Hrudyalysis: A Novel Cloud-Based ECG Analytics Method

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Abstract*: Nowadays, people live in a world that is quite fast paced and competitive. All are running behind the money and success under the stress and fear of falling behind the race ignoring our health. Lack of physical activity due to shortage of time and acquiring the habit of intoxication for the purpose of releasing this stress make the matter worse for our heart. These are the two primary reasons for heart diseases in case of urban people. On the other hand, as the percentage of people staying in rural areas is more than urban areas, the people of rural India also suffer from heart diseases. Acquisition of urban lifestyle by rural people and inaccessibility to costly healthcare services are the two most important reasons for increasing rate of heart diseases in rural India. Even young adults are falling prey to heart diseases in an alarming rate. In short, the problem of heart-related diseases is being evolved as a matter of great concern in context to the Indian Territory. According to the WHO, coronary artery disease will take the form of epidemic in India by the year 2022. So, we need fast, efficient and low-cost devices for beforehand identification of symptoms related to the heart diseases. The most common device to identify and diagnose heart related diseases is the conventional 12-lead ECG device. But, there are various factors that pose complexities in diagnosing cardiovascular diseases by the 12-lead ECG devices. It is a costly device and it needs a trained person for handling complex and burdensome diagnosis method. In the context of unavailability of enough trained medical people this can be a great hindrance in preventing the epidemic of coronary artery diseases. So, in this research work, a single lead ECG device has been proposed which is of low-cost and diagnosis of cardiovascular diseases is carried out with the aid of a cloud computing environment.

Keywords: Electrocardiogram (ECG), Cardio Health Disease (CHD), Application Programming Interface(API) Pulse Arrival Time (PAT), Pulse Wave Velocity (PWV).

I. INTRODUCTION

Most of us are unaware of the utter consequences of extremely worse effect of cardiovascular diseases in India. To have an idea of the reality, let us begin with some statistical facts that can put the real picture in front of us that may shake up all of us.

- Presently, 30 million people of India are suffering from heart-related diseases, among which 14 million patients are from the urban area and 16 million patients are from the rural area.
- The diseases related to blockage or narrowing of coronary arteries may become epidemic by the year 2022, reported by the World Health Organization (WHO).
- The number of heart patients in India is growing at a terrifying rate of 2% annually and every 25% of death occurs due to heart-related disease.
- A report from Cardio Research says the number of patients with hypertension is estimated to rise from 118 million in 2000 to 214 million in 2025.
- Every 8-10 out of 1000 newborn babies worldwide suffer from congenital heart defect- a comment from Symposium of Preventive Cardiology.
- As a result of a survey conducted by the Society of Epidemiology of Congenital Heart Disease in India commented in their report that 661 persons out of 34517 examined are suffering from Congenital Heart Disease (CHD) having a suffering rate of 114 per 1000 individuals. The most frequent diseases diagnosed are ventricular septal defect consisting of 33% of the total number of individuals examined, atrial septal defect which consists of 19% of the total population and tetralogy of Fallot consisting of 16% of the total population examined. 58% of CHD cases have been identified in individuals having 0 to 5 years of age. The atrial septal defect (44.5% of the total population examined) is found to be the most common defect in adults with a rate of 2.4 per 1000 adults suffering from CHD.
- The Saffola life study conducted by India Today on 46000 urban Indians in 2011 stated that 78% of a men in the age group of 30 to 34 have a risk of a heart attack.
- A report from Hindawi states that nearly 29% of auto drivers, 76% of Bus drivers and 40% of Cab drivers in India endangered by mild to severe hypertension.
- In India, every 11000 patients of cardiovascular disease are treated by a single cardio doctor, reflecting a huge scarcity of cardio doctors.

From the above statistical facts, we are getting a very clear picture of the problems regarding cardiovascular diseases in India. The major findings can be summarized as below:

- ✓ People of India are at a very high risk of getting affected by various cardiovascular diseases.
- ✓ People of any age group including newborn babies, young adults and obviously old adults are very much prone to getting attacked by heart-related diseases.
- ✓ Hypertension is one of the important mentionable causes that is making the effect of this disease worse.
- ✓ Lack of cardio doctors with respect to this huge number of patients is hindering against building a proper defense mechanism. Specifically, there is only one doctor for every 2000 patients.

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Various organizations and researchers have already taken the initiative to solve this problem by designing automatic computer-assisted diagnosis systems for the purpose of achieving more accurate result and overcome the problem of low doctor-patient ratio. The most fundamental component of cardiovascular disease diagnosis is the ECG signal. But conventional ECG diagnosis system is a costly device, not easily accessible to every class of people present in the society. So a huge amount of attention has been given in building in cheap ECG machines and automatic ECG detection systems. But traditional ECG device is a 12-lead device which increases its complexity. Hence the focus should be on building low-cost, single-lead ECG devices that will be accessible to all class of people with user-friendly nature. That's why this research work proposes a unique signal processing technique for identifying various abnormal health conditions from single lead ECG of lead II ECG signal. To make the system anywhere access, the concept of cloud computing also has been integrated in the proposed research work.

II. LITERATURE SURVEY

[1] To minimize the mortality of Indonesia, authors have built a tele-ecg system for heart diseases early detection and monitoring. In this research, the tele-ecg system was enhanced using Hadoop framework, in order to deal with big data processing. The system was built on a cluster computer with 4 nodes. The server is able to handle 60 requests at the same time. The system can classify the ECG data using decision tree and random forest. The accuracy is 97.14% and 98,92% for decision tree and random forest respectively. [2] An improvement of bits per sample efficiency was achieved over one reported work using fixed length encoding. Advantageous features of the proposed algorithm are its low latency, memory requirement and low time complexity. This paper describes a real-time, lossy ECG compression algorithm based on delta encoding using variable length symbols. The encoder performs a dynamic bit allocation (DBA) algorithm for each block of ECG samples to optimize the BPS efficiency. [3] They proposed a novel method based on a linear regression model that incorporates static and dynamic PTT features to predict BP measures more accurately. Moreover, the proposed model considers the estimated systolic blood pressure (SBP) when estimating the diastolic blood pressure (DBP). The PTT feature is estimated from the time period between the R-peak of electrocardiography (ECG) waveforms and the peaks of the first-order derivative of plethysmography (PPG) signals, which correspond to the points with the maximum slope of each PPG signal waveform. [4] In this study, an integrated method is presented for the clustering of ECG beats based on an improved semi-supervised affinity propagation algorithm with independent component analysis. Using the MIT-BIH arrhythmia database, the authors find that the resulting clusters to exhibit a high degree of precision. The integrated method outperforms other conventional methods in the MIT-BIH database and has great theoretical and practical significance in the field of cardiac disease. [5] The viability of this claim is demonstrated by comparing the performance of the classifier with periodic TARs as its features with that of a baseline classifier whose features are simple TARs representing the occurrence or not of temporal relationships, without consideration of possible periodic occurrences of the given temporal relationships. In this paper, authors presented an implementation of time series classification by incorporating temporal association rules and their recurrence patterns (periodic TARs) as features to a Naive Bayes classifier, constructed for the purpose of coronary heart disease diagnosis. [6] This paper aims to investigate and compare the accuracy of different data mining classification schemes, employing Ensemble Machine Learning Techniques, for the prediction of heart disease. In this paper, different machine learning techniques including Decision Tree (DT), Na¨ıve Bayes (NB), Multilayer Perceptron (MLP), K-Nearest Neighbor (K-NN), Single conjunctive Rule Learner (SCRL), Radial Basis Function (RBF) and Support Vector Machine (SVM) have been applied. [7] In this analysis, they have focused energies of high frequency (150 to 250 Hz) contained within the QRS complex and the lengths of R-peak. The high frequency ECG and extracted HRV from low frequency ECG signal focus information in heart diseases. This paper presents a data adaptive technique of cardiovascular disease diagnosis by analyzing electrocardiogram (ECG) signals. The separation of high-frequency QRS and low frequency signal are performed by employing empirical mode decomposition (EMD). [8] To validate the feasibility of the estimation of pulse transit time (PTT) by artificial neural network (ANN) from radial pressure waveform alone. A cascade ANN with ten-fold cross validation was applied to invasively and simultaneously recorded aortic and radial pressure waveforms during rest and nitroglycerin fusion (n=62) for the estimation of mean and beat-to-beat PTT. [9] This study focused on assessing impressions of smart devices for heart rhythm monitoring in ambulatory patients presenting to a cardiology practice. Atrial fibrillation (AF) is the most common cardiac arrhythmia in the world and AF predominantly affects older individuals. [10] Authors evaluated several machine learning algorithms in the context of long-term prediction of cardiac diseases. Results from applying K-Nearest Neighbors Classifiers (KNN), Support Vector Machines (SVM) and Random Forests (RF) to data from a cardiological long-term study suggest that multivariate methods can significantly improve classification results.

III. PROBLEM STATEMENT

People of India are at a very high risk of getting affected by various cardiovascular diseases. In addition, there is a very low doctor-patient ratio for the treatment of heart-related diseases. The most commonly used device for diagnosing the symptoms is the ECG device. Conventional ECG acquisition devices use 12-lead for recording every fine detail of electrical activity of the heart. But employing of 12 leads imposes various complexities. Use of 12 leads make capturing of heart rate information burdensome and only properly trained clinical people can handle the complexities of this device. Additionally, high cost and long duration of patient examining are two factors that are associated with this device. Hence, we need low-cost technology for fast and automatic diagnosis of heart problem-related symptoms.

Scientists and researchers are continually focusing on developing cheap and easily accessible efficient ECG system. Recently, integration of the concept of IoT has helped in developing mini versions of this device but the complexity still remains. The above drawbacks as well as the scarcity of trained staff make ECG data acquisition complex and these complexities can't be fully avoided even by employing cloud computing and AI.

If a simple point of care device is developed and relates to cloud-based analysis system that can evaluate and provide detailed analytics of the signal along with tentative interpretation, then the clinician or the paramedics at the point of care can take learned decision about further process. In order to eliminate the complexity of multi-lead ECG, if a comprehensive system can be developed for the analysis of a single lead which can offer accurate enough detection of normal and abnormal system, then better care can be provided to remote patients.

As most of the existing systems require multi-lead ECG for analysis of the patient's condition accurately, a cloud-based single lead ECG Analysis system is needed that can provide accurate enough analysis and interpretation at par as multi lead ECG. This problem is solved by the proposed system.

IV. CONTRIBUTION

The contributions of the proposed research work are as below.

- A new basic theory has been presented which states that lead II acting as the primary axis of electromagnetic axis of the heart provides stable signal correlation. Lead II is also influenced by any abnormal conditions of the heart that is detected by any particular lead of traditional ECG.
- A unique cloud assisted technique has been presented that processes only lead II of a 12 lead ECG signal for the purpose of identifying abnormal conditions.
- The presented solution simplifies ECG signal capturing and analyzing and also provides cheap and effective solution.

V. PROPOSED SYSTEM

The primary objective regarding beforehand detection of heart problem symptoms are to capture ECG signals in an accurate manner and efficient processing of the captured ECG signals for proper diagnosis by the aid of a cheaper system. For the purpose of overcoming the problems of cost-effective processing and beforehand detection demonstrated by existing ECG devices, a system has been built named "Hrudyalysis", which is an efficient cloud assisted artificially intelligent technique for simple ECG signal analysis. Hrudyalysis is based upon Red Hat Linux dependent OpenShift cloud founded ECG processing system. The system accepts a CSV formatted file containing ECG signals, rate of sampling and amplitude resolution data as input. Hrudyalysis obtains different hidden parameters by analyzing an ECG lead II signal. The basic parameters determined are location, amplitude, onset and offset of P, Q, R, S and T peaks**.** Other significant parameters are derived from the basic parameters. A list of parameters thus obtained from time domain ECG signal has been given below.

- RR Interval
- R peak Amplitude Standard Deviation
- Spectral Frequency Max and Min of short 5sec sample
- IBI:- Inter beat Interval
- QRS Complex
- QT interval and Corrected QT interval (QTc)
- ST Segment, ST segment elevation and depression
- Left and Right Axis deviation
- PR interval
- P Morphology (normal, biphasic or inverted)
- S/R ratio
- JT interval
- U' peak detection (Very important for fetal ECG)

All of these above parameters obtained are expressed in a comprehensive way, consequently generating an unprecedented diagnosis system. Next, these parameters are transferred to a decision tree system developed for most efficient cardiac analysis. The system identifies the signal as normal or abnormal as well as categorizes the type of abnormality in the signal.

V.METHODOLOGY

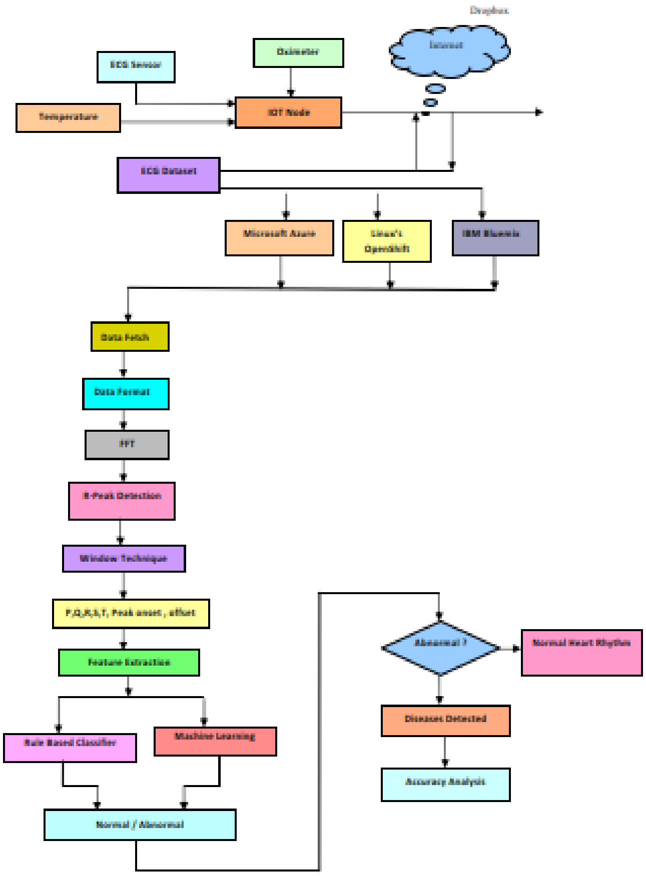

Fig. 1: Block diagram of the presented system

The overall steps of the proposed method have been elaborated below. The following diagram demonstrates normal sinus wave of the ECG signal.

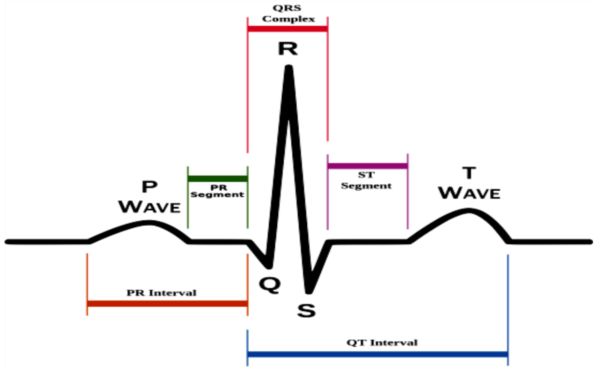

Fig. 2: Sinus wave of a common ECG Signal

In the frequency spectrum, R peaks of the signal are spotted and other insubstantial data are withheld. By using Fast Fourier Transform, the generated envelope is transformed to time domain. A loss in transform occurs and position of the R peaks in original signal is very near to the envelope signals but not in their correct place.

- For the purpose of determining a local maximum, a window supported method has been followed to determine the maxima in the proximity of R peaks with respect to the envelope in the original ECG signal. R peaks are actually indicated by these local maxima.
- The same window supported method is followed for determining other peaks in the signal. For instance, searching ahead from the R peak towards negative local minima determines S peak. Q peak is determined by reverse direction search from R peak towards local minima. Similarly, searching in reverse direction from Q peak towards positive valued maxima denotes P peak. The location of T peak is obtained by searching ahead from S peak towards local maxima. The frequency of search operation and size of the window are obtained by the captured signal properties like frequency spectrum attributes and the frequency of sampling rate. The search process is bounded by maxima and minima of the peaks.
- After determining P, Q, R, S and T signals, the measuring of onset and offset are followed at the starting and terminating points of the peaks, which are actually the points of zero crossing. A DC offset segment is taken as effective point of zero crossing in case of non-appearance of distinct points of zero crossing.
- Various intervals and segments of the combined peaks such as PT interval, ST segment are determined along with some specific factors like standard deviation and variation regarding R peak etc.
- For the objective of diagnosis, these above determined factors are moved to a decision tree or a set of fuzzy rule. A supervised or semi-supervised cloud supported learning algorithm is employed for the categorization of the cloud saved signal for normality or abnormality. In case of abnormal conditions, additional examination is followed for determining the cause of abnormality.

VI. EXPERIMENTAL ANALYSIS

A. Experimental dataset

Sleep Apnea[25], Arterial Fibrillation[26], Normal Sinus Rhythm[27], Ventricular Tachyarrhythmia[28], T Wave Alternans[29], Partial Epilepsy[30] are the datasets used for the evaluation purpose of the proposed system.

B. Experimental setup

Python 3.4 on flask framework in visual studio .Net has been used to build the system. Reading and formatting remote csv files are carried out using Panda's data frame. Processing of the signals is performed by Numpy library. Graphs and charts have been created using matplotlib viewer. Webpage rendering of the resultant signal is performed with D3Js. After the testing phase has been accomplished on localhost, the project is moved to OpenShift cloud platform. The system has been tested also in an alternative cloud platform BlueMix.

Hrudyalysis extracts various parameter hidden in an ECG lead II signal for efficient analysis and diagnosis of the ECG. Hrudyalysis is Red Hat Linux's OpenShift cloud based ECG analysis system that takes ECG signal CSV file, sampling rate and amplitude resolution as input, calculates the location, amplitude, onset and offset of P,Q,R,S and T peaks and then goes on calculate other important parameters like QRS complex, ST Segment ,T Amp, ST,S/R S-R Slope, RT segment, P/R amp, QT segment, QTc, PR interval, TR amp/Ramp, TP Slop/R , TP Duration , JTc and Processing time and so on. Each of these parameters are then passed into a decision tree system developed by best practices of cardiac analysis. It not only detects if the signal is normal or abnormal, at the same time it also classifies the signal abnormality. The system is built with Python 3.4 on flask framework in visual studio .Net . We use Panda's data frame to read and format remote CSV files, Numpy for processing the signals. Visualization is created using matplotlib. Web page rendering of the resultant signal is performed with D3Js Upon successful testing on localhost, the project was pushed to OpenShift cloud platform. OpenShift facilitates automatic deployment of the project in cloud once build of the project is successful, making development and deployment process painless and seamless experience . We also tested the performance on BlueMix which is another popular cloud platform with OpenShift. OpenShift also offers easy and seamless scaling as the number of users of the cloud service is increased. Easy scaling of the application enhances the performance further in a near seamless way.

C. Application Program Interface

An API call sample is provided as below:

https://hrudyalysis.mybluemix.net/apiv1/analyze?lno=1&url=https://www.dropbox.com/s/7rn1oyac1eltqna/normal_mitbih_16420_sr_128_adu_200.csv?dl=1&adu=200&sampling_rate=128

Here,
lno=lead number (1 to 12)
url= CSV location of the file
adu=analog to digital unit (how many values of raw ADC=1mv)
Sampling rate= Sampling rate of the signal acquisition unit

Retrieval Number C4711098319/2019©BEIESP
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D. Experimental Results

Table-I: Overall Accuracy of Different disease and Normal Dataset

Sl.No.	Type of Abnormality	Total Data	Correct Detection of the abnormality	Detected as other abnormality	Detected as Normal	Overall Accuracy	False +ve	False -ve	True +ve	True -ve
1	Sleep Apnea	13	12	1	0	92.31%		0	92.31 %	0.00%
2	Arterial Fibrillation	10	9	1	0	90.00%		0	90.00 %	0.00%
3	Normal ECG	8	7	1	0	87.50%	12.50%	0		87.50%
4	Ventricular Tachyarrhythmia	17	12	5	0	70.59%		0	70.59 %	0.00%
5	Coronary Arties Disease (CAD)	7	6	1	0	85.71%		0	85.71 %	0.00%
		55				85.22%		0.00%		

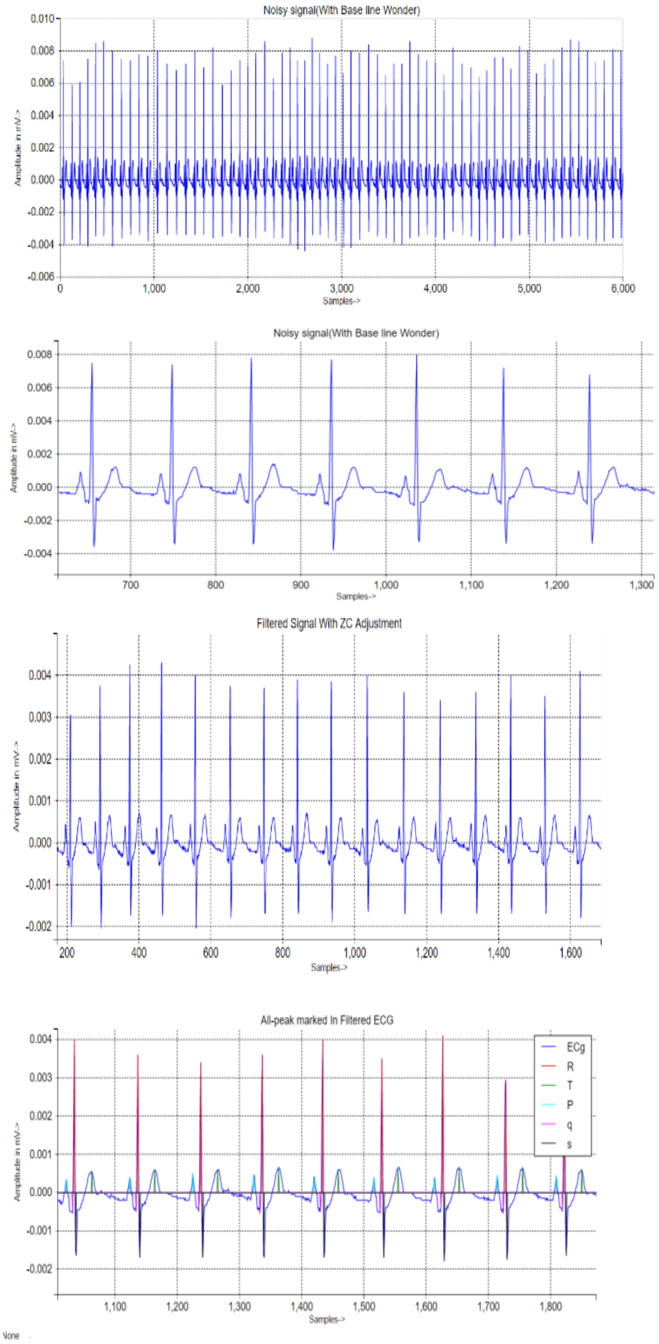
It is clear from table 1 that, in a multiple disease setup, the proposed algorithm results in 85.22% overall accuracy. What is more important to notice in the result is that false negative of the system is found to be zero and false positive was 12.5%. Low false negative indicates that in a screening scenario, the proposed system offers the desired result. As the desired use of the system is in remote point of care, the objective is to not miss the indication of any diseases. Falsely marking certain patient ECG as positive has less consequences in comparison to high false negative.

Table-II: Parameter Evaluation of the signal

Sl No	Type	Reason	Avg RR [600-1000ms]	RR Interval Std	R Amp Std	BPM	QRS	ST Segment	T Amp	ST	S/R	S-R Slope	RT Seg	P/R Amp	QT	Qtc	PR Interval	TP Amp/R Amp	TP Slope/R	TP Duration	ST Amp/T	JTc
1	SleepvApnea	HIGH R Amp variation, PR>200, TP interval > 250 ms	900 ms	5.91	9.42	66	110 ms	71	0.125	CORDANT	-0.48	1.48	165	0.18	367 MS	386 ms	172 ms	0.03	0.08	484 ms	-0.43	270
2	SleepvApnea	QRS > 100 and QTC > 0.2 and QT dispersion> 42.7	751 ms	6.6	17.42	79	118 ms	98 ms	0.1417	CORDANT	-1.03	2.03	180	0.46	393 ms	453 ms	159 ms	0.08	0.21	314 ms	-0.26	317
3	SleepvApnea	HIGH R Amp variation, PR> 200, TP interval > 250 ms	1022 ms	1.19	19.95	58	130 ms	97 ms	31.15	CORDANT	-1	2	182	0.37	413 ms	408 ms	202	0.07	0.29	435 ms	-0.18	279
4	SleepvApnea	Aggregated Conditions	765 ms	0.72	9.4	78	118 ms	47 ms	-0.025	DISCORDANT	-0.06	1.06	145	0.09	291 ms	332 ms	165 ms	0.02	0.05	396 ms	0.86	197
5	SleepvApnea	Presence of of Atrial wave between T and P, Missing P	1054 ms	2.96	1.64	56	68.5 ms	101 ms	36.55	CORDANT	-0.07	1.07	184	0.02	390 ms	377 ms	229 ms	0	0.05	479 ms	-0.45	311
6	SleepvApnea	Presence of of Atrial wave between T and P	747 ms	4.34	4.08	80	103 ms	44 ms	-0.034	DISCORDANT	-0.11	1.11	117	0.07	315 ms	364 ms	200 ms	0.02	0.06	379 ms	1.83	245
7	SleepvApnea	Presence of Atrial Wave between T and p	747 ms	4.34	4.08	80	103 ms	444 ms	-0.034	DISCORDANT	-0.11	1.11	117	0.07	315 ms	364 ms	200 ms	0.02	0.06	379 ms	1.83	245
8	SleepvApnea	HIGH R Amp variation, PR> 200, TP interval > 250 ms	931 ms	5.43	5.91	64	76 ms	24 ms	-0.187	DISCORDANT	-0.01	1.01	155	0.26	356 ms	368 ms	160 ms	0.19	0.27	546 ms	0.01	290
9	SleepvApnea	HIGH R Amp variation, PR> 200, TP interval > 250 ms	1068 ms	13.84	8.77	56	107 ms	111 ms	0.184	CORDANT	-0.47	1.47	203	0.16	403 ms	389 ms	162 ms	0.04	0.1	609 ms	-0.23	286
10	SleepvApnea	T inversion	972 ms	2.56	5.45	61	108 ms	80 ms	-0.123	DISCORDANT	-0.08	1.08	153	0.09	368 ms	373 ms	212 ms	0.01	0.04	526 ms	0.7	263
11	SleepvApnea	Aggregated Conditions	783 ms	7.3	5.35	76	67.5 ms	49 ms	0.316	CORDANT	0.66	1.66	150	0.18	361 ms	407 ms	186 ms	0.04	0.14	342 ms	-0.08	331
12	SleepvApnea	HIGH R Amp variation, PR> 200, TP interval > 250 ms	913 ms	1.15	7.63	65	114 ms	111 ms	0.156	CORDANT	-0.32	1.32	201	0.12	411 ms	430 ms	175 ms	0.03	0.07	456 ms	-0.25	310
13	Artrial Fibrillation	Presence of of Atrial wave between T and P, Missing P	743 ms	124.33	3.62	80	107 ms	102 ms	0.167	CORDANT	-0.12	1.12	183	0.02	333 ms	386 ms	131 ms	0.02	0.08	272 ms	-0.27	262
14	Artrial Fibrillation	Presence of of Atrial wave between T and P	748 ms	270.42	4.7	80	82 ms	31 ms	-0.091	DISCORDANT	-0.15	1.15	97	0.06	275 ms	317 ms	132 ms	0.04	0.14	323 ms	0	223
15	Artrial Fibrillation	Aggregated Conditions	975 ms	143.57	5.77	61	95 ms	163 ms	0.056	CORDANT	-0.16	1.16	232	0.06	425 ms	430 ms	145 ms	0.03	0.1	445 ms	-0.39	334
16	Artrial Fibrillation	Rloc Std > 20	1571 ms	27.26	9.49	38	118 ms	20 ms	0.0051	CORDANT	-1.68	2.68	130	0.06	250 ms	199 ms	150 ms	0.03	0.2	860 ms	0.1	105
17	Artrial Fibrillation	Presence of of Atrial wave between T and P	833 ms	385.99	18.53	71	92 ms	124 ms	0.073	CORDANT	-0.35	1.35	206	0.25	367 ms	401 ms	177 ms	0.05	0.19	340 ms	-0.02	301
18	Artrial Fibrillation	Aggregated Conditions	1042 ms	247.52	3.12	57	75.5 ms	51 ms	0.12	CORDANT	-0.25	1.25	190	0.04	364 ms	356 ms	165 ms	0.03	0.08	424 ms	-0.23	282
19	Artrial Fibrillation	Rloc Std > 20	700 ms	107.42	7.39	85	93 ms	66 ms	1.41	CORDANT	-0.74	1.74	144	0.2	326 ms	389 ms	195 ms	0.11	0.23	267 ms	-0.03	278
20	Artrial Fibrillation	Rloc Std > 21	664 ms	114.16	4.56	90	93 ms	47 ms	0.193	CORDANT	-0.3	1.3	120	0.12	291 ms	357 ms	180 ms	0.06	0.14	274 ms	-0.22	242
21	Normal Synus Rhythm	Normal Synus Rhythm	647 ms	1.68	7.99	92	80	88 ms	-0.03	DISCORDANT	-0.5	1.5	145	0.1	292 ms	362 ms	152 ms	0.01	0.02	248 ms	1.23	263
22	Normal Synus Rhythm	Normal Synus Rhythm	628 ms	0.87	8.36	95	82	58 ms	0.208	CORDANT	-0.45	1.45	112	0.12	270 ms	340 ms	181 ms	0.02	0.1	228 ms	-0.15	237
23	Normal Synus Rhythm	Normal Synus Rhythm	765 ms	8.66	7.46	78	90	114 ms	0.119	CORDANT	0.33	1.33	171	0.07	352 ms	402 ms	167 ms	0.01	0.04	270 ms	-0.33	299
24	Normal Synus Rhythm	Aggregated Conditions	831 ms	3.08	2.06	72	108	67 ms	0.183	CORDANT	-0.08	1.08	143	0.08	309 ms	338 ms	202 ms	0.01	0.05	355 ms	-0.47	220
25	Normal Synus Rhythm	Normal Synus Rhythm	739 ms	3.44	14.77	81	98	64 ms	0.137	CORDANT	-1.38	2.38	136	0.15	313 ms	363 ms	125 ms	0.06	0.19	338 ms	-0.05	250
26	Ventricular Tachycardia	S R Slope <=0.50	800 ms	165.37	17.6	74	115	2 ms	0.0015	CORDANT	0.82	0.17	176	2.01	357 ms	398 ms	95 ms	0.76	1.04	401 ms	-5.95	270
27	Ventricular Tachycardia	Aggregated Conditions	498 ms	0.84	8.6	120	103.5	92 ms	-0.209	DISCORDANT	-0.33	1.33	73	0.22	279 MS	394 ms	96 ms	0.16	0.25	208 ms	0	248
28	Ventricular Tachycardia	Rloc Std > 20	1140 ms	85.46	18.15	52	90	20 ms	0.198	CORDANT	-0.54	1.54	111	0.15	333 ms	311 ms	138 ms	0.09	0.4	784 ms	0.04	227
29	Ventricular Tachycardia	Rloc Std > 20	1210 ms	97.03	10.06	49	79	27 ms	-0.11	DISCORDANT	-0.2	1.2	106	0.22	255 ms	231 ms	147 ms	0.16	0.96	893 ms	0.17	159
30	Ventricular Tachycardia	T inversion	1074 ms	5.9	5.91	55	91.5	2 ms	-0.093	DISCORDANT	-0.07	1.07	133	0.06	320 ms	308 ms	135 ms	0.03	0.12	721 ms	0.4	220
31	Ventricular Tachycardia	Aggregated Conditions	639 ms	4.15	8.13	93	95	21 ms	-0.091	DISCORDANT	0.46	0.53	128	2	299 ms	373 ms	108 ms	1.23	1.84	289 ms	0.14	255
32	Ventricular Tachycardia	S R Slope <=0.50	8184 ms	0	21.8	7	122	122 ms	1.332	CORDANT	0.86	0.13	102	0.07	140 ms	48 ms	68 ms	0	0	0	0	6
33	Ventricular Tachycardia	Rloc Std > 20	736 ms	53.88	9.22	81	80.5	16 ms	-0.376	DISCORDANT	-0.4	1.4	80	0.11	296 ms	344 ms	175 ms	0.08	0.29	393 ms	0.21	251
34	Ventricular Tachycardia	QTc > 440 ms	427 ms	13.82	4.53	140	91	108 ms	0.014	CORDANT	-0.56	1.56	170	0.04	346 ms	529 ms	174 ms	0.01	0.02	0.8 ms	1.33	389
35	Ventricular Tachycardia	Rloc Std > 20	1193 ms	41.27	13.33	50	128	151ms	0.251	CORDANT	-0.74	1.74	250	0.06	468 ms	428 ms	137 ms	0.03	0.1	692 ms	-0.09	311
36	Ventricular Tachycardia	Rloc Std > 20	703 ms	57.05	7.37	85	66	80 ms	-0.147	DISCORDANT	-0.39	1.39	154	0.42	371 ms	442 ms	184 ms	0.03	0.22	291 ms	1.16	363
37	Ventricular Tachycardia	S R Slope <=0.50	7155 ms	511.99	4.79	8	104	21 ms	0.809	CORDANT	1	0	83	1.75	288 ms	107 ms	126 ms	1.2	1.67	4223 ms	0.59	68
38	Ventricular Tachycardia	Presence of Atrial Wave between T and P	596 ms	16.25	6.16	100	77	25 ms	-0.247	DISCORDANT	-0.24	1.24	74	0.03	305 ms	394 ms	145 ms	0.03	0.08	288 ms	0.01	295
39	Ventricular Tachycardia	S R Slope <=0.50	1872 ms	406.43	14.99	32	115	90 ms	0.0708	CORDANT	0.54	0.45	115	1.44	288 ms	210 ms	117 ms	1.29	2.07	1539 ms	0.03	126
40	Ventricular Tachycardia	Presence of Atrial Wave between T and P	716 ms	6.48	6.25	83	103	51 ms	-0.604	DISCORDANT	-0.45	1.45	95	0.18	339 ms	400 ms	175 ms	0.08	0.34	342 ms	0	278
41	Coronary Artery	Aggregated Conditions	984 ms	12.11	3.04	60	111	64 ms	0.119	CORDANT	-0.04	1.04	162	0.07	322 ms	324 ms	159 ms	0.01	0.05	472 ms	-0.25	212
42	Coronary Artery	Normal Synus Rhythm	819 ms	8.89	13.11	73	65	65 ms	-0.043	DISCORDANT	-0.19	1.19	115	0.15	279 ms	308 ms	166 ms	0.03	0.13	387 ms	0.3	236
43	Coronary Artery	Qtc	1107 ms	2.8	2.64	54	100	116	0.125	CORDANT	-0.57	1.57	186	0.07	408 ms	387 ms	211 ms	0.07	0.39	507 ms	0.09	292
44	Coronary Artery	Aggregated Conditions	1069 ms	6.65	2.6	56	109	135	0.125	CORDANT	-1.13	2.13	221	0.16	402 ms	388 ms	191 ms	0	0.04	456 ms	-0.32	283
45	Coronary Artery	Aggregated Conditions	1084 ms	3.33	2.52	55	81	131	0.157	CORDANT	-0.5	1.5	206	0.15	395 ms	379 ms	178 ms	0.02	0.08	510 ms	-0.19	301
46	Coronary Artery	Aggregated Conditions	1111 ms	7.37	3.51	54	106	97	0.295	CORDANT	-0.34	1.34	164	0.09	359 ms	340 ms	180 ms	0.02	0.1	536 ms	-0.02	240
47	Coronary Artery	Rloc Std > 20	858 ms	54.03	23.21	69	125	76	0.1	CORDANT	-1.49	2.49	169	0.32	338 ms	364 ms	120 ms	0.05	0.2	398 ms	0.05	229
48	Coronary Artery	Aggregated Conditions	969 ms	3.91	2.57	61	88	124	0.203	CORDANT	-0.25	1.25	192	0.11	397 ms	403 ms	210 ms	0.02	0.07	412 ms	-0.28	313
49	Coronary Artery	Rloc Std > 20	700 ms	111.66	13.95	85	75	78	0.27	CORDANT	-0.22	1.22	199	0.25	398 ms	475 ms	163 ms	0.02	0.06	292 ms	0.07	385
50	Coronary Artery	Normal Synus Rhythm	977 ms	3.59	3.79	61	99	99 ms	0.108	CORDANT	-0.53	1.53	168	0.08	383 ms	387 ms	195 ms	0.01	0.04	447 ms	-0.39	287
51	Coronary Artery	Rloc Std > 20	1324 ms	22.94	2.83	45	104	113	0.076	CORDANT	-0.34	1.34	174	0.08	360 ms	312 ms	188 ms	0.02	0.07	660 ms	0	222
52	Coronary Artery	Presence of Atrial wave between T and P, Missing P	666 ms	1.96	3.33	90	105	32	-0.042	DISCORDANT	-0.11	1.11	116	0	267 ms	327 ms	162 ms	0.01	0.07	287 ms	1.16	198
53	Coronary Artery	Presence of Atrial wave between T and P	948 ms	121.4	22.67	63	89	100	0.0931	CORDANT	-0.49	1.49	165	0.07	370 ms	380 ms	193 ms	0.03	0.22	448 ms	-0.37	288
54	Coronary Artery	Rloc Std > 20	952 ms	66.45	22.49	62	90	198	0.031	CORDANT	-0.52	1.52	266	0.05	405 ms	414 ms	189 ms	0.02	0.16	370 ms	-0.23	322
55	Coronary Artery	Presence of Atrial wave between T and P	806 ms	8.4	32.7	74	92	145	-0.013	DISCORDANT	-0.53	1.53	212	0.05	355 ms	395 ms	181 ms	0.02	0.05	275 ms	1.33	292
56	T Wave Alternans	Aggregated Conditions	525 ms	15.2	2.69	114	63	22	0.09	CORDANT	-0.14	1.14	79	0.07	227 ms	313 ms	97 ms	0.02	0.08	259 ms	0.03	226
57	T Wave Alternans	ST SegmentedDepression	894ms	435.7	20.37	67	88	29	0.0501	CORDANT	0.35	0.64	178	0.38	366 ms	386 ms	160 ms	0.15	0.6	494 ms	0.55	293
58	T Wave Alternans	Change in subsequent T Peak Morphology	524ms	16.2	1.72	114	67	27	0.0408	CORDANT	-0.1	1.1	90	0.03	198 ms	273 ms	122 ms	0.01	0.05	258 ms	-0.67	180
59	T Wave Alternans	Change in subsequent T Peak Morphology	529 ms	18.7	2.05	113	67	37	0.0405	CORDANT	-0.1	1.1	99	0.03	210 ms	288 ms	122 ms	0.01	0.05	253 ms	-0.64	196
60	T Wave Alternans	Change in subsequent T Peak Morphology	965 ms	18.32	1.73	62	78	98	0.1273	CORDANT	-0.16	1.16	162	0.12	350 ms	356 ms	206 ms	0	0.07	539 ms	-0.29	272
61	T Wave Alternans	Normal Synus Rhythm	834 ms	111.84	6.32	71	72	100	0.0899	CORDANT	-0.31	1.31	166	0.22	350 ms	383 ms	164 ms	0.02	0.13	421 ms	-0.04	304
62	T Wave Alternans	Change in subsequent T Peak Morphology	529 ms	15.54	2.71	113	63	2	0.0457	CORDANT	-0.16	1.16	58	0.07	204 ms	280 ms	100 ms	0.03	0.11	282 ms	0.01	193
63	T Wave Alternans	Change in subsequent T Peak Morphology	520 ms	15.88	1.29	115	24	18	0.062	CORDANT	-0.79	1.79	69	0.16	189 ms	261 ms	143 ms	0.06	0.19	261 ms	0.03	228
64	T Wave Alternans	Aggregated Conditions	692 ms	8.94	3.65	86	115	41	0.00227	CORDANT	-0.1	1.1	136	0.18	326 ms	391 ms	181 ms	0.03	0.09	318 ms	-7	253
65	Partial Epilepsy	High R Amp Variation , PR > 200, TP interval > 250 ms	838 ms	8.64	5.54	71	66	24	0.069	CORDANT	-2.34	3.34	104	0.11	310 ms	338 ms	146 ms	0.1	0.22	485 ms	0.3	266
66	Partial Epilepsy	T inversion	1021 ms	8.6	6.71	58	68	73	-0.0685	DISCORDANT	-0.16	1.16	173	0.11	365 ms	361 ms	155 ms	0.03	0.1	584 ms	0.83	293
67	Partial Epilepsy	T inversion	862 ms	6.03	10.38	69	72.5	8	-0.06	DISCORDANT	-0.16	1.16	122	0.15	296 ms	318 ms	175 ms	0.02	0.12	498 ms	0.54	240
68	Partial Epilepsy	Rloc Std > 20	1019 ms	77.18	17.17	58	75.5	95	0.0536	CORDANT	-0.59	1.59	163	0.18	413 ms	409 ms	143 ms	0.06	0.39	571 ms	0.24	334

The parameter evaluation of different signals and their corresponding condition detection is shown in table 2.

Multiple diseases and normal signal together when analyzed, creates a processing confusion matrix. Accurately extracting all the underneath abnormalities are difficult by a human observer. Often doctors rely on observation of the morphological changes in the ECG signal for tracing the abnormalities. Though for specialists and cardiologists, such abnormality tracking is rather easy, it is extremely difficult for general physicians to evaluate all the conditions. The proposed system not only offers an interpretation of the signal, but at the same time offers the parameters and abnormality in the parameters. This also enables the clinicians to take informed decision about the condition of the patient by correlating the interpretation, parameter abnormalities, clinical history of the patient, physiology, family history and other relevant information. Stepwise signal processing of one abnormal type and one normal Sinus Rhythm data has been illustrated in the figure 3.



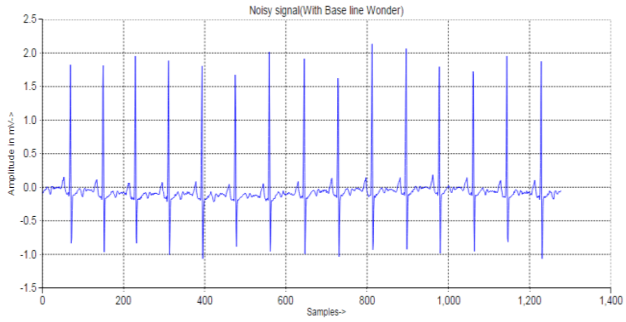


Fig. 3: Sleep Apnea Signal Processing

Processing of the normal is signal is demonstrated in figure 4.

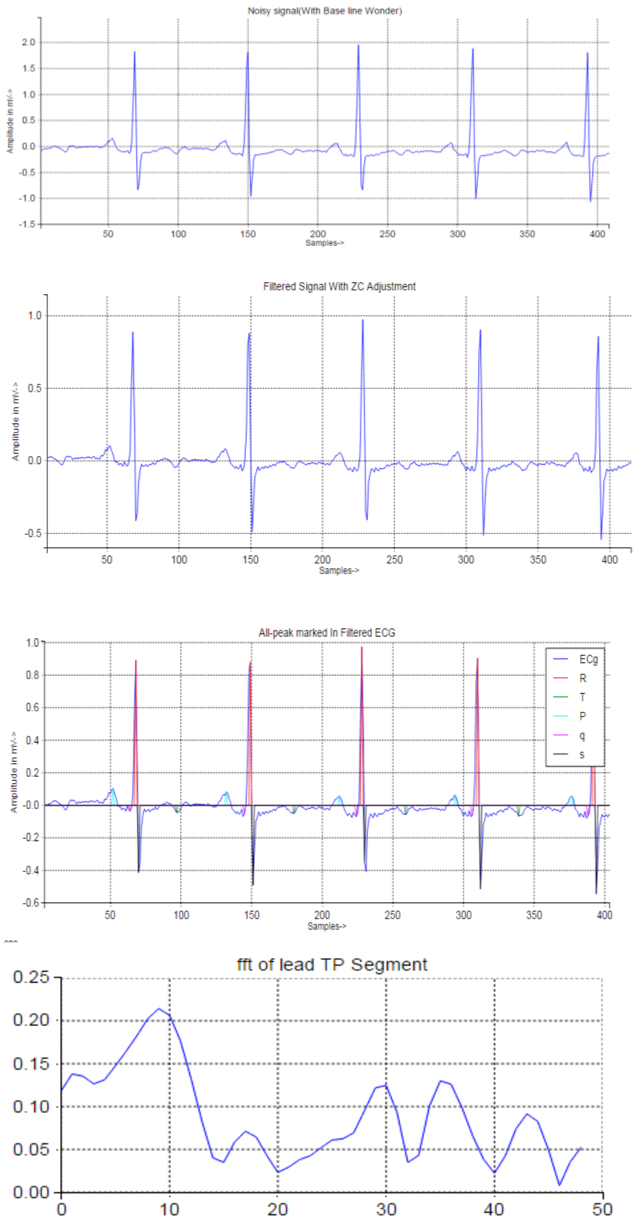


Fig. 4: Processing of Normal Sinus Rhythm

VII. CONCLUSION

Through this work, we have got an opportunity to dig down into one of the extreme challenges India faces for years to come, which is exponential rise in the cardiovascular diseases. Growing population, less doctors, poor transport connectivity and healthcare services in rural areas further elevate the challenge. Therefore, high time to look at cost effective solutions that are easy to scale and deploy. By this work, we have proposed, a cost-effective way of diagnosing cardiovascular issues from only one lead ECG which has never been traditionally proposed or tried out. In this work, we have shown that with high precision cloud-based signal processing it is possible to accurately detect ECG abnormalities even from a single lead ECG signal. Further, clinical study and real time testing is needed as a future extension of this work. If the system can process real-time single lead ECG signal with ground truth data with as much accuracy, then the proposed system can bring down the cost and other complexities of ECG based signal processing and hence, overall cardiac diagnosis significantly.

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