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Forecasting Ventricular Deviation in Monitoring of Live ECG Signal

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Abstract

Number of coronary artery disease cases and ventricular arrhythmias have been increasing in India. One of the common forms of cardiac disorder is Ventricular Tachycardia (VT). Due to improper electrical activities in the ventricles, consistent and rapid heart rate occurs, which produces Ventricular Tachycardia disorder. Short time period may not lead to severe heart problem, but the longer duration increases; it may be a severe heart issue. In this disorder, for short durations it is possible that there may not be any symptoms or few symptoms with palpitations (increase / decrease in heart beats), dizziness or pain in chest. This disorder may result in cardiac arrest. This may also results into ventricular fibrillation. Initially it was found that near about 7% of people in cardiac arrest are caused by Ventricular Tachycardia. In this work, a novel platform for real time diagnosis of Ventricular Tachyarrhythmia with the help of a portable Single lead ECG device is proposed. The gateway for signal analysis and combined edge and cloud based processing for the diagnosis is used. The bio-signal captured by the device in LEAD II configuration is pushed to a cloud based diagnosis API through a mobile gateway. An algorithm in the cloud analyses this signal and finds out P, Q, R, S, T, their amplitude positions, onset and offset. From the onset and offset ST segment slope, elevation, depression, S morphology and ST segment variation statistics is captured and classified using rule based classifier. The work evaluates the performance of the classifier with PhysioNet dataset. The accuracy of the system was found to be 90% with accuracy of detecting normal ECG being 100% where as the accuracy of detection of VT being 80%. Results shows that the system is extremely efficient in detecting Ventricular Tachyarrhythmia and many related cardio vascular diseases.

Keywords

Ventricular Tachyarrhythmia, Ventricular Fibrillation, Heart Rate, Heart Rate Variability, Cardio Vascular Disease, Artificial Intelligent, Machine Leaning, Rule Based Learning, Semi Supervised Learning, Decision Support System**.**

1. Introduction

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Heart is one of the most important part of human body. India has a huge number of cardiovascular patients (approximately 50 million) and the number is growing by every day. Very low cardiologist to patient ratio is another factor that adds to the problem. India is on the verge of near epidemic of CVD by the year 2022 (as per WHO). Several handheld and mobile ECG devices have been proposed in the past. Many of these ECG devices are also available commercially. The devices are broadly categorized as Holter, Tact-3, Event and Physiological monitoring. Most of the existing Holter ECG devices which are used for heart diagnosis are not portable and affordable enough. Also due to less number of trained pathologists and Cardiologists, timely and accurate diagnosis of signal acquired from these devices remains a major challenge.

Ventricular Tachycardia is a disorder caused by irregular heartbeats that includes ventricular tachycardia, ventricular fibrillation, and pointes of Torsade. ECG is used to diagnose this disorder. An ECG (Electro-Cardiogram) signal is a representation of the electrical activity of the heart. Usually 12-lead ECG is used where 10 electrodes are used on the patient's chest. A lead in ECG is a vector potential of the electrical signals across two points in Heart's electro-magnetic field.

Aortic stenosis, coronary heart disease, electrolyte problems, cardiomyopathy, or a heart attack may be the cause for Ventricular Tachycardia disorder. This can be diagnosed by an electro-cardiogram. ECG, showing a rate, greater than 120 bpm and at least three wide QRS complexes, in a row shows the presence of this disorder. If it lasts less than 30 seconds then it can be classified as non-sustained otherwise it can be classified as sustained.

Anatomically, a heart is divided into upper left and right artery and lower left and right ventricle. The electrical impulse in the heart is generated from a small node called Sinoatrial node. Sinoatrial node is also known as natural pacemaker of the heart. Sinoatrial node generates electrical impulses. These impulses are carried through the two arteries to artio-ventricular node. Artio-ventricular node stops the signal for short time duration to complete ventricular depolarization. The electrical signal is then sent through artio-ventricular chamber to the ventricles. The signal is finally sent out of the ventricles to complete the ventricular repolarization and in turn the electrical cycle of the heart which is represented by the ECG signal. The processed discussed above is depicted by figure 1.

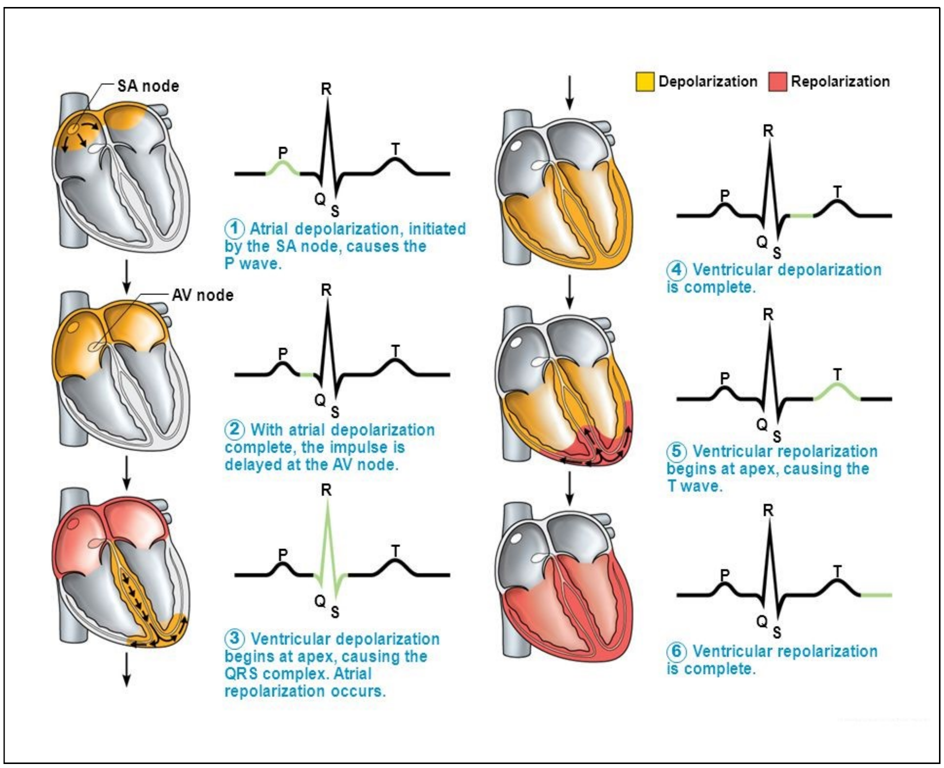

Figure 1. Generation of a Typical ECG Signal

Heart's activities **are** accurately represented by 12 lead ECG. It gives more accurate results in representing true state of the heart. A standard 12 lead ECG of a Ventricular Tachyarrhythmia (also called Ventricular Tachycardia) is shown in figure 2.

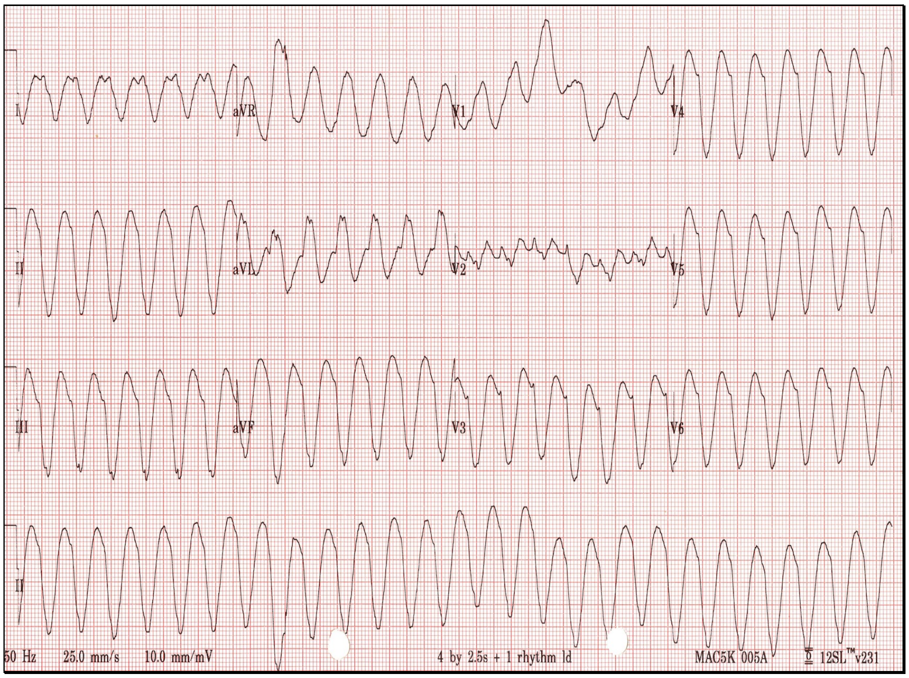

Figure 2. A typical 12 Lead ECG of VT

There are different forms of Ventricular Tachyarrhythmia, resulted from different abnormalities. Some of the common VTs are:

- Monomorphic- Monomorphic VT has regular rhythm in it. It is generated from a single focus point, so in each lead it creates uniform but identical QRS in the ventricles except the fusion and capture beats. It has broad QRS of approximately 200 ms.
- Polymorphic VT (PVT) - PVT have multiple QRS waves exists in ventricular focus. These waves are changing in axis, amplitude, and duration. Mostly myocardial ischemia causes PVT. TdP (Torsades de Pointes) and BVT (Bidirectional VT) are special cases of PVT.
- Torsades de Pointes(TdP)- TdP is a specialization of PVT having Polymorphic with QT prolongation property. QT prolongation occurs because of multiple drugs. In this type of PVT, QRS waves "twist" along the isoelectric line. It has very less life span and it terminates by itself.
- Right Ventricular Outflow Tract Tachycardia (RVOT)- The RVOT is the most familiar Tachycardia. These tachycardias have an identical characteristic property in ECG appearance. They have a left bundled branch, block appearance. They are also positive in the lower ECG leads.
- Fascicular Tachycardia- It is common form of IVT(Idiopathic ventricular Tachycardia) of left ventricle. The arrhymia mechanism appears to be macro reentry. It involves calcium dependent slow response fibers. These are part of purkinje network. Some tachycardia has been observed automatic. Mostly it occurs in young patients without structural symptoms of heart disease. It is a reentrance tachycardia.
- Bidirectional VT (BVT)- BVT is a rare ventricular dysrhythmia. Its frontal QRS axis is characterized by a beat to beat change. The QRS axis shifts by 180 degree from left to right with each changing beat.

- Ventricular Flutter(VF)- VF is an arrhythmia more specific type of tachycardia. The ventricles with a heartbeat rate in the range of 250-350 beats/minutes. The ECG shows sinusoidal waveform in this case, without exact definitions of the QRS and T waves.
- Ventricular Fibrillation(V-Fib)- VF is a heart rhythm problem. It occurs when patient have fast heart beats with erratically impulses. Due to this pumping chambers of heart vibrate unnecessarily, instead of pumping blood.

Re-entry of ventricular signal is one of the most common causes for VT. Triggered abnormality of either early or late depolarization may also be responsible for VT. Abnormal impulse generation by ventricular cells is third most common causes of VT.

Though it is difficult to classify different VT cases, even a single lead ECG has good traces of VT. A VT can be commonly detected by:

- It shows very broad bandwidth more than 160ms.
- Deviation on Extreme axis ("NW-axis") - QRS is +ve in a VR and –ve in I + a VF.
- Absence of typical RBBB (Right Bundle Branch Block) or LBBB (Left Bundle Branch Block) morphology.
- Atrio-ventricular (AV) dissociation (P and QRS complex waves at different rates).
- Positive or negative concordance throughout the chest leads, i.e. R shows all positive in leads V1-6 or QS shows entirely negative complexes, with no RS complexes.
- Fusion beats :Fusion beats occur when a ventricular and sinus beat overlap each other. It produces a hybrid complex of intermediate morphology.
- Brugada's sign : The distance from, QRS complex to the nadir of the S-wave is more than 100ms.
- Josephson's sign : Achieve near the nadir of the S-wave.

Though conventionally 12 lead signals are being preferred by doctors for VT diagnosis, it is possible to detect the traces of VT by analysis of Lead II (which is the major electrical axis of the heart) signal and looking for traces.

Single lead ECGs are easy to carry and operate. Therefore we present an easy and affordable option for heart diagnosis. As single lead ECGs does not give complete view of the heart, powerful analytics solution should be adopted to simulate the signal for the diagnosis rules. This is precisely the contribution of the proposed work. The research work intends a custom device to capture heart's electrical signal in Lead II configuration and analyze it through the aforementioned rules for detecting VT.

RTEPVA is an end to end system which has an affordable hardware upfront to acquire such signals and classify the signals using cloud platform. As connectivity remains a major challenge in rural India. RTEPVA offers algorithm which can efficiently tell if the person has any form of CVD (cardio vascular disease) or not and in particular ventricular Tachyarrhythmia or not, detecting such pathological abnormalities. Ventricular abnormalities can happen due to several reasons, for example shortening of the ventricular valves due to cholesterol deposition, re-entry of the current to the ventricular blocks due to improper functioning of the Parkinson's muscle and so on. Ventricular cycle of the ECG is determined by the ST segment and TP segment of an ECG signal.

Not only VT, but other cardio vascular problems too needs timely and continues monitoring. A whole new approach is needed to view and solve the clinical challenges of today. The basic needs are highlighted as follows:

Tracking parameters which matter & implementing meaningful Interventions

- Collecting human health data till now possible only with costly and cumbersome instruments. This needs to change and new instruments must be introduced that are easy to use, connected and that provides a means of remotely observing the patient by the clinician.

- Using minimum instrumentation and time thus enabling user to perform multiple recordings to track the changes with adverse or desirable interventions. Today medical tests are costly and therefore often user hesitates to go for periodic tests. This problem needs to be solved with devices and methods that enable multiple test takings.
- Simultaneous assessment of three major parameters of health (disease, origin and progression)- Autonomic Nervous System, Cardio-Respiratory Fitness & Endothelial Dysfunction. Modern ECG only reacts with the electrical activity of the heart and is unable to detect problems other than cardiomyopathy. However, proper prognosis requires other traits like autonomic neuropathy.
- Easy to understand analysis and interpretation. Plotting results against timeline (showing changes over short, medium and long term duration).
- Long term tracking of these dynamic parameters helps doctor to assess the impact of pharmacological & lifestyle interventions and adjust the treatment .
- Autonomic neuropathy detection.
- Psycho-physiological stress assessment.
- Arterial health(Endothelial Dysfunction) assessment.
- Psycho-physical readiness(fatigue) assessment for undertaking exercise.
- Biological age assessment (against the chronological age of an individual).
- Incorporation of all these parameters in a single ‘Lyfas Health Score’ – representing the impact of autonomic nervous system, cardio-respiratory fitness, endothelial function, body composition and stress on human health.

Even though the proposed work doesn’t provide any framework for Arterial health assessment and endothelium dysfunction, but providing an easy, affordable and yet accurate system for continues and efficient cardio health check, we enable better diagnosis and monitoring solution. Further the proposed system can easily be used to build more robust mechanism for better psycho-physiological analysis along with current cardio-electrophysiology.

Tracking parameters conveniently & economically Immediate Feedback

Immediate feedback is another essential aspect of efficient detection of the cardio vascular disease. It is important to be remembered here that the cardio events are not sudden and are developed over a period.

- Any healthcare provider (physician, diabetologist, cardiologist, preventive medicine specialist, nutritionist, fitness trainer & psychologist) should be able to conduct a five minute assessment with proposed Lyfas app and gather unique and actionable information. In the absence of a trained physician the system must enable gathering and processing the data locally and providing users with the insight about whether they may require any medical intervention or not and to what degree of intervention is required.
- The app must be extremely easy to use. Even OPD non-technical staff can implement the Lyfas assessment. There is no recurring cost involved.
- The ease of access and the collaborative framework among different group and specialty of the care providers must be seamless to enable a better care structure.
- A doctor can get all these parameters without patient coming to the clinic/hospital on a regular basis thus allowing him to fine tune the interventions continuously & earn revenue.
- Patient can save on money and time as there is no need to go to the clinic/hospital but can send important health information to the doctor. Easy monitoring can show the changes in parameters after adverse or beneficial lifestyle interventions. This real time feedback helps in modulating health related behaviour.

In summary we can say that by building a simple IoT and edge analytics driven system that comprises of low cost hardware, high end data analysis and offering a great degree of connectivity to the system we can offer a better cardio care. Further by incorporating suitable detection mechanism we can extend the framework efficiently for detecting, monitoring and managing Ventricular Tachyarrhythmia.

2. Related Work

Y.H. Noh, et.al [1] worked on a convenience healthcare monitoring system and a real time arrhythmia or abnormal ECG detection algorithm is developed. M Hadjem, O Salem [2] proposed a new Cardio Vascular Disease detection system. Authors used the Wireless Body Area Network(WBAN) technology. In this system ECG is processed the captured using filtering. They used Un-decimated Wavelet Transform (UWT) techniques to remove noises and extract the required nine parameters, which are used in diagnosis. S Gradl, et.al. [3] discussed about an Android application for real time ECG monitoring and detect automated arrhythmia by analyzing patterns of ECG parameters. M Romano et. al. [4], explained the heart rate variability, They worked on a tool to study the auto cardiac control and better functioning of the autonomic nervous system. M Romano, et.al._[5], depicts that parameters integration, derived from the non-linear techniques, like symbolic dynamic analysis, and traditional ones derived from frequency domain analysis, could improve the complexity of cardiac regulation systems. A new ECG de-noising method was proposed by Binwei Weng, et.al. [6], It was based on the Empirical Mode Decomposition (EMD). The EMD based method was able to remove high frequency noise with minimum signal distortion.

Prof. Dr. S.M.Rajbhoj, et.al. [7], studied the stress monitoring of humans wearable sensors. They also discussed the issues to be noticed to tackle the challenges. Dedi Kurniadi et.al[8], presents signal processing technique and data analysis to suppress any noise in the recorded signal and classified it into two groups which are normal heart sounds and pathological heart sounds that contain Ventricular Septal Defect (VSD) inside. A.Mjahad, [9], worked on fiction approach to signal analysis. The main objective was to safely select the proper therapy for Ventricular Fibrillation(VF) that is required to identify it correctly from Ventricular Tachycardia (VT) and other rhythms. According to them the required therapy would not be the same in all cases, an erroneous detection might lead to serious injuries to the patients or even cause Ventricular Fibrillation (VF). In the paper "Support vector machine based expert system for reliable heartbeat recognition", Osowski S, et.al.[10] worked on reliable heartbeat recognition system. They use SVM in classification mode to recognize the heartbeat in the system. They proved that this expert system gives average performance.

Kohler B.U et.al. [11], provides a review of advancement in the QRS detection using Artificial intelligence. Gokhale P.S[12], experimented the de-noising of the real noisy ECG signals with the help of wavelet transform. PLI noise is added to various ECG signals. They used MIT/BIH arrhythmia database to accomplish the task. Pahlm O et.al. [13], explained the one-channel QRS detectors. Authors explained the current detection scheme with its structure, evaluation of performance , features of QRS detectors, and the problem of multichannel detection. Demiao Ou et.al.[14], developed an electronic stethoscope for heart diseases. It is based on micro electro mechanical system microphone. This paper describes the design of this electronic stethoscope with its circuit that amplifies sound generated from heart beat. They also explained the background noise remove with a band-pass filter. Liu, Huang, and Weng [15], proposed a CKLM (cascaded kernel learning machine), EMG classifier. They used it to achieve the high accuracy recognition of EMG. First, G.O.Addio, el.al. [16]worked on Indices of Symbolic Dynamics in heart patients, Voss A, et.al. [17], studied and introduced the new methods of non-linear dynamics. They compare them with traditional methods of HRV (heart rate variability) and HRECG (high resolution ECG) analysis. That analysis was helpful to improve the reliability of high risk stratification.

Guzzetti S, el.al.[18] explained the variability of heart rate using symbolic dynamics. For this they worked on Cardiac Autonomic Modulation. In the paper "Cardiovascular and Cardio respiratory Coupling Analyses: A Review ", S. Schulz, et, al.[19], reviewed coupling analysis of cardiovascular and cardio respiratory. They explained the review work on controlling the heart rate from rapidly reacting systems. They also covered parasympathetic and sympathetic systems. Jose M. Sanchez et.al. [20], described the Optimal Ablation Techniques for Ventricular Tachycardia Management. Wilbur J et.al. [21] explained the diagnosis and management of heart failure in the outpatient setting. N. Paquette [22] et.al. worked on abnormalities in preterm neonates for ventricular shape and relative position.

3. Methodology

As we can see that even with advancement of technology, mobile ECG devices still relies on the analysis by doctors. This is one of the major drawbacks in the context of India where number of doctors are obviously very less. The proposed solution brings ML and AI into the context and offers a signal diagnosis through AI. But as there is a lack of internet connectivity in rural India, it offers a local cloud running in powerful PC like Gigabyte. This local cloud can be synced with a core cloud when sufficient connectivity is available. The present system and proposed system is as shown in Figure1.

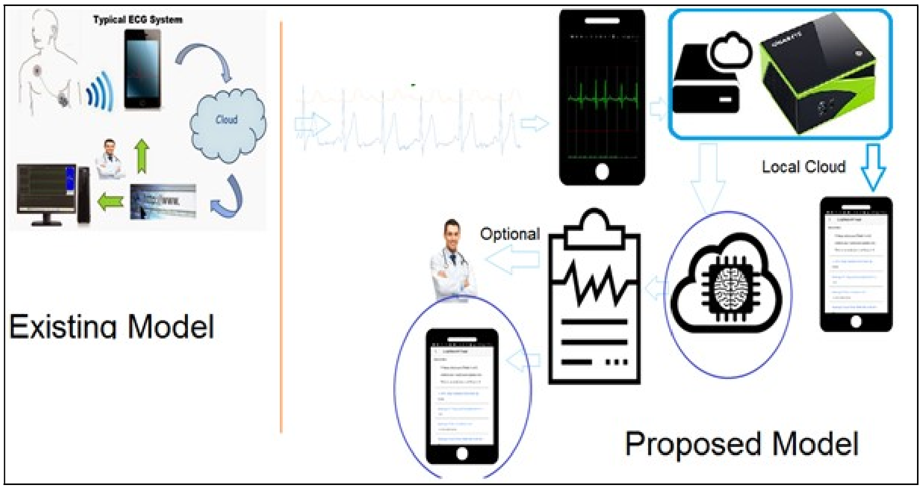

Figure 1. Present System v/s Proposed System

The user has to access the RTEPVA hardware device and data is transmitted via Bluetooth to the Mobile. The ECG signal, Pulse Signal is sent to the Local Server running ML and AI and Store Locally. Then the signals are Sync with Cloud. The Local Server running ML and AI, classify the signal normal or abnormal. If abnormal then it has to tell the type of abnormality.

The work is specifically focus on detection of Ventricular Tachyarrhythmia. The overall system architecture is presented in figure 2.

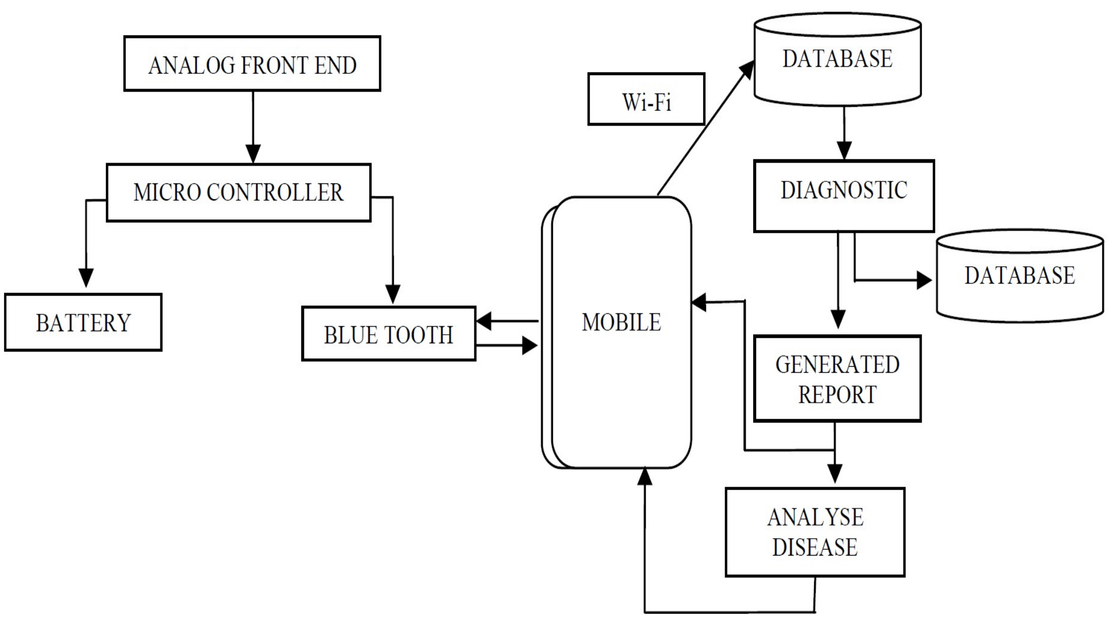

Figure 2. Block Diagram of the architecture

The proposed system leverages open source hardware and Arduino for writing firmware. This allows the user to acquire Single Lead ECG. However, one of the question that 12 Lead ECG is the standard norm, how can a single lead ECG provide comprehensive analysis of the heart? The best thing about our Single Lead ECG acquisition is that all the 12 leads can be acquired based on the three electrodes (one lead at a time). For non-axial leads, ground and -ve electrodes can be grounded together and signal can be measured with respect to the positive lead. Figure 3 Shows the Lead 1 and Lead 2 configuration.

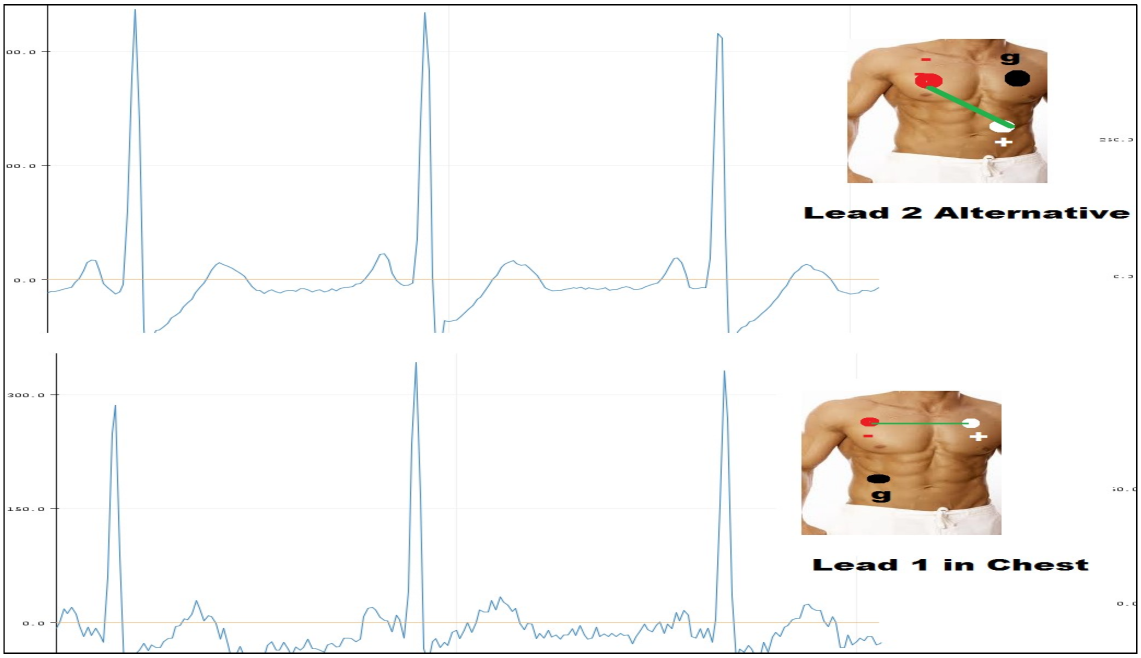

Figure 3. Lead I and Lead II Data Acquisition by Proposed Device

The proposed device also supports Lead I data acquisition through finger or wrist configuration as shown in figure 4.

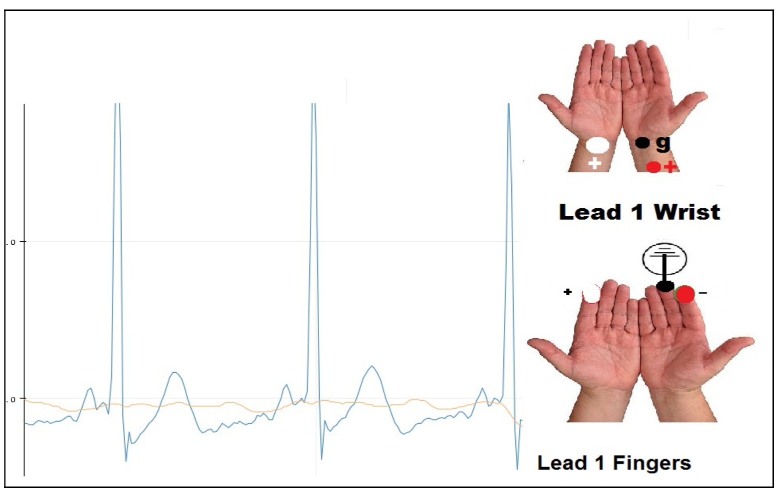

Figure 4. Lead I wrist and finger configuration.

It is also possible to acquire chest leads from the proposed device as shown in the figure 5 and 6.

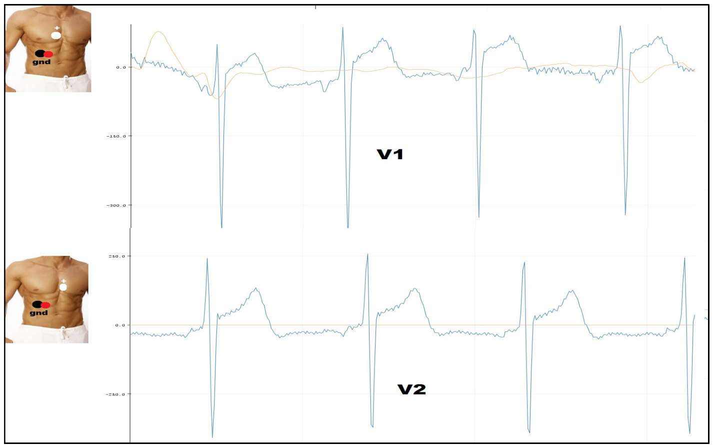

Figure 5. Lead V1 and V2 Acquisition from the proposed device.

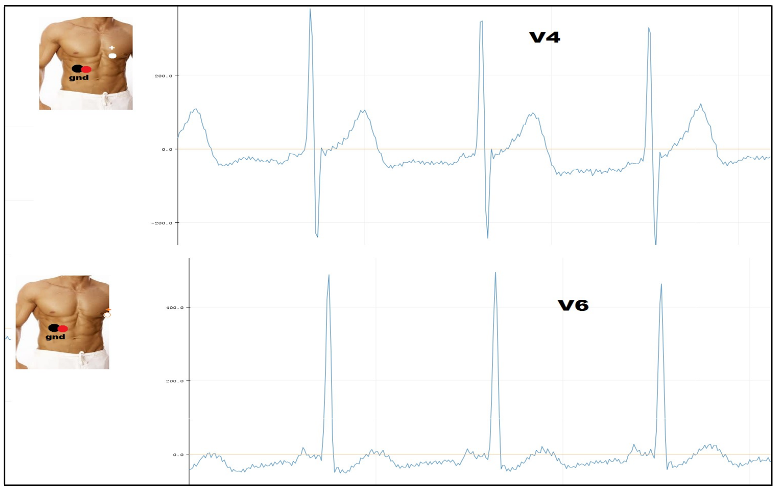

Figure 6. Acquisition of V4 and V6 through Proposed device.

Thus, this low budget device not only is capable of acquiring all 12 lead ECG, but at the same time it is mobile and affordable. The proposed work focuses on acquiring LEAD II configuration signal from the ECG and classifies the signal with a machine learning based classifier. In case the decision is not conclusive user can go for data acquisition of the chest leads.

3.1. Mathematical Model of Machine Learning

Phi(x0wk0+x1wk1...xn*wkn,Theta_k)->NA/A1/A2...An Where: x0,x1..xn are input parameters as specified above(RR, PTT, ST etc.) Wk0,Wk1..Wkn are the weights of the Neurons Phi is the activation function NA- No Abnormality, A1...An- Different abnormalities and Theta_k is the threshold.X0---Xn are called input NA, A1--An are called output layers Phi is the hidden layer.

For training the network, a vector V is given as input which is specified as V={ {x0 .. xn}1,{x0 .. xn}2...,{x0, xn}D} where notations 1,2...D of the set specifies the Signals stored in database (locally).

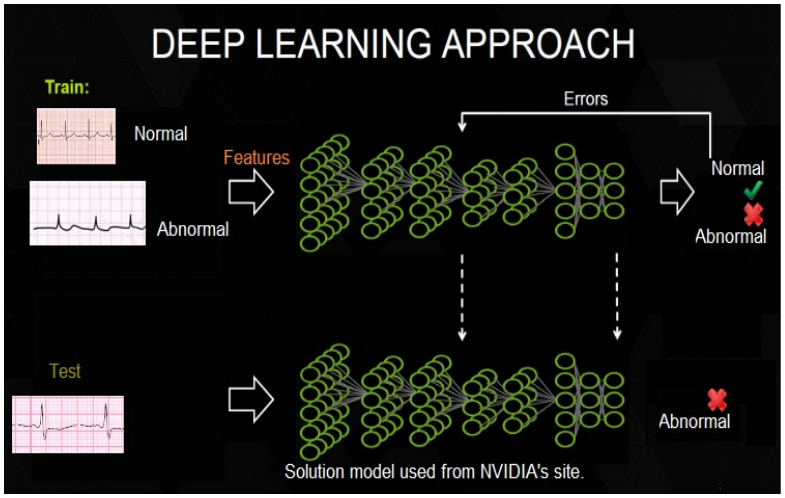

Figure 7. Deep Learning Neural Network for ECG classification

This database is updated and synced with cloud with enough Wi-Fi/Internet connectivity is available. A high level design is as presented in Figure 7. The overall steps in the proposed solution can be presented below:

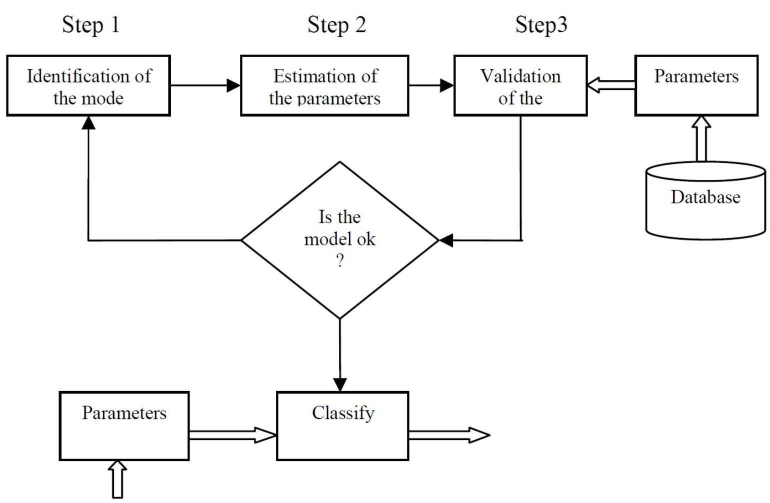

Figure 8. Proposed solution steps

It can be seen from above diagram that every local/Fog Server has set of above defined parameters. These parameters from existing and already classified records are downloaded from cloud storage when a data connection is available. MLP Neural Network (The AI Model) is updated. The process aims for an error rate of 1e-6 and maximum epochs of 4000. Once the model reaches steady state, it is saved and used for classifying new signal. The new signal is marked temporary file for a validation with doctor. Once the result is validated, it is also accommodated in the training dataset. It needs to be noticed that as the optimization of neural network model depends on the training data, at the initial phase, a doctor's manual classification of the signal is essential. However, as the model keeps learning, slowly the accuracy of classification improves and manual evaluation by a doctor starts reducing. The initial model is trained with PhysioNet's Ventricular Tachycardia and Normal Sinus Rhythm datasets.

4. Results

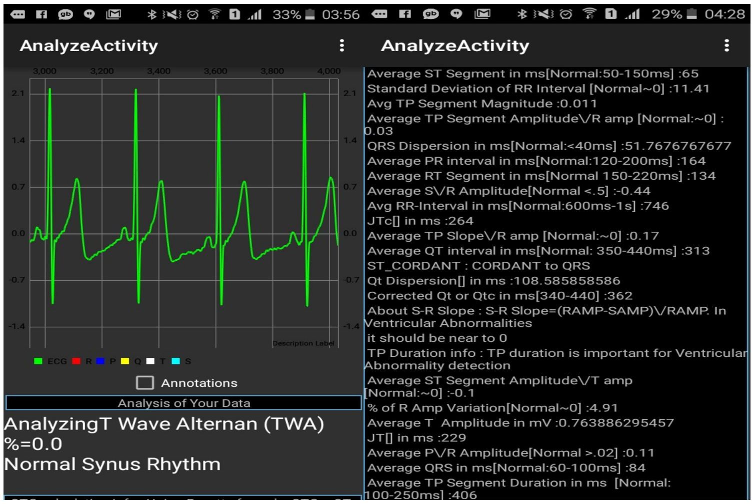

Figure 9. Mobile Screenshot of ECG Analysis

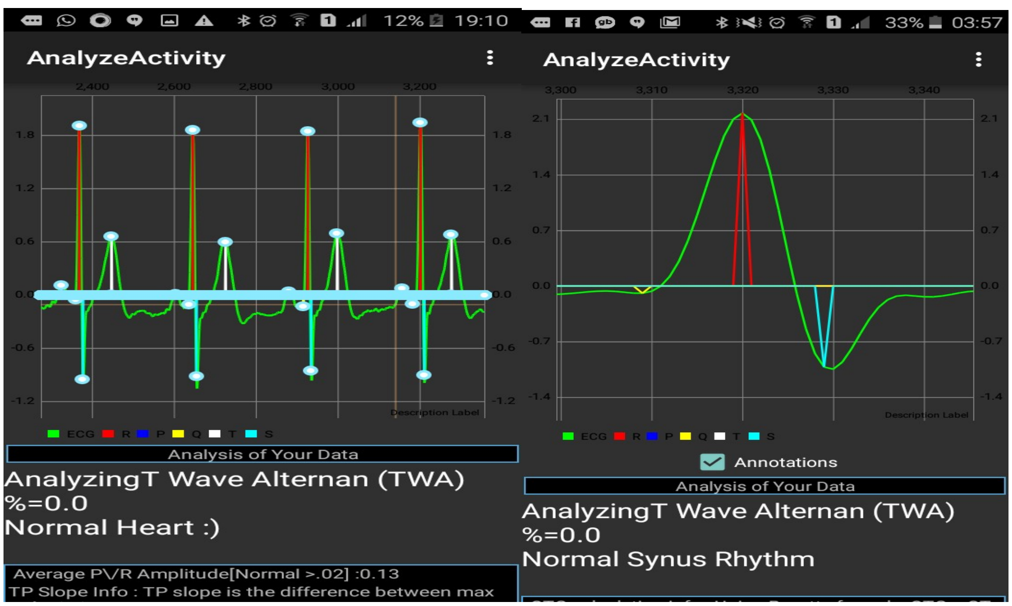

Figure 10. Detection and Annotation of Peaks

10-30 seconds of data is captured in mobile and is analyzed through the proposed system. Figure 9 and 10 shows the analysis result and detailed peak detection respectively.

Figure 11 shows the peak annotation of the analysis of VT and Normal signals. From the figure the morphological difference in Lead II of both the types of ECG can be seen. The average values of the parameters for both normal as well as VT signals are shown in Table 1. It can be clearly seen from the tables that many of the parameters for the two are linearly separable. For instance the R peak standard deviation is extremely high for the VT.

Table 1. Average Parameter Values of Normal and VT signals

Parameters	Normal Sinus Rhythm	Ventricular Tachyarrhythmia
Average RR-Interval [Normal:600ms-1s]	647	800
Standard Deviation of RR Interval[Normal~0]	1.68	165.37
% of R Amp Variation[Normal~0]	7.99	17.6
Average Heart Beat Rate[Normal:60-100 bpm]	92	74
Average QRS [Normal:60-100ms]	80	98.5
Average ST Segment[Normal:50-150ms]	88	2
Average T Amplitude(ms)	-0.030928286	0.0015002996059
Average S/R Amplitude[Normal <.5]	-0.5	0.82
Average S-R Slope [Normal ~1]	-1.5	0.17
Average RT Segment [Normal 150-220ms]	145	176

Parameters	Normal Sinus Rhythm	Ventricular Tachyarrhythmia
Average P/R Amplitude[Normal >.02]	0.1	2.01
Average QT interval [Normal: 350-440ms]	292	327
Average PR interval [Normal:120-200ms]	152	128
Average TP Segment Amplitude/R amp [Normal:~0]	0.01	0.76
Average TP Slope/R amp [Normal:~0]	0.02	1.04
Average TP Segment Duration [Normal:100-250ms]	248	401
Average ST Segment Amplitude/T amp [Normal:~0]	1.23	-5.95
QRS Dispersion[Normal:< 40ms]	23.4375	78.0
Qt Dispersion[]	125.0	196.0
Corrected Qt or Qtc [340-440]	362	
Uing Bazetts formula: QTC = QT / sqrt(RR) JT[](ms)	212	228.5
JTc[](ms)	263	255
T Wave Alter nan (TWA) %	0.0	0.0

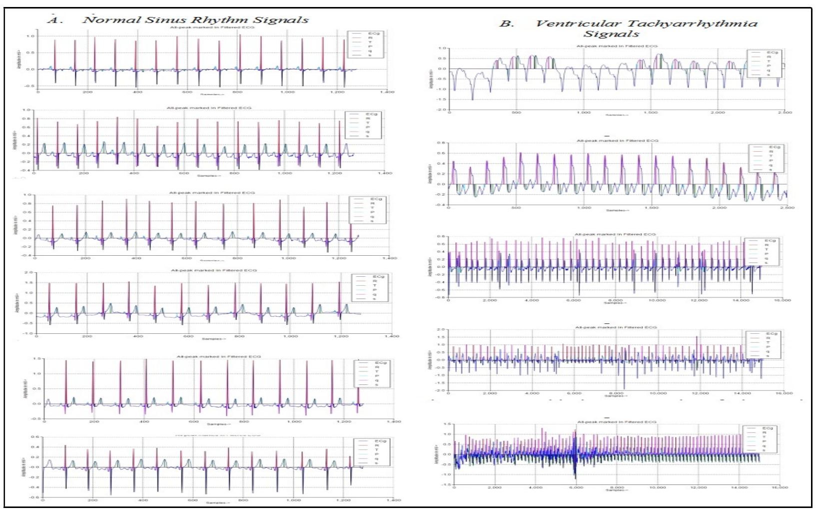

Figure 11. Analysis of Normal and VT Signals

5. Conclusion

India has a very low doctor/patient ratio than standard (as specified by WHO). With the increased stress and change in urban as well as rural lifestyle and food habits the chances of heart related diseases are being increasing. At the same time the average age of the heart abnormalities and heart failure is reducing in India. Hence we need more AI assisted solutions to tackle this problem. Through this work we have proposed a cost effective way of extracting ECG signals from human body and analyses them through cloud based machine learning techniques. This work was evaluated in two folds: firstly the live signal from the subjects were acquired, processed and checked through Lyfas device, secondly the algorithm and classification performance was evaluated with standard PhysioNet database. The access to real Ventricular Tachycardia patients were not high for us, we evaluated the performance using standard dataset. Results shows that the system is extremely efficient in detecting Ventricular Tachyarrhythmia and many related cardio vascular diseases. The system can improve further by incorporating other Models like support vector machine and self-organizing map with current machine learning context.

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