampops and the Arduino were furnished with batteries. Other feasible interference sources are muscular endeavor, together with respiration and movement.

It is additionally necessary to refer the barriers of breadboards and the good sized variety of connections which has interfered in the circuit stability and contributed to sign distortions. Moreover, the electrodes ought to also be as tighten as possible to the skin. To enhance conductivity in the interface between the skin and the electrode, a conductor gel should be used (although we didn't use it for the sake of mannequin simplicity and low cost). To dispose of all these distortions sources, we designed two analog low-pass filter and one analog high pass.

Low-Pass Filters two low-pass filters with two extraordinary cutoff frequencies (24Hz and 44Hz) have been used to do away with electricity line frequency at a higher rate than 20 db/dec . Since, we bought an perfect frequency response with these 2 passive filters, we avoid the use of energetic filtration (with ampops) to get a circuit as energetically environment friendly as possible, thinking about energy boundaries present in transportable devices.

4.2 SOFTWARE USED

4.2.1 *Arduino IDE*

The IDE source code is released under the GNU General Public License, version 2. T

he Arduino IDE u78 `12ses special code structuring guidelines to support the languages C and C++. The Arduino IDE supplies a wiring project software library that provides a number of common input and output procedures. User-written code only needs two simple functions to start the sketch and the main program loop, which are compiled and connected into an executable cyclic executive program with the GNU tool chain, which is also included with the IDE distribution. The Arduino IDE uses the software to translate the source codes to a text file in hexadecimal that is loaded into the Arduino board by a loader program in the circuitry of the board.

Your facts will be covered with two extra replication, encrypted storage and optional TLS/SSL data support. You can additionally customize permission corporations to each module of the platform, making sure that right fact is shown to the right user.

❖ Initial step

If the Arduino IDE has been opened, here is what it looks like. It opens in a blank sketch where you can start programming right away. First, we need to customize the board and port settings to enable us to upload code. Connect your Arduino board to your PC with a USB cable.



Fig 4.10:Arduino IDE

CHAPTER 5

RESULTS AND DISCUSSION

5.1 RESULTS

The proposed model of design for cardiac monitoring for the detection of various arrhythmias where we live. Parameters tested include RR interval, QRS complex and R amplitude. These parameters were monitored for five persons.

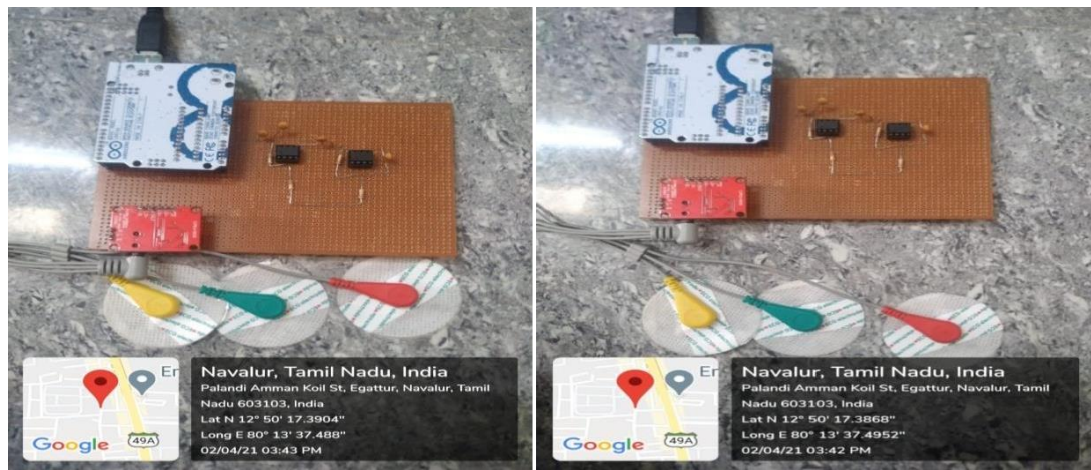


Fig 5.1: Proposed Hardware Model

Figure 5.1 shows the complete hardware of the proposed design. The hardware consists of the Arduino board to which the AD8232 sensor gives the ECG signal. Data from the Arduino board is sent to the Arduino Uno platform via the USB cable.

In the end, we were successful in obtaining a good-looking ECG signal and plot it in the computer.

Heart Rate (HR) We were able to compute either the instantaneous heart rate (from the time between each R-peak) as the average heart rate (from the time of a 5 sequence of R-pulses).

We chose to show in the 4 digits – 7 segments an average of both (so the displayed value was not as volatile as the instantaneous HR nor as static as the 5 sample HR).

We also compared our HR computed values with the ones obtained with the ubidots and found them to be similar. It was also possible to note the HR increase with deep inhalation and decrease with exhalation.

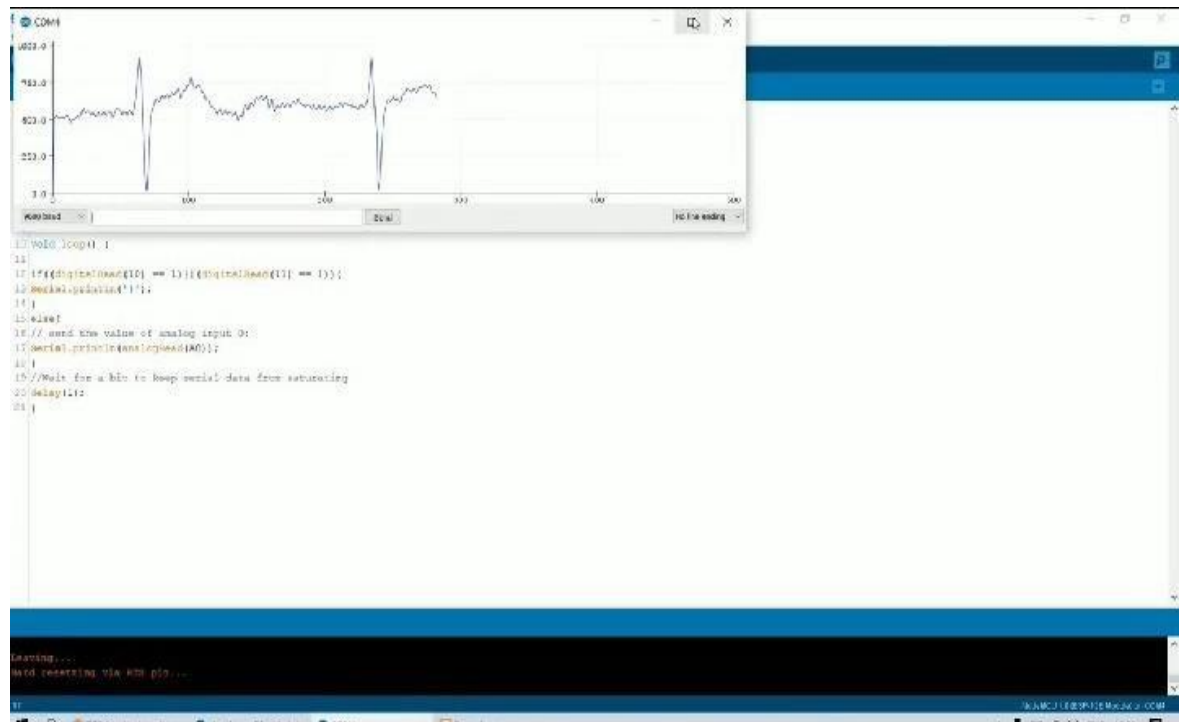


Fig 5.2: Output obtained on arduino IDE

The above fig 5.2 is the original signal displayed in the programmed ECG output display in arduino IDE.

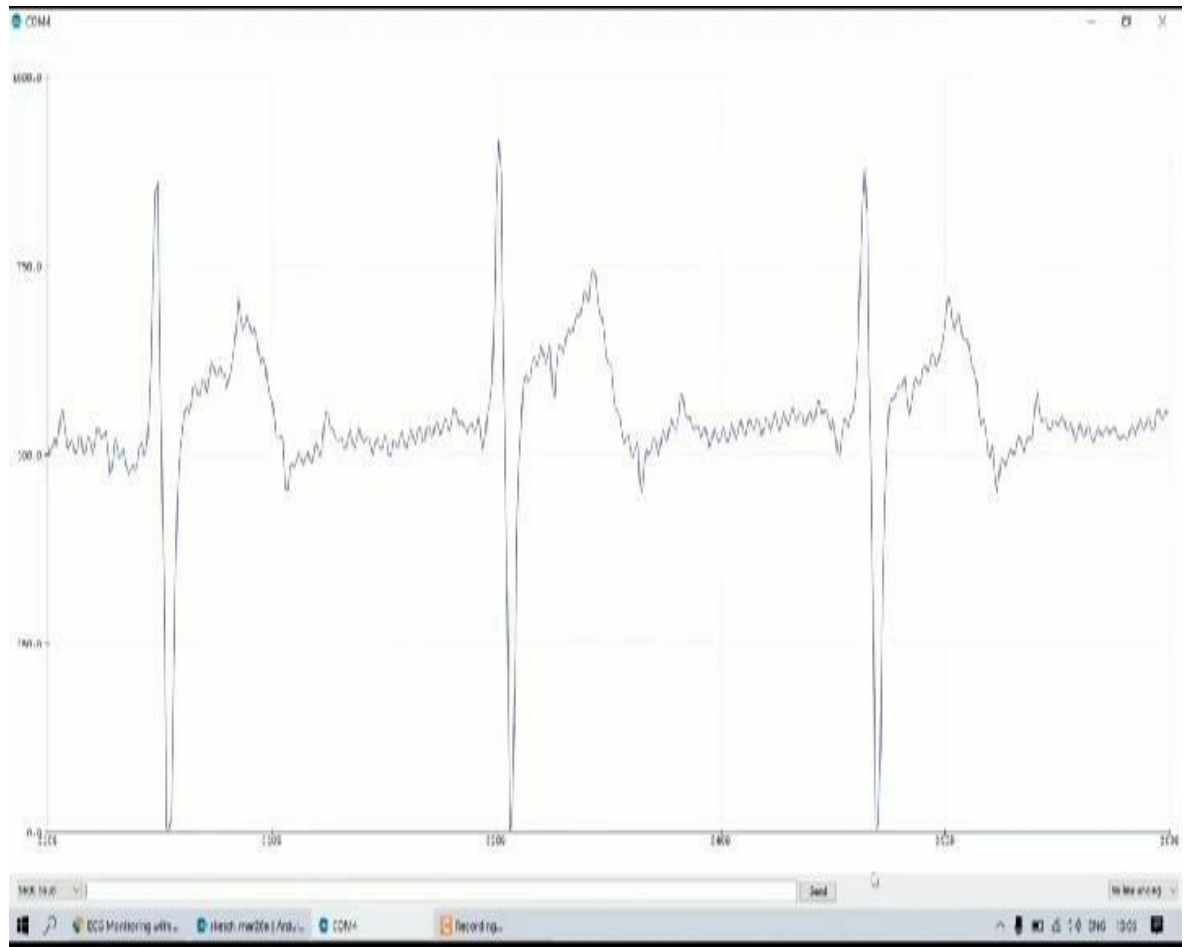


Fig 5.3: Zoomed image of output obtained on Arduino IDE

The above fig 5.3 is the zoomed image of the ECG signal in the arduino IDE. In the x-axis it has the wave length and in the y-axis it has the time, from that we can know the variations in the waveforms.

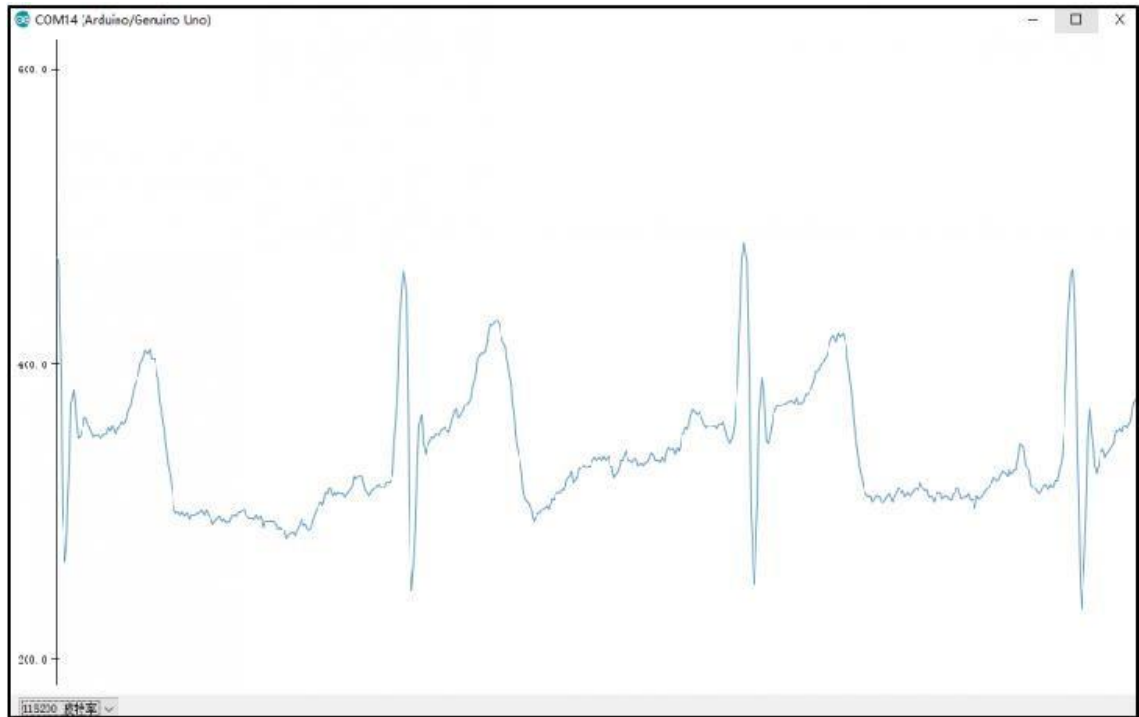


Fig 5.4: Filtered signal obtained on Arduino IDE

From the fig 5.4 it shows the ECG signal without the noise after adding the filter.

5.2 DISCUSSION

The coaxial cables, the analogue and digital filters alongside with the discount in the range and size of wires made viable the 50 Hz noise removal from the body's ECG signal.

Nevertheless, the output sign barely incorporates its facts compromised due to the noise. Its attenuation was not absolutely achieved given that the sketch and the choice of certain compounds may not be the most correct:

Different ampops have exclusive frequent mode rejection ratios.

Depending upon the diameter of the coaxial cables, they will better conduct low or excessive frequency signals. These factors have been solely barely addressed due to time constraints. Nevertheless, we were capable to become aware of virtually a hundred percent of all R-wave peaks, 78, 3% of S-wave and 72, 5% T-wave peaks, in real time, present in the signal. Last one with much less accuracy due to the decreased dimensions and area in the signal, extra tough to threshold. Relatively to the processing task, we had been capable to increase an algorithm to measure heartbeat, the ST- segment time interval, as properly as, the time throughout the QRS-complex. The maximum amplitude of this complicated used to be also determined.

Table 5.1: Average output readings obtained on 5 different persons

TRAIL NO	RR INTERVAL(SEC)	R AMPLITUDE(MV)	QRS COMPLEX(SEC)	BPM
1	0.806	0.942	0.086	78
2	0.856	0.972	0.085	72
3	0.993	0.956	0.079	66
4	0.695	0.748	0.065	90
5	0.667	0.901	0.078	84

From the above table 5.1 we can observe that variations in the ECG signal parameters. The standard value for RR interval is 600-1200ms but in the table it varies for person to person and this variations is also in the other parameters like R amplitude and QRS complex. So, we can conclude that this variations will helps for the detection of different types of arrhythmias.

CHAPTER 6

SUMMARY AND CONCLUSION

6.1 SUMMARY

In this project, an electrocardiograph was once designed and developed. A small prototype which acquires with three electrodes, one positioned in the forelimb and two in the chest, the cardiac electrical activity. The literature review enabled an appropriate method of selection for the sensor utilized in order to achieve ECG signal recognition for the detection of arrhythmia. Despite the exceptional subject in recognizing the cardiac recreation from the input signal, we managed to considerably attenuate the noise and gain a clean, function recognizable, closing signal.

The AD8232 ECG sensor used in this project has the capability of monitoring real time electrical activity of the heart and obtaining reliable data output. The filtered data has been sent to Arduino IDE via the USB cable and the output signal will be display on PC.

6.2 CONCLUSION

In this project, an arduino program is used to collect the sample readings of electrical activity of the heart using AD8232 ECG sensor. This acquired ECG signal is filtered by the fourth order filter. The signal readings obtained are transferred to Ubidots website in the PC for reading and testing the relied data. That data can be used to detecting the R amplitude variation, R-R interval. so, It is examined to many persons, from the results we observed that the R amplitude, R-R interval can various from one person to another person. so, we conclude that if we check for arrhythmia patients we can detect various types of arrhythmia and other heart diseases.

REFERENCES

1. Afadar Y, A. Akram, A.Alkeebali and S. Majzoub, "Heart Arrhythmia Detection & Monitoring Using Machine Learning & ECG Wearable Device", *Seventh International Conference on Information Technology Trends (ITT)*, Abu Dhabi, United Arab Emirates,2020, pp. 107-112.
2. Afkhami.R.G, G. Azarnia and M. A. Tinati, "Cardiac arrhythmia classification using statistical and mixture modeling features of ECG signals", *Pattern Recognit. Lett.*,2016, vol. 70, pp. 45-51.
3. Afadar.F, A. Akram, A. Alkeebali and S. Majzoub, "Heart Arrhythmia Detection & Monitoring Using Machine Learning & ECG Wearable Device",*Seventh International Conference on Information Technology Trends (ITT)*, Abu Dhabi, United Arab Emirates, 2020, pp. 107-112.
4. AlRahhal.M.M, Y. Bazi, H. AlHichri, N. Alajlan, F. Melgani and R. R. Yager, "Deep Learning Approach for Active Classification of Electrocardiogram Signals", *Inf. Sci. (Ny)*.,2016,vol. 345, pp. 340-354.
5. Apandi.Z.F.M, R. Ikeura and S. Hayakawa, "Arrhythmia Detection Using MIT-BIH Dataset: A Review",*International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA)*, Kuching,

Malaysia,2016,pp.1-5.

6. Akdeniz.F and T. Kayikcioglu, "Detection of ECG arrhythmia using large choi williams time-frequency feature set",*Medical Technologies National Congress (TIPTEKNO)*, Trabzon, Turkey,2018,pp. 1-4.
7. Ben Salah.R, T. Hadidi and S. Chabchoub, "Intelligent diagnosis method of cardiovascular anomalies using medical signal processing", *World Congress on Information Technology and Computer Applications (WCITCA)*, Hammamet, Tunisia,2015,pp.1-5.
8. Bhatia.Y, A. Mittal, S. Athavale, T. Mohanani and G. Bhatia, "Classification of Cardiac Arrhythmia using Kernelized SVM",*4th International Conference on Trends in electronics (ICOEI)*(48184),Tirunelveli,India,2020,pp.922-926.
9. Cao.L, W.B. Huang and F.-C. Sun, "Building feature space of extreme learning machine with spares denoising stacked autoencoder", *Neurocomputing*,2016,vol. 174, pp. 60-71.
10. Caldas.W.L, J. Paulo V. Madeiro, C. L. C. Mattos and J. P. P. Gomes, "A New Methodology for Classifying QRS Morphology in ECG Signals",*International Joint Conference on Neural Networks(IJCNN)*,Glasgow,UK,2020,pp.1-9.

11. Chen.S.L, T.L. Lin, M.-C. Tuan and T.K. Chi, "VLSI architecture of lossless ECG compression design based on fuzzy decision and optimisation method for wearable devices", *Electron. Lett.*,2015, vol. 51, no. 18, pp. 1409-1411.
12. Clark.N, E. Sandor, C. Walden, I. S. Ahn and Y. Lu, "A wearable ECG monitoring system for real-time arrhythmia detection",*IEEE 61st International Midwest Symposium on Circuits and Systems (MWSCAS)*, Windsor, ON, Canada,2018,pp. 787-790.
13. Dash S K and G. S. Rao, "Robust multiclass ECG arrhythmia detection using balanced trained neural network", *International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*,Chennai,India,2016,pp.186-191.
14. FatihaBouaziz, HamoucheOulhadj, Daoud Boutana, Patrick Siarry,"An Efficient Algorithm for Cardiac Arrhythmia Classification Using Ensemble of Depthwise Separable Convolutional Neural Networks", *Applied Sciences*, Ihsanto,Eko et al.,2018.
15. Gupta V and M. Mittal, "R-peak based Arrhythmia Detection using Hilbert Transform and Principal Component Analysis",*3rd International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH)*,Ghaziabad,India,2018,pp.1-4.

16. Harkat, A., R. Benzid and L. Saidi, "Features extraction and classification of ECG beats using CWT combined to RBF neural network optimized by cuckoo search via levy flight", *Proc. 4th Int. Conf. Electr. Eng. (ICEE)*, 2015, pp. 1-4.
17. Hannun A Y, Rajpurkar P, Haghpanahi, M. *et al*, "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network", *Nat Med* 25, 2015, pp. 65-69.
18. Hosseini-Asl, E., J. M. Zurada and O. Nasraoui, "Deep learning of part-based representation of data using sparse autoencoders with nonnegativity constraints", *IEEE Trans. Neural Netw. Learn. Syst.*, 2016, vol. 27, no. 12, pp. 486-498.
19. Izci, E., M. A. Ozdemir, M. Degirmenci and A. Akan, "Cardiac Arrhythmia Detection from 2D ECG Images by Using Deep Learning Technique", *Medical Technologies Congress (TIPTEKNO)*, Izmir, Turkey, 2019, pp. 1-4.
20. Javier, G., M. Davis, V. Cristian and N. Johann, "R-wave detection algorithm using integration of virtual instruments", *20th Symposium on Signal Processing, Images and Computer Vision (STSIVA)*, Bogota, Colombia, 2015, pp. 1-6.
21. Joseph, F. and V. Anoop, "Detection of Waves in ECG for Arrhythmia Classification", *3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, Tirunelveli, India, 2019, pp. 478-481.

- 22.D. Kalita, "An Automatic Detection of Arrhythmia Disease Diagnosis System based on Artificial Neural Network and Support Vector Machine", *International Conference on Computational Performance Evaluation (ComPE)*, Shillong, India,2020,pp. 728-732.
- 23.Krishnaiah.V, G. Narsimha and N. S. Chandra, "Heart disease prediction system using data mining technique by fuzzy K-NN approach", Proc. 49th Annu. Convention Comput. Soc. India (CSI) Adv. Intell. Syst. Comput. Emerg. (ICT),2015, vol. 1, pp. 371-384.
- 24.Kiranyaz.S, T. Ince and M. Gabboujo,"Real-time patient-specific ECG classification by 1-D convolutional neural networks", IEEE Trans. Biomed. Eng.,2016,vol. 63, no. 3, pp. 664-675.
- 25.Lek-uthai.A, P. Somboon and A. Teeramongkonrasmee, "Development of a cost-effective ecg monitor for cardiac arrhythmia detection using heart rate variability",*9th Biomedical Engineering International Conference (BMEiCON)*, Laung Prabang, Laos,2016, pp. 1-5.
- 26.Muppalla.V, N. S. S. K. Suraj, D. Suman and B. Mukherjee, "Implementation of an Arrhythmia detection scheme with cellular based alert framework",*IEEE Calcutta Conference (CALCON)*, Kolkata,2017, pp. 438-442.
- 27.Naik.G.R and K. A. Reddy,"Comparative analysis of ECG classification using

neuro-fuzzy algorithm and multimodal decision learning algorithm: ECG classification algorithm", Proc. 3rd Int. Conf. Soft Comput. Mach. Intell. (ISCMI),2016, pp. 138-142.

28.Pavel.M.S.R, M. R. Islam and A. M. Siddiquee, "Fetal Arrhythmia Detection Using Fetal ECG Signal",*IEEE International Conference on Telecommunications and Photonics (ICTP)*, Dhaka, Bangladesh, 2019, pp. 1-4.

29.Saini.R, N. Bindal and P. Bansal, "Classification of heart diseases from ECG signals using wavelet transform and kNN classifier", Proc. Int. Conf. Comput. Commun. Auto.,2015,pp. 1208-1215.

30.Sassi.R et al., "Advances in heart rate variability signal analysis: joint position statement by the E-cardiology ESC working group and the european heart rhythm association co-endorsed by the asia pacific heart rhythm society", *Europace*,2015,vol. 17, no. 9, pp. 1341-1353.

31.Schmidhuber.J,"Deep learning in neural networks: An overview", *Neural Netw.*,2015,vol. 61, pp. 85-117.

32.Verma.D and S. Agarwal, "Cardiac Arrhythmia Detection from Single-lead ECG using CNN and LSTM assisted by Oversampling",*International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, Bangalore, India,2018, pp. 14-17.

APENDICES

```
void setup()
{

  Serial.begin(9600); // initialize the serial communication:
  pinMode(10, INPUT); // Setup for leads off detection LO +
  pinMode(11, INPUT); // Setup for leads off detection LO -

}

void loop()
{

  if((digitalRead(10) == 1)||(digitalRead(11) == 1))
  {
    Serial.println("!");
  }
  Else
  {

    Serial.println(analogRead(A0)); // send the value of analog input 0:

  }

  delay(1); //Wait for a bit to keep serial data from saturating

}
```