

Classification of ECG signals using Machine Learning Techniques: A Survey

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Abstract— Classification of electrocardiogram (ECG) signals plays an important role in diagnoses of heart diseases. An accurate ECG classification is a challenging problem. This paper presents a survey of ECG classification into arrhythmia types. Early and accurate detection of arrhythmia types is important in detecting heart diseases and choosing appropriate treatment for a patient. Different classifiers are available for ECG classification. Amongst all classifiers, artificial neural networks (ANNs) have become very popular and most widely used for ECG classification. This paper discusses the issues involved in ECG classification and presents a detailed survey of preprocessing techniques, ECG databases, feature extraction techniques, ANN based classifiers, and performance measures to address the mentioned issues. Furthermore, for each surveyed paper, our paper also presents detailed analysis of input beat selection and output of the classifiers.

Keywords—ECG classification; survey; preprocessing; neural network; mit-bih database; feature extraction; pan-tompkins algorithm.

I. INTRODUCTION

An electrocardiogram (ECG) is a medical test which detects cardiac abnormality by measuring the electrical activity generated by the heart. A heart produces tiny electrical impulses which spread through the heart muscle. These impulses can be detected by an ECG machine. An ECG machine records the electrical activity of the heart and displays this data as a trace on a paper. This data is then interpreted by a medical practitioner. ECG helps to find the cause of symptoms or chest pain and also helps to detect abnormal heart rhythm or cardiac (heart) abnormalities.

ECGs from normal healthy hearts have a characteristic shape. Any irregularity in the heart rhythm or damage to the heart muscle can change the electrical activity of the heart, so shape of the ECG gets changed. A doctor may recommend an ECG for patients who may at risk of heart disease because of family history of heart disease, smoking, overweight, diabetes, high cholesterol or high blood pressure. The heart disorders that can be detected using ECG include abnormal heart rhythms, heart attack, and an enlarged heart.

ECG is the recording of the electrical property of the heartbeats and has become one of the most important tool in the diagnosis of heart diseases. Due to high mortality rate of heart diseases, early detection and precise discrimination of ECG signal is essential for the treatment of patients. Classification of ECG signals using machine learning techniques can provide substantial input to doctors to confirm the diagnosis. Classification and detection of arrhythmia types can help in identifying the abnormality present in ECG signal of a patient. After identifying the abnormality, the heart diseases can be detected and the better treatment of the patient can be done. Accurate ECG classification into arrhythmia types provides sufficient information to detect the heart diseases and helps doctor in finding best treatment therapy for patients.

Classification of ECG signals is a challenging problem due to issues involved in classification process. Major issues [1, 2] in ECG classification are lack of standardization of ECG features, variability amongst the ECG features, individuality of the ECG patterns, non existence of optimal classification rules for ECG classification, and variability in ECG waveforms of patients. Developing the most appropriate classifier that is capable of classifying arrhythmia on real-time is also an issue in ECG arrhythmia classification. Applications of ECG signal classification are in detecting abnormality type and diagnosing a new patient more precisely than manually. It is also used in heart diseases diagnosis and treatment of patients.

ECG classification includes steps namely preprocessing, feature extraction, feature normalization, and classification. In this paper, basic introduction of ECG and ECG classification (section-2), issues in ECG classification (section-3), a detailed survey of ECG classification (section-4) and databases - techniques available for ECG classification (section-5) are discussed. Finally the paper presents conclusions (section-6). Detailed analysis of input beat selection and output of classifiers is also included in this paper. This work can be useful for the other researchers in identifying issues in ECG classification and to analyze the research area. The detailed analysis and basics of ECG classification can help beginners to understand the research area.

II. BACKGROUD KNOWLEDGE

One ECG signal consists of several ECG beats and each ECG beat contains P wave, QRS complex, and T wave. Each peak (P, Q, R, S, T, and U), intervals (PR, RR, QRS, ST, and QT) and segments (PR and ST) of ECG signals have their normal amplitude or duration values. These peaks, intervals, and segments are called ECG features. Fig 1 shows these features for one ECG cardiac cycle, which are described in Table I. Table I presents ECG features along with their description and their durations.

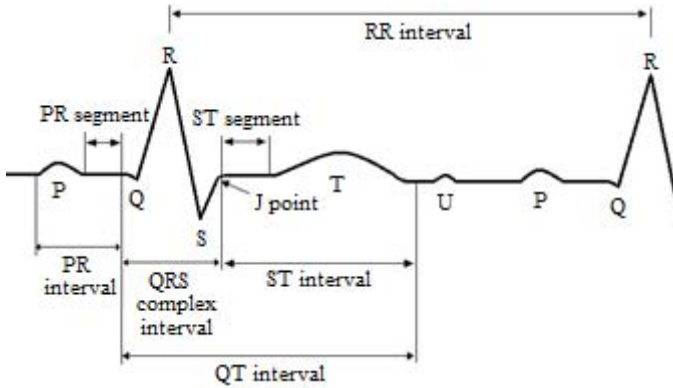


Fig. 1. Normal ECG waveform [3]

TABLE I. ECG FEATURES AND THEIR NORMAL DURATIONS [4]

Feature	Description	Duration
RR	interval between R wave and the next R wave	0.6-1.2 s
P	first short upward movement of the ECG	80ms
PR	measured from the beginning of the P wave to the beginning of the QRS complex	120-200 ms
QRS	normally begins with a downward deflection Q, a larger upwards deflection R and ends with a downward S wave	80-120 ms
PR	connects the P wave and the QRS complex	50-120 ms
J-point	The point at which the QRS complex finishes and the ST segment begins is called J-point.	Not applicable
ST	connects the QRS complex and the T wave	80-120 ms
T	normally a modest upward waveform	160 ms
ST	measured from the J point to the end of the T wave	320 ms
QT	measured from the beginning of the QRS complex to the end of the T wave	420 ms
U	normally has low amplitude and often it is completely absent	Not mentioned

Classification of ECG signals plays an important role in clinical diagnosis of heart disease. The main problem in diagnosing heart disease using ECG is that the normal ECG may differ for each person and sometimes one disease has dissimilar signs on different patient's ECG signals. Also, two distinct diseases may have approximately identical effects on normal ECG signals. These problems complicate the heart disease diagnose. Therefore, the utilization of pattern classifier techniques can improve the new patients ECG arrhythmia diagnoses. The ECG classification problem is a multi-class classification problem containing classes such as Normal, Left Bundle Branch Block (LBBB) and Right Bundle Branch Block (RBBB). ECG data can be classified into two ways: (i) classification of ECG signal, and (ii) classification of

individual ECG beat. One cardiac cycle consists of P, Q, R, S, T and U wave which defines one ECG beat. One ECG signal contains thousands of such beats.

Preprocessing, feature extraction, normalization, and classification are main sequential steps of ECG classification. Researchers have applied different preprocessing techniques for ECG classification. For noise removal, techniques such as low pass linear phase filter, linear phase high pass filter etc. are used. For baseline adjustment, techniques such as median filter, linear phase high pass filter, mean median filter etc. are used. Feature extraction techniques used by researchers are Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), Discrete Cosine Transform (DCT), S-Transform (ST), Discrete Fourier transform (DFT), Principal Component Analysis (PCA), Daubechies wavelet (Db4), Pan-Tompkins algorithm, Independent Component Analysis (ICA) etc. For normalization of features, techniques such as Z-score and Unity Standard Deviation (SD) are used. Classification techniques used are Multilayer Perceptron Neural Network (MLPNN), Fuzzy C-Means clustering (FCM), Feed forward neuro-fuzzy, ID3 decision tree, Support Vector Machine (SVM), Quantum Neural Network (QNN), Radial Basis Function Neural Network (RBFNN), Type2 Fuzzy Clustering Neural Network (T2FCNN) and Probabilistic Neural Network (PNN) classifier etc.

III. ISSUES IN ECG CLASSIFICATION

In this section, we discuss the issues that are involved in ECG classification. The presented issues would help beginners to understand the challenges involved in classification of ECG. These issues are described below:

1. **Lack of standardization of ECG features:** ECG wave boundaries, heuristically on time and amplitude domain are not standard or fixed. Feature extraction method temporally selects ECG features so accuracy of this method depends on these detected features. A small variations in the values of these features may cause a misclassification over large data sets.
2. **Variability of the ECG features:** Heart rate of individual is changing as per physiological and mental conditions. Stress, excitement, exercise, and other working activities may change the heart rate. The changes in the heart rate accordingly vary the features such as RR interval, PR interval, and QT interval. These features need to be carefully transformed and the impact of the varying heart rate needs to be eliminated.
3. **Individuality of the ECG patterns:** Individuality of the ECG pattern refers to the likelihood of intraclass similarity and interclass variability of testing patterns observed in ECG data. It shows up to what extent the ECG patterns are scalable in sufficiently larger dataset.
4. **Non existence of optimal classification rules for ECG classification:** For ECG classification, no such optimal classification rules exist which can help in classification process.
5. **Patients may have different ECG waveforms:** ECGs from different patients may have different slopes of

signal, timing, and amplitude which change the ECG waveforms. Therefore, the classification process needs to carefully classify the ECG signal.

6. **Beat variations in a single ECG:** Single ECG may contain thousands of beats and these beats may be of different types (i.e. arrhythmia types). Therefore, classification model needs to get trained in such a way that it produces small errors on test dataset.
7. **Finding out the most appropriate classifier:** Finding out the classifier which is capable of classifying arrhythmia on real-time is an issue because classification accuracy depends on many parameters such as type of arrhythmia, diversity in arrhythmia, selected arrhythmia database, selected feature extraction technique etc.

IV. SURVEY OF ECG CLASSIFICATION

Many researchers have worked on classification of ECG signals. They have applied different pre-processing techniques, various feature extraction techniques and classifiers. Most of the researchers have used MIT-BIH arrhythmia database for ECG classification. A.Dallali et al. [5] have extracted RR interval using DWT and normalized the RR interval using Z score. They used FCM to classify ECG beats. They achieved 99.05% accuracy. In [6], features extracted are RR interval and R point location by using DWT. Pre-classification was done using FCM and final classification was done using 3-layer MLPNN. They achieved accuracy of 99.99%.

R peak and RR interval are extracted using DWT in [7]. ECG classification was done using MLPNN. The obtained Mean Squared error (MSE) was 0.00621. H.Khorrami and M.Moavenian [8] have extracted RR interval using DWT. Performance of MLPNN and SVM were compared in this

paper. D.Patra et al. [9] have manually extracted R peak and RR interval from the annotation file of the MIT-BIH arrhythmia database. Features are normalized using Zero mean and reduced using FCM. 3 layer FFNN with back propagation algorithm is used as classifier. F.Naima and A.Timemy [10] have extracted R location and RR interval using Db4 discrete wavelet transform. FFNN trained with back propagation algorithm is used. Sensitivity, specificity and accuracy achieved by NN are 90%, 90%, 95% respectively. A.Khazaei [11] calculated nrtRR, prevRR, and ratRR from RR interval and normalized with mean of zero and standard deviation of unity. PSO-SVM classifier is used for ECG classification. In [12], RR interval is calculated from the recordings of MIT-BIH arrhythmia database. MLPNN and SVM classifier were compared in this paper. Result shows that MLPNN is good for testing performance while SVM shows good training performance.

A.Vishwa et al. [13] have extracted RR interval and R peak using DWT and normalized by Zero mean. Noise was removed by band pass filter. MIT-BIH arrhythmias database and Normal sinus rhythm database were used. FFNN with error back propagation algorithm was used as a classifier. In [14], features extracted were R peak, RRt interval (current RR interval at t time), RRt+1 interval (next RR interval at t+1 time), QRS_h (QRS complex height), and QRS width. Pan Tompkins algorithm is used to extract R peak and QRS complex. Low pass linear phase filter is used for noise removal and median filter is used for baseline correction. Sensitivity and specificity achieved using PSO-RBFNN classifier were 96.251 % and 99.104% respectively. Table II shows survey of ECG classification. It includes number of features, features name, pre-processing techniques, database, modeling techniques, performance measures used, and accuracy achieved in each paper.

TABLE II. SURVEY OF ECG CLASSIFICATION

Researchers	No. of features	ECG Features	Preprocessing Technique	Database	Modeling Technique	Performance Measures	Accuracy (%)
R.Ceylan et al. (2008)	1	RR interval	Feature extraction: DWT	MIT-BIH arrhythmias	3-layered FFNN, T2FCNN, fuzzy clustering neural network	Sensitivity, Specificity, Average detection rate	96.7 100 98.35
J.Wang et al. (2012)	2	R peak, RR interval	Feature normalization: Z score, Feature reduction: PCA and LDA	MIT-BIH arrhythmias	PNN classifier with probability density function (pdf) as training rule	Sensitivity, Specificity, Accuracy	97.98 99.10 99.71
V.Kumari and P.Kumar (2013)	1	RR interval	Feature extraction: Symlets, CWT, Feature reduction: Symmetric uncertainty	MIT-BIH and UCI arrhythmia	Modular neural network – MLPNN	Precision, Recall, Root MSE	95.1 95.1 0.1765
S.Jadhav et al. (2012)	1	RR interval	Feature extraction: DWT	UCI arrhythmia	MLPNN, Generalized FFNN, Modular neural network	Sensitivity, Specificity, Accuracy	93.75 93.1 86.67
A.Dallali et al. (2011)	1	RR interval	Feature normalization: Z score, Denoised: Baseline adjustment, Feature extraction: DWT	MIT-BIH arrhythmias database	FCM and heart rate variability (HRV)	Accuracy	99.05
M.Vijayavanan et al. (2014)	12	Peaks-R, Q, S, P, T, Intervals- RR, PR, QT, ST, QRS duration, Segments-ST, PR	Feature extraction: DWT level-8, Remove baseline wander	MIT-BIH arrhythmias	Feed forward PNN classifier Trained with extracted features	Accuracy	96.5
A.Dallali et al. (2011)	2	RR interval R point location	Feature extraction: DWT using Daubechies wavelet Of order 3	MIT-BIH arrhythmias	Pre-classification: FCM, Final classification: MLPNN	Accuracy	99.99

F.Naima and A.Timemy (2009)	2	R location (max peak) RR interval	Feature extraction: DFT, DWT, Db4 and Haar	MIT-BIH arrhythmias	FFNN training algorithm Back propagation algorithm DWT-FFNN, DFT-FFNN	Sensitivity, Specificity, Accuracy	90 90 95
V.Srivastava and D.Prasad (2013)	2	QRS amplitude RR interval	Feature extraction: DWT	MIT-BIH arrhythmias	Feed forward neuro fuzzy Combination of Fuzzy logic and MLPNN	Sensitivity, Specificity, Accuracy	80 90 85
D.Patra et al. (2010)	2	R peak RR interval	Feature normalization: Zero mean (reduce the effect of bias), Data reduction: FCM, PCA	MIT-BIH arrhythmias	3 layer FFNN back propagation algorithm, FCM-FFNN, PCA-FFNN, FCM-ICA-FFNN, FCM-PCA-FFNN	Sum of square error (training, testing error), Training time	3.99*10-4 0.13 656.42
A.Sadiq and N.Shukr (2013)	10	Peaks-R, P, Q, T, S, avg PR interval, avg QRS duration, avg RS amplitude, avg RT and max QS amplitude	Denosed using: DWT, Low pass and High pass filter, Wavelet selection: Harr filter, Daubechies wavelet	MIT-BIH arrhythmias	ID3 Decision tree Haar-ID3, Db4-ID3	Elapsed time, Classification accuracy	0.0046 94
H.Khorrami and M.Moavenian (2010)	1	RR interval	Baseline reduction, Feature extraction: DWT, CWT, DCT	MIT-BIH arrhythmias	3 layer FFNN trained using back propagation algorithm, SVM, DWT-MLP, CWT-MLP	Mean square error (training and testing)	0.0349 0.0438 0.0056 0.1048
M.Korurek and B.Dogan (2010)	5	R peak, RRt, RRt+1 interval, QRSh, QRS width	noise removal: Low pass linear phase filter, Baseline correction: median filter, Feature extraction: Pan Tompkins algorithm	MIT-BIH arrhythmias	RBFNN classifier RBFNN parameters (neuron centers, bandwidth of each neuron) obtained by PSO PSO-RBFNN	Sensitivity, Specificity	96.251 99.104
S.Yu and K.Chou (2008)	3	R peak, QRS segment, RR interval	Normalization: Zero mean & unity standard deviation, ICA	MIT-BIH arrhythmias	PNN, 3-layer FFNN with back propagation algorithm	Sensitivity, Specificity, Accuracy	98.508 99.906 98.710
A.Khazaei (2013)	1	RR interval	RR interval detection and baseline reduction	MIT-BIH arrhythmias	MLPNN with back propagation training algorithm, SVM classifier with Kernel-Adatron (K-A) training algorithm	MSE (Training and Testing error), Training time	0.007656 0.1539 04:45
M.Moavenian and H.Khorrami (2010)	3	nxtRR, prevRR, ratRR	Normalization: mean of zero and standard deviation of unity, Cutting of signals by use of annotation file, Identification of peaks and valleys	MIT-BIH arrhythmias	PSO-SVM Optimize feature selection and SVM kernel parameters	Penalty parameter c, Kernel function parameters r, Best fitness	28597.68 0.0086 97.21
N.Joshi and P.Topannavar (2014)	2	R peak (Pre-R segment, Pro-R segment), RR interval (avg RR, local RR, previous RR, post RR)	Baseline wander correction: DWT, Feature extraction: ICA, Feature reduction: PCA	MIT-BIH arrhythmias	SVM classifier	Class oriented and Subject oriented evaluation	99 86
E.Zeraatkar et al. (2011)	4	R peak, RR interval, QRS complex detection, T wave	To eliminate power line effect: Notch filter, To reduce the effect of EMG noise: Discrete Butterworth filter, Baseline shift: median filter	MIT-BIH arrhythmias, Normal sinus Rhythm, QT and T-wave alternans challenge	MLPNN classifier	Sensitivity, Specificity, Positive predictive value, Negative predictive value	96.77 88.50 96.18 90.16
D.Joshi and R.Ghongade (2013)	1	QRS complex	Feature extraction: Pan Tompkins algorithm (QRS), Reduction: PCA, DWT	MIT-BIH arrhythmias	MLPNN, SVM, RBFNN classifier, PCA+RBF, PCA+SVM, DCT+RBF, DCT+SVM, DWT+RBF, DWT+SVM	Accuracy	99.55
X.Tang and L.Shu (2014)	27	Peaks-P, Q, R, S, T, 3 angle features, 19 temporal features (distance between points)	Baseline wanders removal and denoised: High pass and Low pass filter, Feature extraction: DWT, Feature reduction: rough sets	MIT-BIH arrhythmias	QNN trained using gradient descent method	Accuracy	91.7
M.Das and S.Ari (2014)	3	QRS detection, RR interval, R peak	Feature extraction: ST, DWT level4, Pan Tompkins QRS detection algorithm, Normalization: Zero mean, Denoised and baseline wander removal: Band pass filter	MIT-BIH arrhythmias	MLPNN classifier ST+MLPNN, ST+WT+MLPNN	Sensitivity, Accuracy	69.38 97.5
J.Nasiri et al. (2009)	22	19 temporal features, Intervals- RR, PQ, PR, PT, ST, TP, 3 morpho- gical features	Noise removal: DWT, Feature reduction: PCA, GA (meta-heuristic)	MIT-BIH arrhythmias	Genetic algorithm-SVM	Accuracy	93.46

A.Vishwa et al. (2011)	2	R peak, RR interval	Remove low frequencies: Fast Fourier transform (FFT), To restore ECG: Inverse FFT, Baseline noise reduction: segmentation of ECG beats	MIT-BIH arrhythmia, QT and Normal sinus rhythm	Feed forward ANN with error back propagation	Classification accuracy, Youden Index	96.77 0.9415
Y.Ozbay et al. (2006)	2	R peak, RR interval	Not mentioned	MIT-BIH arrhythmia	Pre-classification: Fuzzy clustering NN architecture Classification: MLPNN with back propagation	Average training error, Testing error Training time,	0.28 0.22 196.95
A.Muthuchudar and S.Baboo (2013)	6	QRS interval, QRS amplitude, P wave, T wave, PR interval, ST interval	Noise removal: Wavelet transform (UWT)	MIT-BIH arrhythmia	Feed forward network with back propagation algorithm as training algorithm	Accuracy	96
M.Sarkaleh and A.Shahbahrani (2012)	2	R peak, RR interval	Feature extraction: DWT Up to 2 Level	MIT-BIH arrhythmia	MLPNN trained with error back propagation algorithm	Recognition rate	Not mentioned
S.Ayub and J.Saini (2011)	2	R peak, RR interval	Not mentioned	MIT-BIH arrhythmia	Cascade forward neural network with back propagation algorithm	Mean squared error	0.00621
A.Daamouche et al. (2011)	6	QRS complex duration, RR interval, RR interval averaged over 10 last beats, 3 morphological features	Wavelet filter, QRS detection: ecgpuwave software (http://www.physiotools/ecguwave/src/)	MIT-BIH arrhythmia	SVM classifier	Sensitivity, Specificity, Positive predictivity	91.75 96.14 74.26
Z.Zidmal et al. (2013)	2	RR interval QRS complex duration	Denosed and feature extraction: DWT using db4, Data normalization, R peak detection- wavelet coefficient, Q, S peak- simple peak detection method	MIT-BIH arrhythmia	SVM with rejection	Average accuracy with no rejection, Minimal classification cost	97.2 98.8
R.Acharya et al. (2004)	2	R peak RR interval	Feature extraction: Pan-Tompkins algorithm, Noise removal	MIT-BIH arrhythmia	4 layer FFNN classifier and fuzzy classifier	Accuracy	80-85%
N.Kannathal et al. (2003)	13	Heart rate, Change in Heart rate, QRS width, Normalized (entropy QRS, ST wave), Complexity parameter (QRS, ST), Spectral entropy, RR interval, ST segment length, ST segment deviation, ST angle of deviation, ST segment area	Feature extraction: Tompkins algorithm (R) Noise removal: Bandpass filter and algorithm of Van Alste and schilders	MIT-BIH arrhythmia	5 layer FFNN classifier with error back propagation algorithm, SOM classifier (self-organizing maps), PNN architecture	Sensitivity, Specificity, Positive predictivity accuracy	99.3 98.3 99.3

Table III shows detailed analysis of input beat selection and output of a classifier. It includes how many beats taken from single file for classification (D-Depend on class and N-Not mentioned), number of classes (i.e. arrhythmia types), beat selection (R-Random, S-Sequence, and N-Not mentioned), proportion of beats for classes and classification

type (B-Beat, S-Signal, and N-Not mentioned). This survey table helps beginners and other researchers in selection of input beat proportion, appropriate approach to select beats and number of outputs of classifier. Table II and III also shows that for getting abnormality type as output which features are need to take as input to classifiers.

TABLE III. DETAILED ANALYSIS OF INPUT BEAT SELECTION AND OUTPUT OF A CLASSIFIER

Researchers	No. of beats	No. of classes	Beat selection	Proportion of beats: Class (training, testing)	Classification type
A.Dallali et al. (2011)	20	4	R	Normal (20, 18), Sinus arrhythmia (20, 18), LBBB (20, 18), RBBB (20, 18), APC (20, 18)	B
D.Patra et al. (2010)	16	7	R	Normal (8, 8), LBBB (8, 8), RBBB (8, 8), PVC (8, 8), APB (9, 9), PB (9, 9)	B
R.Ceylan et al. (2008)	D	10	R	Normal (15, 9), Sinus bradycardia (15, 9), Ventricular tachycardia (6, 5), Sinus arrhythmia (15, 9), APC (6, 5), Paced beat (10, 6), RBBB (10, 6), LBBB (10, 6), Atrial fibrillation (10, 6), Atrial flutter (9, 6)	B
J.Wang et al. (2012)	D	8	R	Normal (3600), PVC (2460), Paced (800), RBBB (800), LBBB (800), APC (764), VLWAV (472), AESC (104). 50% beats for training	B
M.Vijayavanan et al. (2014)	N	2	S	Normal (5, 10, 15, 20 min), Abnormal(5, 10, 15, 20 min)	S
A.Dallali et al. (2011)	20	4	R	Normal (20, 18), Atrial fibrillation (20, 18), Ventricular fibrillation (20, 18), Ventricular Tachycardia (20, 18)	B
A.Khazaei (2013)	180	3	S	Normal (22476), PVC (5394), Other (3003). 70% beats for training, 30% beats for testing	B

F.Naima and A.Timemy (2009)	27	2	R	Normal (26, 12), Abnormal (19,8)	S
A.Sadiq and N.Shukr (2013)	20	5	R	Normal (10, 10), LBBB (10, 10), RBBB (10, 10), PVC (10, 10), APB (10, 10), Paced (10, 10)	N
H.Khorrami and M.Moavenian (2010)	90	5	N	Normal (50, 10), LBBB (50, 10), RBBB (50, 10), PAB (50, 10), PAV (50, 10)	S
M.Korurek and B.Dogan (2010)	D	6	S	Normal (836), APB (165), RBBB (150), Fusion of paced and normal beats (130), PVC (605), Fusion of ventricular and normal beats (248). 50% beats for training and testing	B
E.Zeraatkar et al. (2011)	N	3	N	Normal, LQT, TWA. 50% or 60% or 70% beats for training and 50% or 40% or 30% beats for testing	B
M.Moavenian and H.Khorrami (2010)	90	7	R	Normal (50, 10), LBBB (50, 10), RBBB (50, 10), PVB (50, 10), PAB (50, 10), Fusion of paced and normal (50, 10), Paced beats (50, 10)	S
S.Yu and K.Chou (2008)	D	8	R	Normal (100, 100), LBBB (100, 100), RBBB (100, 100), PVC (100, 100), APB (100, 100), PB (100, 100), VFW (236, 236), VEW (52, 52). 50% beats for training and testing	B
N.Joshi and P.Topannavar (2014)	100	16	R	Normal, RBBB, LBBB, APC, PVC, Paced, APB, Ventricular flutter wave, Fusion of ventricular and normal, Blocked AP beat, Nodal escape beat, Fusion of paced and normal, Ventricular escape beat, Nodal premature beat, Atrial escape, Unclassified. Total 1252 beats for training and testing	B
D.Joshi and R.Ghongade (2013)	200	3	S	Normal (200,200), PVC (200, 200), Fusion (200, 200)	B
M.Das and S.Ari (2014)	N	5	S	Normal, Fusion beat, Ventricular ectopic beat, Supra ventricular, Unknown beat. First 5 min for training and other 25 min of a signal for testing	B
X.Tang and L.Shu (2014)	60	2	R	Normal (20, 40), Abnormal (20, 40)	S
J.Nasiri et al. (2009)	D	4	S	Normal (243), RBBB (110), LBBB (600), Paced beat(450). 50% beats for training and testing	B
A.Vishwa et al. (2011)	300	2	S	Normal, Abnormal. Total 21200 beats	S
Y.Ozbay et al. (2006)	200	10	R	Normal (15,15), SB (15, 15), VT (6 ,6), Sinus arrhythmia (15, 15), APC (6, 6), Paced (10, 10), RBBB (10, 10), LBBB (10, 10), Atrial fibrillation (10, 10), Atrial flutter (9, 9)	
M.Sarkaleh and A.Shahbahrani (2012)	45	3	R	Normal (30, 15), Paced (30, 15), APB(30, 15)	B
S.Ayub and J.Saini (2011)	D	4	S	Normal (1285, 300), Fusion of beats (584, 150), VPB (796, 120), Unclassified (180, 80)	B
A.Daamouche et al. (2011)	D	6	R	Normal (37, 24000), APB (24, 238), VPB (25, 3939), RBBB (13,3739), LBBB (13, 6771), Paced beat (13, 1751)	B
Z.Zidelmal et al. (2013)	150	2	S	Positive: Normal, LBBB, RBBB, Negative: Ventricular ectopic beats, PVC, Fusion of ventricular and normal. 150 beats from first 5 min for training and other 25 min for testing	B
A.Muthuchudar and S.Baboo (2013)	D	8	R	Normal (60, 30), LBBB (28, 14), PVC (45, 25), Atrial fibrillation (30, 25), Ventricular fibrillation (28, 21), Complete heart block-CHB (28, 21), Ischaemic cardiomyopathy (30, 18), Sick sinus syndrome (30, 18)	N
R.Acharya et al. (2004)	D	8	R	Normal (28, 14), LBBB (60, 30), PVC (45, 25), Atrial fibrillation (30,20), Ventricular fibrillation (28, 21), CHB (28, 21), Ischaemic cardiomyopathy (30, 18), Sick sinus syndrome (30, 18)	N
N.Kannathal et al. (2003)	D	3	R	Normal, Abnormal: RBBB, LBBB, Paced, PVC, Life threatening: Sick sinus syndrome, Ischemic heart diseases, Ventricular vibrillation beat. 600 beats for training and 400 beats for testing	S

V. ANALYSIS OF THE SURVEY

This section discusses about different ECG databases, feature extraction techniques and ECG classification using neural network.

A. ECG Databases

Datasets used by researchers for ECG arrhythmia classification are: UCI Arrhythmia dataset [35] and MIT-BIH arrhythmia dataset (mitdb) [36]. The MIT-BIH database contains 48 recordings (i.e. 100 to 109, 111 to 119, 121 to 124, 200 to 210, 212 to 215, 217, 219 to 223 and 228 to 231 records). Each record has duration of 30 minutes and includes two leads namely modified limb lead II (MLII) and one out of the modified leads V1, V2, V4 or V5. The database contains more than 109000 beats which are individually labeled, belonging to one of possible 15 beat types. The database contains three files namely signal.dat, annotation.atr and header.heh. The signal.dat binary file contains the ECG signal. The annotation.atr file describes events within the recording such as heart beats. For converting signal.dat and

annotation.atr into .txt form, online PhysioBank service i.e. PhysioBank ATM is available [37].

B. Feature extraction techniques

Feature extraction techniques used by researchers are DWT [5, 8], CWT [8], DCT [8], Db4 [6, 10], Pan-Tompkins algorithm [14] etc. For feature extraction using wavelet, decomposition levels used are 2, 3, 4 or 8. Disadvantage of using wavelet is that as the decomposition level increases, complexity of feature extraction process increases and to remove noises with feature extraction, higher level of decomposition should be used.

Pan-Tompkins algorithm is developed by Pan and Tompkins [38]. This basic algorithm covers 5 steps namely band-pass filtering, differentiation, squaring, moving window integration, and thresholds adjustment. Band pass filtering reduces noise from ECG signal. Derivative operator finds the high slopes that normally distinguish the R peak from other ECG waves and suppresses the low frequency components of P and T waves. Squaring operation is point by point squaring of ECG signal. It is used for further enhancing high frequency

components and suppressing the small differences arising from P and T waves. Integration sums the area under the squared waveform over a suitable interval. It extracts the slope of the R wave. Signal to noise ratio increases after the ECG signal has passed from the band pass filter. Therefore, threshold adjustment is done and sensitivity of the algorithm is improved. Advantages of using Pan-Tompkins algorithm compared to other available techniques for feature extraction are sensitivity and efficiency of Pan-Tompkins algorithm are more than 99% [38]. The computational efforts are also less. It includes noise removal and baseline wander removal steps, so no need to use other techniques separately.

C. Classification of ECG using neural network

Many researchers have used different types of neural network for classification of ECG signals. Artificial neural networks (ANNs) are data driven, self adaptive, non-linear, fast, and accurate. It is also robust to noise and easily scalable. Advantages of ANN are: 1) it provides non-linear mapping between inputs and outputs using activation function such as sigmoid to solve non-linear problem such as classification of ECG signals. 2) It can achieve similar or better results than statistical or deterministic approaches. Statistical methods performs good for linear problems but it cannot generate good results for non-linear problem because statistical methods are developed based on the assumption of given linear time series. 3) ANN can adaptively model the lower frequencies of the ECG which are inherently non-linear. 4) ANN removes time-varying and nonlinear noise characteristics of ECG signal [39]. Problems with ANN are: 1) training algorithm of ANN is unable to ensure a global minimum is reached 2) it may not necessarily give optimal solution for the entire 12-lead ECG classification process.

MLPNN, RBFNN, QNN, PNN etc. are used for ECG classification. All these NNs are static and feed-forward in nature and not having any delay or feedback loops and have time-series data as input like ECG signals. Using MLPNN, ECG signals are recognized and classified more accurately [3, 8, 9, 12, 28]. Accuracy of MLPNN increases with number of hidden neurons [25, 40]. MLPNN performs static mapping, there are no internal dynamics. To add dynamics, add static synaptic weights by dynamic connections or add recurrent loops in the hidden layer. In MLPNN, sometimes overfitting problem may occur. To overcome problem of overfitting we need early stopping criteria. MLPNN trained with back propagation suffers from slow convergence to local and global minima and from random setting of initial values of weights, which may makes poor mapping of inputs to outputs [8]. In RBFNN, if new sets of input values fall outside all the existing classes then these input values could be classified as other class except the existing classes. In the design of an RBFNN it is necessary to set the values for the positions of the centers and the radius for each radial basis functions in hidden layer. RBFNN needs other techniques to find these centers like k-mean or PSO technique for better accuracy or performance in ECG classification. With compare to MLPNN, RBFNN has slightly increased misclassification error. PNN needs small or no training except spread optimization [40]. Experiment of

PNN is limited to very small sets of data. Performance of PNN slightly decreased with the decrease of training data size [41].

Many measures are used by practitioners for evaluation of classification accuracy of neural network. For beat classification, measures used are sensitivity, specificity, accuracy, MSE, Rate of Misclassification (RMC), and MCN etc. For signal classification, measures used are sensitivity, specificity, accuracy, ROC curve, MSE, training time etc. Moreover, confusion matrix is also used by researchers as a performance measure. Evaluation measures calculated from confusion matrix are Sensitivity, Specificity and Accuracy. Sensitivity is the ratio of true positive beats to total of true positive and false negative beats. Specificity is the ratio of true negative beats to total of true negative and false positive beats. The overall accuracy is the ratio of total number of true negative and true positive beats to total number of beats.

$$\text{Sensitivity} = TP / (TP + FN) \quad (1)$$

$$\text{Specificity} = TN / (TN + FP) \quad (2)$$

$$\text{Accuracy} = (TN + TP) / (TN + FN + FP + TP) \quad (3)$$

VI. CONCLUSION

In this paper, a detailed survey of different issues in ECG classification, databases available for ECG, different preprocessing techniques available for noise removal, various ANN based classifiers available for classification of ECG data, and performance measures for evaluating accuracy of the classifiers are presented. From this survey we can conclude that ECG data are classified into two ways i.e. ECG beat classification and ECG signal classification. Only few researchers have worked on signal classification and it is more difficult compared to beat classification because normal ECG signal may differ for each person, sometimes one disease has dissimilar signs on different ECG signals and two distinct diseases may have approximately identical effects on ECG signals. For preprocessing and feature extraction, techniques mostly used are wavelets and algorithms such as Pan-Tompkins algorithm. Amongst these one should use algorithms other than wavelet techniques for pre-processing and feature extraction because for extracting features and removing noise using wavelet one should use higher level of decomposition. Moreover, a wavelet technique is more complex and time consuming. For ECG classification, most researchers have used different classification techniques such as neural networks and SVM. However, it is observed from the survey that neural networks are good candidates for ECG classification in terms of classification accuracy on training and test datasets. Most of the researchers have used sensitivity, specificity, and accuracy to evaluate the performance of the classifiers. These measures can be calculated using confusion matrix. Particularly for beat classification, many researchers have used the MIT-BIH arrhythmia database as dataset and neural network as a classifier. It is observed from the survey that MLPNN gives good accuracy for ECG beat classification.

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