Performance Evaluation for Detection of Cardiovascular Disease using Different Methods

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In today's fast-moving world, where people are busy at work and less aware of their health. Our cities become smart cities, and villages connect with them. However, health facilities in villages and remote areas of the country are still not significantly developed. Treatment costs for low-income people are out of budget, so we are trying to create a system where the system can be used remotely. Here we diagnose the arrhythmia's while capturing the ECG and sending both components to the end-user for diagnosis.

Keywords: Electrocardiographic signal (ECG), cardiovascular diseases (CVD), regions of interest (ROI), Artificial Neural Networks (ANN).

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1 Introduction

1.1 Overview

In the last many decades, many studies have centered on the research of biomedical signals. Routine scientific exercise drives to many biomedical indicators like ECG throughout the tracking of sufferers and for diagnostic purposes. Therefore automated processing structures are regularly utilized in clinical exploration. The medico check a patient based on several numerical values measured during the examination. Arrhythmia identification through the electrocardiographic signal (ECG), plays a crucial role in monitoring and diagnosing the patients. As pea a survey [1] by the World Health Organization (WHO) described CVD's as the primary killer worldwide in the current and forecasts the same ranking up to 2030.

1.2 What is ECG?

Electrocardiograms (ECG) are an electrical sense of the human heart. The electrodes attached to the body at specific points sense muscle movement and convert it in to electrical signal which we called potential of the heart. All signals received from individual electrode are summarized for conclusion at that moment of time. The live ions in a blood cell make body conductive in nature which helps in generation of electrical signals or the voltages for electrocardiography. It is drawn against time axis (milliseconds) and the potential axis (millivolts). Individual ECG is a progressive mix of waves as P-wave, Q-wave, R-wave, S-wave, and T-wave [1][4].

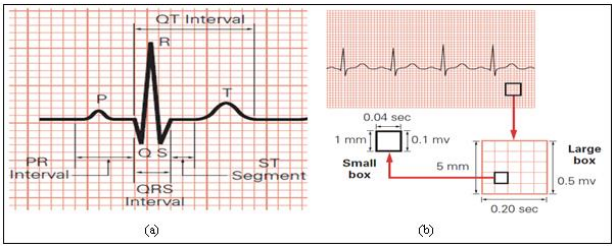

Fig. 1. (a) ECG curve (b) ECG graph paper values [2]

1.3 What is a Cardiovascular Disease (CVD)?

Cardiac arrhythmia, a type of CVD, can affect the electrical system of the heart's sensing cells lead to change in heart beats, which is a cause of scarcity of the oxygenated blood pumped by the heart leads to a loss of life. To avoid or control this condition quick analysis, recognition, and classification of ECG beats of heart malfunctioning (arrhythmia) like Normal Cardiac Rhythm (NCR), Ectopic Heartbeat (EH), Atrial Premature Beats (APB), Ventricular Fibrillation (V-Fib), Fast Heart Rhythm (FHR) and Paroxysmal Supra Ventricular Tachycardia (PSVT), Etc plays vital role in life saving [3][4][5]. Therefore, to avoid above and to enhance segregation on more heart rhythm we need to implement it in real-time [6]. Thus, there is a need to develop classifiers for clinical practices.

2 ECG Signal and Cardiovascular Disease

The coronary heart incorporates two pair of chambers, as shown in figure 2. The functioning is repetitive and rhythmic. Hunan body requires oxygenated blood which is oxygenated by lungs and send back to heart for rotation in the body so that the individual cell should get energized. Heart can be broadly divided in to four chambers as collection of deoxygenated blood followed by next chamber pumping of deoxygenated blood to lungs followed by receiving oxygenated blood from

lungs followed by pumping oxygenated blood to whole body. It is a distribution at some stage in the frame.

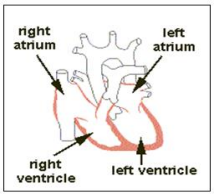

Fig. 2. Structure of the heart

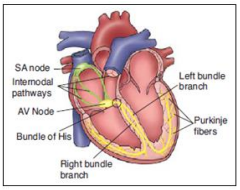

Fig. 3. Conduction system of the heart [2]

As per the figure 3 the sino-atrial (SA) and atrio-ventricular (AV) nodes are the natural pacemakers of human heart which provides rhythm to blood circulation cycle. They synchronize themselves as per the requirement of human body exertion.

The periodic cycle of a heartbeat can be summarized as:
A) The impulse generated by SA node spreads throughout each atrium.
B) It results into synchronous compression in both left as well as right atria.
C) The same is sensed by the AV node internally through fibers and the sensing time is about 40 msec.
D) When atria compressed blood enter to from the atria is driven to the corresponding ventricle.
E) After this process there is delay of about 110 msec, sense transferred by fibers from node to node.
F) The pumping capability of heart by AV node oxygenates the pulmonary machine's right ventricle components wherein the blood returns from lungs.
G) Finally, it becomes chain reaction as muscles of the heart got relax, and blood circulates throughout body.

3 Features Extraction using Discrete Wavelet Transform

3.1 Details

The valuable information hidden in ECG spikes and baseline is required for subsequent automatic analysis. The prime facie aims in analyzing the ECG is monitoring the patient in real time as well once the signal reached the system in standard form, the diagnosis of disease the patient is suffering from and that too immediately so that medico can start medication immediately based on inference provided by the system. The visual record information retrieval model helps in system based diagnosis. The features extraction system must perform accurately, and feature extraction aims to make it enable self-made abnormality capture and sorting in class.

In this study, features are retrieved by two different modified techniques i.e.
(i) Get the information details from signal by breaking it in to time domain
(ii)Morphological and statistical features extraction in Wavelet Transform (WT) domain approach.

3.2 Morphological and Statistical Features Extraction in Wavelet Transform (WT) Domain

Morphological and statistical feature extraction in the wavelet transform (WT) domain is explored [9]. The following steps are used to extract the morphological and statistical features.

(1) Slope information is enhanced by squaring the preprocessed signal explained in chapter 7.
(2) A wavelet db6 is justified in step 3.2(2)
(3) For extracting feature vectors, R peak & QRS detection of each beat and delineation of individual beats in ECG signal is done.

(4) Squared o/p passed through moving window integrator.
(5) Window size of 700ms (-300ms to 400ms is chosen around R peak) which corresponds to 252 samples.
(6) Feature vectors at five different levels of DWT decomposition are extracted.
(7) For extracting morphological and statistical features; samples of ECG derived in step 6 are collected to form new features vector of 24 samples. The figures in the bracket indicate level numbers. The samples are subsequently given to ANN/ANFIS classifier for training. The block diagram of features extraction using morphological and statistical features extraction approach.

4 Experimental Results and Discussions

4.1 Overview

After deep study and literature review we have concluded our work for Lead-II ECG signals which we get from standard databank and checked the efficiency of the ECG classifier with one second random window length for following six arrhythmias:

1. Normal Cardiac Rhythm (NCR)
2. Ectopic Heartbeat (EH)
3. Atrial Premature Beat (APB)
4. Fast Heart Rhythm (FHR)
5. Ventricular Fibrillation (V-Fib)
6. Paroxysmal Supra Ventricular Tachycardia (PSVT).

We have used four databanks

1. MIT-BIH Arrhythmia Databank referred as MITD
2. Creighton University Ventricular Tachyarrhythmia Databank referred as CUDB
3. MIT-BIH Malignant Ventricular Fibrillation Databank referred as VFDB
4. MIT-BIH Supra ventricular Arrhythmia Databank referred as SVDB

To evaluate our algorithm, we have used total datasets (10890) out of that for training (6210), and for testing (6750), are depicted in Table 1. It includes 1290 (Almost 10% of total samples) Local hospital contribution in databank.

Table 1. Databank signal distribution

Name of heart arrythmias	Type	Databank for Training/ Learning/ Total
CVD-NCR	I	4200/4500/8700
CVD-EH	II	825/900/1725
CVD-APB	III	825/900/1725
CVD-V-Fib	IV	120/150/270
CVD-FHR	V	120/150/270
CVD-PSVT	VI	120/150/270
Database		6210/6750/10890

4.2 Testing Results

Comparative results for different models as ANN as well ANFIS-Decimation, ANFIS as well ANN - Morphological model are presented in Table 2 to Table 5, respectively.

Table 2. Testing results for ANN (decimation model)

Decimation System for ANN									
Classes	Testing Set	CVD-NCR	CVD-EH	CVD-APB	CVD-V-Fib	CVD-FHR	CVD-PSVT	NA	Time elapsed (sec)
CVD-NCR	4500	4484	0	20	0	0	0	6	224.3
CVD-EH	900	0	889	0	0	0	6	5	
CVD-APB	900	12	0	888	0	0	0	0	
CVD-V-Fib	150	0	0	0	146	0	0	4	
CVD-FHR	150	0	0	0	2	146	0	2	
CVD-PSVT	150	0	2	0	0	0	148	0	

ANN-Decimation model requires 224.3 Sec of computational time for testing 6 Classes as mentioned above. The average unknown samples in testing are less than1% and can be neglected.

Table 3 Testing results for ANFIS - decimation model

Decimation System for ANFIS									
Classes	Testing Set	CVD-NCR	CVD-EH	CVD-APB	CVD-V-Fib	CVD-FHR	CVD-PSVT	NA	Time elapsed (sec)
CVD-NCR	4500	4419	0	50	0	0	0	31	240.9
CVD-EH	900	0	868	0	0	13	0	19	
CVD-APB	900	15	0	877	0	0	8	0	
CVD-V-Fib	150	0	0	0	136	8	0	6	
CVD-FHR	150	0	0	0	1	148	0	1	
CVD-PSVT	150	0	5	0	0	0	145	0	

ANFIS-Decimation model requires 240.9 Sec of computational time for testing 6 Classes as mentioned above. The average unknown samples in testing are less than1% and can be neglected.

Table 4. Testing results for ANFIS – morphological model

Morphological System for ANFIS									
Classes	Testing Set	CVD-NCR	CVD-EH	CVD-APB	CVD-V-Fib	CVD-FHR	CVD-PSVT	NA	Time elapsed (sec)
CVD-NCR	4500	4382	0	95	0	0	0	23	238.05
CVD-EH	900	0	858	0	0	0	30	12	
CVD-APB	900	23	0	876	0	0	0	3	
CVD-V-Fib	150	0	0	0	147	2	0	1	
CVD-FHR	150	0	3	0	5	138	0	4	
CVD-PSVT	150	0	3	0	0	0	147	0	

ANFIS- Morphological model requires 238.05 Sec of computational time for testing 6 Classes as mentioned above. The average unknown samples in testing are less than1% and can be neglected.

Table 5. Testing results for ANN - morphological model

Morphological System for ANN									
Classes	Testing Set	CVD-NCR	CVD-EH	CVD-APB	CVD-V-Fib	CVD-FHR	CVD-PSVT	NA	Time elapsed (sec)
CVD-NCR	4500	4422	0	55	0	0	0	23	253.2
CVD-EH	900	0	858	0	0	0	25	17	
CVD-APB	900	20	0	878	0	0	0	2	
CVD-V-Fib	150	0	0	0	147	2	0	1	
CVD-FHR	150	0	0	0	1	144	0	5	
CVD-PSVT	150	0	1	0	1	0	147	1	

ANN- Morphological model requires 253.2 Sec of computational time for testing 6 Classes as mentioned above. The average unknown samples in testing are less than1% and can be neglected.

4.3 Performance of the Classification

The crucial part of the research performance evaluation appropriately. So we focused on the following parameters: Sensitivity (Se), Specificity (Sp), Accuracy (A)

4.3.1 Calculation of Sensitivity (Se), Accuracy (A) and Specificity (Sp)

Se (True Positive rate) it is correlated with the check to identify positive results. The Se of a trial is the share of human beings with positively tested disease. Sp (True Negative Rate) it is correlated with the check to identify negative results. The Sp can be demonstrated as the proportion of human beings with negatively tested disease. Thus sensitivity (Se) and specificity (Sp) helps in determining how the databank identify groups without missing them as well measures how exclusively it is measured respectively.

$$Sensitivity\ \% = \frac{Number\ of\ Total\ Tested\ Sample\ set - FN}{Number\ of\ total\ Tested\ Samples\ Set} \times\ 100$$

$$Specificity\ \% = \frac{Number\ of\ Total\ Tested\ Sample\ set - FP}{Number\ of\ total\ Tested\ Samples\ Set} \times\ 100$$

$$Accuracy\ \% = \frac{Number\ of\ Total\ Tested\ Sample\ set - FP - FN}{Number\ of\ total\ Tested\ Samples\ Set} \times\ 100$$

here FP and FN stands for false positive and false negative respectively.

Now Table 6 show the classification performance for analysis as ANN-Decimation model, ANFIS-Decimation model, ANFIS - Morphological model, and ANN - Morphological model can be calculated in same manner. Later on Table 7 shows compare these methods for performance efficiency and Accuracy (%).

Table 6. Performance achievement - ANN-decimation model

Achievement: ANN-Decimation model						
Specification	CVD-NCR	CVD-EH	CVD-APB	CVD-V-Fib	CVD-FHR	CVD-PSVT
Se-Sensitivity in %	99.55	99.33	98.67	100	98.67	98.67
Sp-Specificity in %	99.87	99.44	100	97.33	98.67	100
A-Accuracy in %	99.47	98.77	98.67	97.33	97.33	98.67

The above table clearly shows the classification performance by three parameters as Sensitivity, Specificity and Accuracy for the ANN- Decimation model.

Various ECG analyses is practiced on Discrete Wavelet Transform (DWT) with the help of tools ANN, and ANFIS and compared them, the optimum system has been developed. The ANN-Decimation model is more accurate and computationally fast than the four models, as shown in Table 7 below. Also, the overall accuracy of other methods is shown in the table for reference.

Table 7. Comparison between different methods

Reference	Tools	Number of beat types	Overall Accuracy (%)
Recommendation 1	ANN-Decimation	6	98.60%
Recommendation 2	ANFIS-Decimation	6	96.34%
Recommendation 3	ANN-Morphology	6	96.30%
Recommendation 4	ANFIS-Morphology	6	97.20%
[12]	ANFIS-ICA	6	97.1%
[9]	FFNNICA	6	94.35%
[4]	ANFIS for CVD	4	96.385%
[15]	FNN for CVD	6	9.59%

5 Conclusion

Various ECG analyses is practiced on Discrete Wavelet Transform (DWT) with the help of tools ANN, and ANFIS and compared them, the optimum system has been developed. An optimum system has been developed, which gives better results than previously published results. Out of the four models, the ANN-Decimation model is more accurate and computationally fast. The system may be used for real time data analysis in Holter visual display, which ceaselessly copy the heart's rhythms for 24 - 48 hours. It is time-consuming to analyze such large data manually.

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