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REAL TIME ARRHYTHMIADIAGNOSTIC SYSTEM

[1]W.Sherine Mary, [2]Sapna Kumari Pandey, [2]S.Surya,[2]M.Gadsiya, [2]D.Deepa

[1]Associate Professor, Adithya Institute of Technology, Coimbatore, India.
[2]UG scholar, Adithya Institute of Technology, Coimbatore, India.

ABSTRACT:

Cardiovascular disease contributes to a large percentage of deaths worldwide. Arrhythmia is a cardiovascular disease which can be identified and predicted through ECG signal analysis. Accurate analysis of ECG signal is crucial in disease detection. In or system we have designed an IoT based Arrhythmia detection system which can analyze the ECG signal acquired from the human agent. QRS detection is an important portion of ECG signal analysis. Developing and accurate and computationally fast QRS algorithm is the main focus of our work. The algorithm is carried forward using the various processes like preprocessing, peak finding, and QRS detecting. Once the dynamic features of the ECG signal are extracted we use these feature to detect the R-R interval variations. Based on variations in R-R rate cardiac arrhythmias are classified. This information acquired from the user agent is transmitted via internet to the cloud which can be used by health care professional to diagnose arrhythmias and hence save lives.

Keywords:ECG signal, IoT

1. INTRODUCTION:

ARRHYTHMIA AN OVERVIEW:

Arrhythmia contributes approximately 200,000-300,000 sudden deaths per year across worldwide.An arrhythmia is an uneven heart rhythm or an irregular heartbeat, in which the heart rate is too fast or too slow. Depending upon the heart rate, arrhythmia can be classified into following types. If the heart rate is too fast or the beats are above 100 per minute then it is called as Tachycardia. If the heart rate is too slow or bpm ranges below 60, then it is called as Bradycardia. The most common life-threatening Arrhythmia is ventricular fibrillation, which is an erratic, disorganized firing of impulses from the ventricles (the heart's lower chambers). When this occurs, the heart is unable to pump blood and death will occur within minutes,if left untreated. Thus early detection of arrhythmia is essential to prevent deaths.The most common test used to diagnose an arrhythmia is an electrocardiogram (EKG or ECG). Your doctor will run other tests as needed. She or he may recommend medicines, placement of a device that can correct an irregular heartbeat, or surgery to repair nerves that are overstimulating the heart. If arrhythmia is left untreated, the heart may not be able to pump enough blood to the body. This can damage the heart, the brain, or other organs.

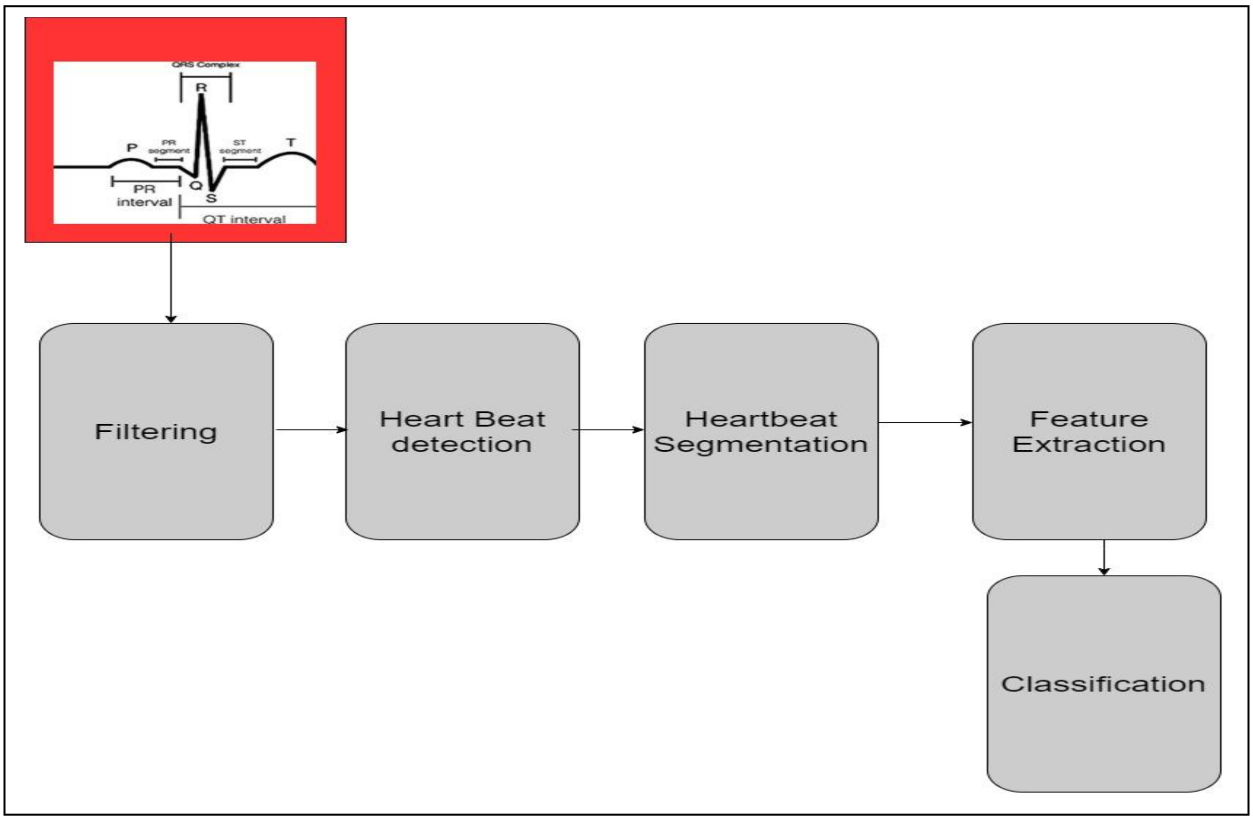
2. PROPOSED SYSTEM:

In this work, we have developed a system that supports ECG signal analysis for feature extraction and the corresponding classification technique for diagnosis of the heart condition. The implementation is done on ESP32 and server combinations wherein computational tasks are split between the end device and the server. We have chosen the Discrete Wavelet Transform (DWT) as feature extraction method and Support Vector Machine (SVM) as classification method. In order to derive an optimized and cost effective solution, we perform exploration over the ECG extracted features space. The execution times weobtained from implementing the application on the ESP32 board show that the ECG analysis.

3. PEAK DETECTION ALGORITHM:

This algorithm will automatically detect the fiducial points, namely the P wave, QRS complex and T wave which is necessary for early detection of the cardiovascular disease. We are taking more number of ECG samples and analyze it to produce the better results. The system is fed with the medical information and based on that the output is produced through AI based peak detection algorithm.

4. BLOCK DIAGRAM:



5. DESCRIPITION OF BLOCK DIAGRAM:

Above figure represents the block diagram of the proposed system. In our project we have used database from MIT, and it is one of the most utilized databases for research purposes. The database is composed of 48 half-hour excerpts of two-channel (two leads) ambulatory ECG recordings, obtained from 47 subjects. The data are band pass filtered at 0.1-100Hz and digitized at 360 samples per second, per channel. The first-channel lead of 45 records are used, which is a modified lead II (MLII), leaving out records 102, 104 and 114, whose first-channel lead is not a MLII.

The MIT-BIH database also provides annotations for each record, where cardiologists have placed a diagnosis label for every heartbeat included in the record. The American Heart Association (AHA) heartbeat classes (N,V,F,E,P,Q,O) were used as reference for the two arrhythmia groups examined, ’Normal’ (N) and ’Abnormal’ (V,F,E,P,Q,O). The initial stage of the analysis was implemented in Matlab environment. Figure 3.1 illustrates the proposed structure of a typical ECG analysis and heartbeat classification.

5.1 Filtering:

The power line interference and the baseline wandering are significant noise sources that can strongly affect the ECG signal analysis. The signals were band-pass filtered at 1-50Hz.

5.2 Heartbeat detection:

WFDB function wqrs() is applied to the signal, which gives us the locations of all QRS complexes found in the signal. This information along with the ECG signal, are the inputs to WFDB function ecgpuwave(), which gives us the exact position of all the R peaks found in the signal. QRS detection, especially detection of R wave, is easier than other parts of the ECG signal due to its structural form and high amplitude. Each R peak detection corresponds to the detection of a single heartbeat.

5.3 Heartbeat segmentation:

Having located the R peaks, we proceed to segment the ECG signal into single heartbeats. We choose a window width of 257 samples, which having as center the detected position of the R peak, will cover the whole heartbeat waveform.

5.4 Feature extraction:

A stage for feature extraction follows, in order to extract a feature vector for each produced heartbeat, containing a smaller number of elements than the ECG samples forming the heartbeat. We use Discrete Wavelet Transform (DWT) as a feature extraction mechanism, since it has been proven to produce very accurate results.

The wavelet base for the DWT is Daubechies of order 2 (db2) and we perform 4 levels of decomposition. The 4 levels of decomposition produce 8 sets of coefficients eachone for 4 levels of detailed and 4 levels of approximate coefficients. Since the heartbeat on which the DWT is applied consists of 257 samples, the number of wavelet coefficients for the first, second, third and fourth level, are respectively 130, 66, 34 and 18. Thus, 494 wavelet coefficients are obtained for each heartbeat. The final feature vector that serves as input to the classification stage, resulted from a design space exploration performed on all combinations of these 8 sets of coefficients.

5.5 Classification:

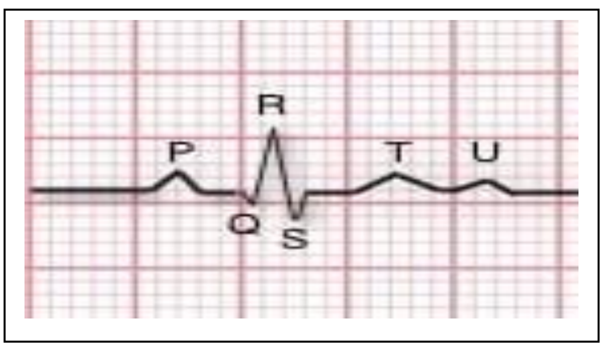
The last stage consists of a binary classifier, which labels each heartbeat as either ’Normal’ or ’Abnormal’. We focus on using a Support Vector Machine (SVM) classifier, with RBF as kernel function, mainly due to its ability to support nonlinear classification with efficient accuracy and computation cost. The Matlab interface of LIBSVM was used for the implementation of the SVM classifier. We use the 104581 heartbeats detected in the 45 selected ECG records to form the training and testing data sets.

As feature vector we use the DWT coefficients extracted in the previous stage, and as target value we use the diagnosis label given for each heartbeat in the annotation files. The training process of the SVM model can be done offline. Having a training data set and a testing data set for evaluation, we perform the design space exploration that is described below to decide upon the feature vector which gives the model with the best performance results.

Then, with a fixed feature vector, the SVM model is produced offline.

6. HARDWARE ARCHITECTURE:

This model is used for classification of heartbeats inputted in the algorithmic flow, in real time. An ECG is a paper or digital recording of the electrical signals in the heart. It is also called an electrocardiogram or an EKG. The ECG is used to determine heart rate, heart rhythm and other information regarding the heart’s condition. ECGs are used to help diagnose heart arrhythmias, heart attacks, pacemaker function and heart failure.



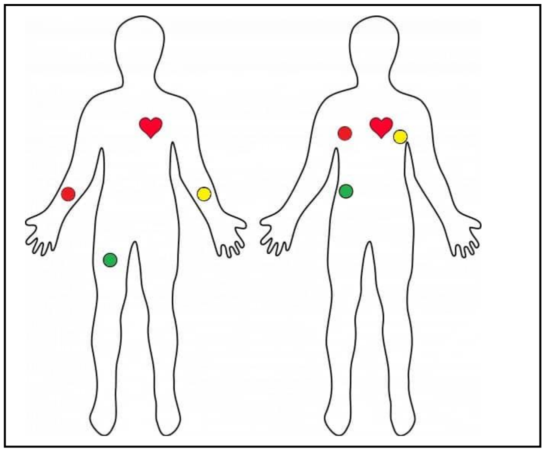
7. LEAD PLACEMENT:

It is recommended to snap the sensor pads on the leads before application to the body. The closer to the heart the pads are, the better the measurement. The cables are color coded to help identify proper placement

Red: RA (Right Arm)

Yellow: LA (Left Arm)

Green: RL (Right Leg)



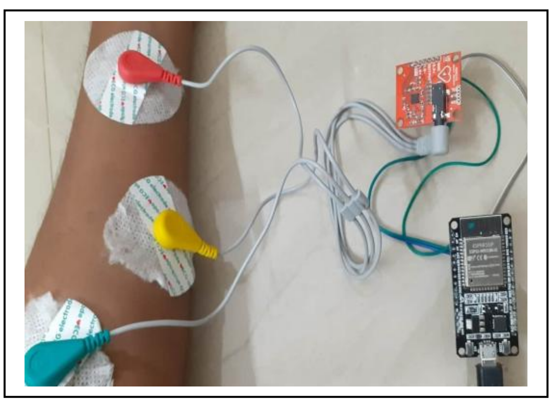
ESP32	AD8232
GND	GND
3.3 V DC power supply	3.3 V DC power supply
VP	Output
D3	LO-
D2	LO+

8. AD8232 AND ESP32 CONNECTION:

To interface AD8232 ECG Sensor with ESP32 IOT Chip, follow the circuit diagram above. Supply the AD8232 with 3.3V from ESP32 and connect GND to GND. The output pin of AD8232 is an analog signal and is connected to VP pin of ESP32. Similarly LO+ and L0- of AD8232 is connected to D2 & D3 of ESP32.

9. EXPERIMENTAL RESULT:

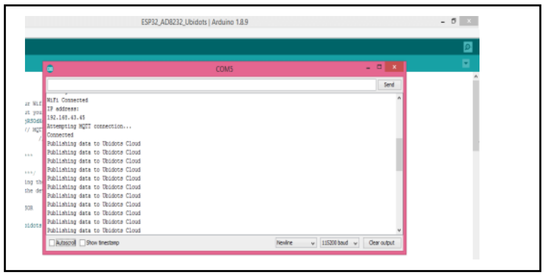
9.1 HARDWARE SETUP:



9.2 SOFTWARE SRTUP:

9.2.1 Setting up Ubidots Account:

To publish the data to IoT Cloud, we need some IoT platform. So Ubidots is one such platform. Ubidots offers a platform for developers that enables them to easily capture sensor data and turn it into useful information. Use the Ubidots platform to send data to the cloud from any Internet-enabled device.Once the code is uploaded to ESP32 Board, click on serial monitor. If the ESP32 connects to wifi, it will start sending data to Ubidots Cloud.



10. ADVANTAGES OF THE PROJECT:

Early allowance of arrhythmia illness lessen the versatility rate. Exact discovery of arrhythmia illness taking all things together cases and conference of a patients for 24 hours by a specialist is absurd since it requires time and mastery. Lessen the human mistake and improves their way of life. Minimal effort framework.

11. RESULT:

You can now go to Ubidots Dashboard and click on esp32, there you will be able to see the ECG Graph.

11.1 Filtering: A band-pass filter at 1-50Hz is implemented:

Heartbeat detection: since the source code of just wqrs()is available in C, we alter the algorithm to only apply wqrs to the signal, with no substantial divergence in the output of this stage. Wqrs gives back the onsets of the QRS complexes. Instead of passing this information to ecgpuwave(), in orderto get the exact position of the R peak, we keep the QRS onset information as the heartbeat reference point, and adapt the window applied to cover the heartbeat waveform.

11.2 *Heartbeat segmentation:*

We decide on a window of 86samples before the QRS onset, and 170 samples after the QRS onset (window width of 257 samples). Comparing the output of the two implementations up to this stage, we see that there is no substantial difference between the Matlab and the C implementation.

11.3. Feature extraction:

The convolution of the signal with the wavelet decomposition low-pass and high-pass filters associated with wavelet Daubechies of order 2, is implemented to produce the approximation and detail coefficients. This stage is implemented parametrically in terms of the coefficients that compose the feature vector of the heartbeat used in the classification stage. For each decomposition level, the coefficients produced are stored in a matrix if they are part of the final feature vector, or else they are only used for the computation of the next decomposition level. The process stops whenever all required coefficients have been produced.

11.4. Classification:

We use the LIBSVM library which includes the source code of svmpredict() in C. We convert the SVM model under examination, which has already been produced by the same function in the Matlab environment, into the format that is used in the C implementation. The SVM model is only created once, in an initialization section of the program, and used in the classification stage for each heartbeat.

12. CONCLUSION:

We have implemented our project on ECG classification, and have implemented it on an IoT-based embedded platform. This algorithm is our proposal for a wearable ECG diagnosis device, suitable for monitoring of a human. In almost all cases, the classification accuracy achieved is high and the best result comes of the feature vector which contains the approximate coefficients of the 4th level of decomposition, with 98% accuracy, a feature vector of size 18, and 2493 support vectors. In our work we have split the processing section between the end device and the server wherein the end device performs computationally less intensive tasks and the server performs computationally intensive tasks and hence the end device cost is greatly reduced and the battery performance of the end device increases.

REFERENCES

[1] . Raj S, Ray KC (2017) ECG signal analysis using DCT-based DOST and PSO optimized SVM. IEEE Trans Instrum Meas 66(3):470–478

[2] Rad AB, Eftestøl T, Engan K, Irusta U, Kvaly JT, Kramer-Johansen J, Wik L, Katsaggelos AK (2017) ECG-based classifcation of resuscitation cardiac rhythms for retrospective data analysis.

[3] IEEE Trans Biomed Eng 64(10):2411–2418 Escalona-Moran MA, Soriano MC, Ingo F, Mirasso CR (2015) Electrocardiogram classifcation using reservoir computing with logistic regression. IEEE J Biomed Health Inform 19(3):892–898

[4] Gutta S, Cheng Q (2016) Joint feature extraction and classifer design for ECG-based biometric recognition. IEEE J Biomed Health Informat 20(2):460–468

[5] Trace BH, Miller EL (2012) Nonlocal means denoising of ECG signals. IEEE Trans Biomed Eng 59(9):2383–2386

[6] Jain SK, Bhaumik B (2017) An energy efcient ECG signal processor detecting cardiovascular diseases on smartphone. IEEE Trans Biomed Circuits Syst 11(2):314–323

[7] Li P, Wang Y, He J, Wang L, Tian Y, Zhou T, Li T, Li J (2017) High-performance personalized heartbeat classifcation model for long-term ECG signal. IEEE Trans Biomed Eng 64(1):78–86

[8] Satija U, Ramkumar B, Manikandan MS (2018) Automated ECG noise detection and classifcation system for unsupervised healthcare monitoring. IEEE J Biomed Health Informat 22:722–732

[9] Spanò E, Di Pascoli S, Iannaccone G (2016) Low-power wearable ECG monitoring system for multiple-patient remote monitoring. IEEE Sens J 16(13):5452–5462

[10] Roonizi EK, Sassi R (2016) A signal decomposition model-based Bayesian framework for ECG components separation. IEEE Trans Signal Process 64(3):665–674

[11] Luz EJS, Schwartz WR, Cámara-Chávez G, Menotti D (2016) ECG-based heartbeat classifcation for arrhythmia detection: a survey. Comput Methods Programs Biomed 127:144–164

[12] de Chazal P, O'Dwyer M, Reilly RB (2004) Automatic classifcation of heartbeats using ECG morphology and heartbeat interval features. IEEE Trans Biomed Eng 51(7):1196–1206

[13] Soria ML, Martinez JP (2009) Analysis of multidomain features for ECG classifcation. In: Computers in Cardiology, pp 561–564

[14] Mar T, Zaunseder S, Martínez JP, Llamedo M, Poll R (2011) Optimization of ECG classifcation by means of feature selection. IEEE Trans Biomed Eng 58(8):2168–2177

[15] Llamedo M, Martínez JP (2011) Heartbeat classifcation using feature selection driven by database generalization criteria. IEEE Trans Biomed Eng 58(3):616–625