A Survey Paper on Arrhythmia Classification Using ECGSignals

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***Abstract* --- Cardiovascular diseases (CVDs) rank among diseasesof highest mortality. Electrocardiography (ECG) is a non-invasive tool to assess the generalcardiac condition of a patient and is therefore as first-in-line examination for diagnosis of CVD.Arrhythmia Classification plays a major role while diagnosing heart diseases. Any change in the regular sequence of electric impulses is called as arrhythmia. Identifyingarrhythmia as early as possible helps the patient in choosing appropriate treatment. Classification of ECG arrhythmia with high accuracy is a challenging problem. Arrhythmiaclassification requires Acquisition of ECG signal, preprocessing ECG Signal, extraction of features, and optimization of the features and classification of arrhythmia. This paper presents survey on ECG denoising, feature extraction, optimization and classification. Furthermore, methods used to analyze the performance are also discussed. Limitations and drawbacks involved in ECG denoising, Feature Extraction and Classification are discussed concluding remarks and future scope.**

Keywords— ECG signal, Denoising, Feature Extraction, Arrhythmia Classification.

I. INTRODUCTION

An arrhythmia, or irregular heartbeat, is a problem with the rate or rhythm of heartbeat[8].Heart rhythm problems (heart arrhythmias) occur when the electrical signals that coordinate the heart's beats don't work properly. Arrhythmia can be of various types and each type is associated with a different pattern. Classification of arrhythmia depending on the pattern can be of two types. One is morphological arrhythmia which is formed due to abnormality in single heartbeat and other is rhythmic arrhythmia formed due to set of irregular heartbeats. The condition of the heart is reflected in an Electrocardiogram (ECG)[1]. Arrhythmias are predicted through an Electrocardiogram signal. Many researcher developed novel algorithms for analyzing and classification of arrhythmia[10][13].

A. ELECTROCARDIOGRAM

Even more than a century after its invention, electrocardiogram (ECG) still remains the primary choice of the physicians for preliminary level investigation of patients against chest pains and a helpful clue to the generalized disorders that affect the rest of the body too. ECG signal is represented as P Wave, QRS complex and T wave as shown in Fig.1.

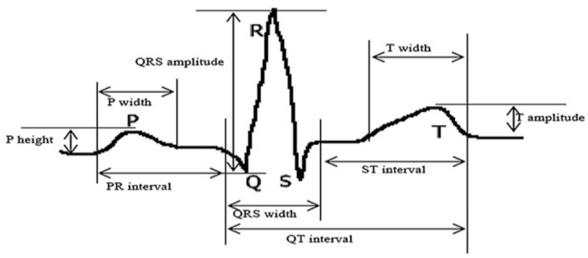

Fig.1. ECG clinical signature

Many ECG databases are available for researchers to test their newly developed algorithms. The cardiac events and corresponding ECG waves are summarized in Table 1

Wave/Segment	Event Name
P wave	Atrial Depolarization
PR Interval	Start of Atrial Depolarization to start of Ventricular Depolarization
QRS Complex	Ventricular Depolarization
ST Segment	Pause in Ventricular electrical Activity Before Repolarization
T Wave	Ventricular Repolarization
U Wave	Slow Ventricular Repolarization

Table 1. The cardiac events and corresponding ECG waves

Typical values of each segment is shown Table 2 which are considered as values of healthy ECG

Clinical Signature	Typical Values	Normal Limit
P width	110 ms	+-20 ms
T width	180 ms	+-40 ms
PR Interval	120 ms	+-20 ms
QRS Width	100 ms	+-20 ms
QT Interval	400 ms	+-40 ms
P amplitude	0.15mV	+-0.05 mv
T amplitude	0.3 mV	+-0.2 mV
QRS Amplitude	1.2 mV	+-0.5 mV

Table 2. Common ECG signature values

B. Types of Arrhythmias

Arrhythmia describes a group of conditions that affect the heart's natural rhythm. Different types of arrhythmias cause the heart to beat too fast, too slowly, or in an irregular pattern.

There are four main types of arrhythmia Supraventricular arrhythmias, Ventricular arrhythmia, inherited arrhythmia, Bradycardias.

Arrhythmia Databases

Many ECG databases are available for researchers to test their newly developed algorithms.The use of wellannotated, validated databases produces results that are comparable with real-world signals. The database must contain a large number of ECG signals for all kinds of arrhythmia and also signals that are rarely observed but more significant in clinical environments

PhysioNet

The Laboratory for Computational Physiology develops and maintains PhysioNet, a widely-used repository of biomedical data and software. PhysioNet enables researchers around the world to share and reuse resources that underpin clinical studies, promoting reproducible research and lowering barriers to data access[8][9][10][20].

Around 150 open databases are available for various cardiovascular functions

The 16 classes of arrhythmia in MIT-BIH database are as follows

Sr .No	Symbol	Class of Arrhythmia in MIT-BIH Database
1	N	Normal beat
2	L	Left bundle branch block beat
3	R	Right bundle branch block beat
4	A	Atrial premature beat
5	A	Aberrated atrial premature beat
6	J	Nodal (junctional) premature beat
7	F	Fusion of ventricular and normal beat
8	X	Blocked atrial premature beat
9	V	Premature ventricular contraction
10	J	Nodal (junctional) escape beat
11	!	Ventricular flutter wave
12	E	Ventricular escape beat
13	E	Atrial escape beat
14	P	Paced beat
15	F	Fusion of paced and normal beat
16	Q	Unclassifiable beat.

Table 3 Classes of Arrhythmia in MIT-BIH database

II. Methodology

Many researcher uses five stages foe arrhythmia classification, ECG signal acquisition, signal preprocessing, feature extraction, optimization, classification.

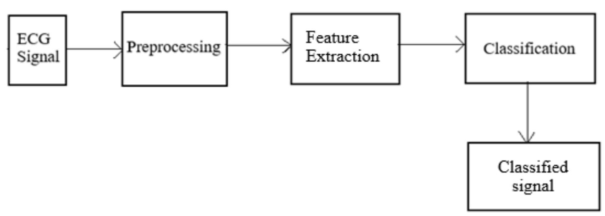

Fig.2. Block diagram of Arrhythmia Classification

Many research was done on the available database on the physionet, other signal banks, and some on real database taken from cardiologist. These ECG signals get affected due to noise such as muscles artifacts, respiratory moments, many high-frequency noises due to electrode contacts, power line interference etc. signal preprocessing is needed to remove all kind of noises present in the signal.

1. Preprocessing

ECG preprocessing means denoising is aimed to eliminate (or, at least minimize) the unwanted signals from an ECG record, without hampering the clinical information contained within the signal itself. A detailed review of the denoising methods is available in [Table 3]. The available literature on ECG denoising mostly discusses PLI and BW removal. [2][17][19]In many reported works, the researchers have validated the algorithm by introducing a simulated noise with a 'clean' ECG signal to generate a composite noisy signal and then denoising it using their proposed algorithm. In general, the ECG denoising techniques can be classified into one of the following categories:

(a) Digital filtering techniques- Low pass filter [8]adaptive and non-adaptive, morphological Filter, Finite Impulse Response (FIR) filter, Infinite Impulse Response (IIR) filter , moving average filter , Kalman filter , nonlinear filter bank, change in features. These features have to be carefully extracted.patient has to considered and compared to avoid unwanted transformed so as to eliminate unstable heart rate conditions like stress, working activity or exercise. This causes the ECG features to fluctuate. More beats of same Butterworth Filter, sovatzky-Golay (SVG) Filter Extracting more number of features make the feature of a person changes from time to time as per biological
extraction algorithm more complex. Heart beat or heart rate

(b) Source separation methods—principal component analysis (PCA) and independent component analysis (ICA);

(c) Neural networks: Deep recurrent denoising neural networks is one of the denoising technique, in this a transfer learning technique by pretraining the network using synthetic data, generated by a dynamic ECG model, and fine-tuning it with a real data is used.

(d) Wavelet-based methods: One of the widely used technique of the ECG signal denoising is the discrete wavelet transform (DWT)[19]. This technique offers an important solution to deal with this issue. Several research works propose the use of different sets of wavelet coefficients and thresholding techniques of the DWT .Some other wavelet-tranform tequniqes are also used like stationary wavelet transform, 2-D wavelet transform;

(e) Other non-adaptive methods like empirical mode decomposition (EMD): one of the method is windowing in the EMD domain in order to reduce the noise from the initial IMFs instead of discarding them completely thus preserving the QRS complex and yielding a relatively cleaner ECG signal[19].

2. Feature Extraction

After preprocessing the signal next step is to extract the features. ECG Signal features mainly depends on time interval, Amplitude and segment duration. Normal attributes of ECG are given in table 2. Temporal and statistical features [18] like slopes, pre-intervals can also be considered for effective classifications. Before finding the amplitudes and intervals identification of peaks P, R, T and QRS complex is required. Various Algorithms like Peak detectionalgorithms , QRS Complex detection, Wavelet transforms, Empirical Mode Decomposition, Most of the researchers have proposed feature extraction algorithms based on the feature they have usedfor classification. If only R amplitude and RR interval are considered for classification then fixed level thresholding or peak detection algorithm is sufficient. Researchers have extracted feature in range of 1 to 13.

3. Classification

For the classification Most of the researchers used Genatic Algorithm, LSMT deep convolutional neural networks, SVM, OSACN, K-NN, and Recurrent Neural Network can be employed. Deep learning methods such as CNN and RNN [4] [8] [17]are most commonly used because they have proven to provide high accuracy results. These methods can be seen in Table 3.

Deep Learning uses more mathematics, neural networks and computation that enables computer itself to identify better features for generating accurate and useful results.

Below table shows the comparative analysis of various preprocessing, feature extraction and classification methods used by various researchers. Depending up on which type of database used, type of preprocessing method for denoising ang scaling input signal for getting balanced dataset, feature extraction techniques and selection of useful feature, proper classification method for classification of signal to particular type of arrhythmia plays very important role to increasing classification accuracy, sensitivity of the proposed model. for achieving this detail review of various research paper is very important

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Sr. no	**Name of paper**	**Database Used**	**Preprocessing methodology**	Classification Method
1	A Deep Biometric Recognition and Diagnosis Network With Residual Learning for Arrhythmia Screening Using Electrocardiogram Recordings	MIT-BIH arrhythmia database	Wavelet decomposition is used. segmentation:The original raw ECG signals with denoising are segmented into a mass of heartbeats centered around the R-peak	deep convolutional neural network
2	A Multitier Deep Learning Model for Arrhythmia Detection	MIT-BIH arrhythmia database	Preprocessing operation is that to convert them to the same length by padding or truncating for the convenience of DNN training	**Deep Neural Network, Genatic Algorithm**
3	An Ensemble of Deep Learning-Based Multi-Model for ECG Heartbeats Arrhythmia Classification	MIT-BIH arrhythmia database	Preprocessing and segmenting the input ECG signals. median filters, low-pass filter.	Convolutional Neural Network - LSTM
4	Deep Learning for ECG Analysis: Benchmarks and Insights from PTB-XL	PTB-XL	No preprocessing	Deep Convolution Neural Network (CNN).
5	Generalization of Convolutional Neural Networks for ECG Classification Using Generative Adversarial Networks	15 different classes from the MIT-BIH arrhythmia dataset	Butterworth bandpass filter and segmentation	deep convolutional neural networks (CNNs)
6	MATLAB-based ECG R-peak Detection and Signal Classification using Deep Learning Approach	MIT-BIH arrhythmia database	The strategies employed for denoising the noisy ECG signal containing random noise, White Gaussian noise, 50 Hz AC Hum and high-frequency noise	Deep Convolution Neural Network (CNN).
7	Multilabel 12-Lead ECG Classification Based on Leadwise Grouping Multibranch Network	CINC2020 DATABASE and SPH DATABASE	Denoising- Butterworth bandpass filter and zeropadding	CNN and LSTM
8	OSACN-Net: Automated Classification of Sleep Apnea Using Deep Learning Model and Smoothed Gabor Spectrograms of ECG Signal	Sleep Apnea database	Gabor Transfoer and Savitzky-Golay filter	OSACN
9	An intelligent learning approach for improving ECG	MIT-BIH arrhythmia	IIR elliptic high pass 3 order	Hidden Markav Model

	signal classification	database		
10	Sequence to Sequence ECG Cardiac Rhythm Classification Using Convolutional Recurrent Neural Networks	University of Virginia (UVA) Heart Station and MIT-BIH arrhythmia database	R-Peak Detection and produces a spectrogram Short-Time Fourier Transform (STFT) of the ECG signal is first computed	Recurrent Neural Networks
11	ML-Net: Multi-Channel Lightweight Network for Detecting Myocardial Infarction	PTB diagnostic database classi: ML-Net	Deep learning model only needs a small amount of data preprocessing.Z-scores normalization method is used to normalize each segment of data,	Multi-label-classification
12	Empirical Mode Decomposition and Wavelet Transform Based ECG Data Compression Scheme	MIT-BIH arrhythmia database	Savitzky-Golay filter (SGF) EMD	-

Table 3. Comparative table for various databases used, preprocessing methods, classification methods

III. PERFORMANCE EVALUATION METHODS

In most of the research the performance of classification model is evaluated using the precision (PRE), sensitivity (SEN), specificity (SPE), accuracy (ACC).where the TP, FP, TN, and FN indicate the true positives, false positives, true negatives, and false negatives cases, respectively. Which shown in the confusion matrix.

1. Accuracy

Accuracy gives number of classes correctly predicted of total classes.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

2. Precision

Precision gives ratio of correctly predicted values to total number of values in a particular class.

$$Precision = \frac{TP}{TP + FP}$$

3. Specificity

Specificity can be said as the opposite of Sensitivity. It is the sensitivity of negative class i.e. the ratio of incorrectly predicted values to the total number of misclassified values

$$Specificity = \frac{TN}{TN + FP}$$

4. Detection Error Rate

DER gives ratio of total misclassified value to correctly classified values of a particular class.

$$DER = \frac{FP + FN}{TP}$$

IV. CONCLUSION

Researchers have proposed different methods in each step for classification of arrhythmia. Most of the researchers used MIT-BIH database and other databases from physionnet which are very unbalanced. Real time scheme must be included. Classification algorithms were mainly trained and tested on a specific dataset captured with a specific device and generalizability of developed algorithms was not evaluated.

Machine learning algorithms works effectively for normal class of arrhythmia as the database has large number of normal beats. In some of the research preprocessing stage is eliminated which in turn reduces the accuracy of prediction.For training the algorithm with large data sets improves accuracy. Classifying all 16 classes of arrhythmia becomes difficult. Research community needs to study on heat beat arrhythmia problem and provide an extension to database with all classes of arrhythmia. It is required to develop automated classifier using balanced dataset. Moreover, performance of a classifier is evaluated based on its accuracy and sensitivity, but the energy consumption aspect is neglected. For fast detection of CVDs real time monitoring system needs to be developed for prevention of health loss.

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