Cardiac Episode Detection and Classification – A Systematic Review

Avvaru Srinivasulu, Srinivasa Rao Lam

Abstract*: *As the death rate is increasing in India due to heart diseases, there is a need for developing an automatic cardiac diagnostic system. Therefore, the heartbeat classification is a key to diagnose arrhythmias automatically. Here, a review is presented on different Cardiac Episode detection and classification methods, which help to develop the automatic cardiac diagnostic system. This review includes online datasets available for cardiac episode classification, features extracted and the extraction methods, Feature selection for reduced feature vector and methods of classification. Finally, the review discusses the limitations of the existed methods.

Index Terms*: *Cardiac episode, Electrocardiogram (ECG), Feature extraction, Feature selection, Heartbeat classification.

I. INTRODUCTION

Most of the population in India is suffering with cardiac diseases due to many reasons. The main cause of cardiac death is hypertension. The death rate is increasing even in rural areas due to lack of awareness and facilities. Even though, there are many hospitals in India, there is no effective automatic diagnostic system to help the doctor or physician for early diagnosis of the patient. In this context, [1], Sana (an Open-Sourced Student-Manageable, mobile tele-medicine group in MIT well associated to transmit and collect electro-cardiograms (ECGs) from village patents) for furnishing the on-location analysis by cardiologist at a city-center hospital to enable a nurse or paramedic who is not having experience, Narayana-Hrudayalaya (it is the most leading health-care professionals). Even though Sana had developed the open-source software for transmitting ECG via Bluetooth and archiving it, still significant obstacles remained. By this, we can understand the need for developing the optimal cardiac diagnostic methods. Therefore, in this review paper, we have presented different methods of cardiac episode detection and classification which is helpful for research and development in smart ECG monitoring & diagnosis, and IoT (Internet of Things). Further, this paper is structured as follows. Open source database of ECG available online in section 2 given for the reference to the readers, feature extraction and feature selection methods are discussed in section 3 to find out the most significant characteristics of ECG for the detection of abnormal cardiac episodes. In section 4, the cardiac episode (beat) classification methods are discussed to identify the cardiac abnormalities. Finally, we end the paper with discussion and conclusion in section 5.

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II. DATABASE

There are many datasets available in the physionet database, which are free to download. In previous work, many authors used this database for training and testing purpose for beat classification into AAMI (Association for Advancements in Medical Instrumentation) beats. The details of some of the database used in previous work are illustrated in Table 1.

Table.1. Details of online database available

Database	No:of records available	Max recording period	Sample rate	Subjects age group
MIT-BIH Arrhythmia	48	30min	360Hz	32-89-M 23-89-F
MIT-BIH Supraventricular arrhythmia	78	30min	128Hz	-
St.petersburg Institute of Cardiological Technics (INCART)	75	30min	257Hz	18-80
BioSigna*	56	1h	500Hz	-
Physionet / computing in cardiology (CinC) Challenge- 2011	-	10sec	500Hz	-
MIMIC – II Waveform	4458	vary	125Hz	-
European ST-T	90	2h	250Hz	30-84-M 55-71-F
Hypertrophic Cardiomypathy (HCM) patient's dataset	754	10sec	-	-
MIT-BIH ST Change	28	-	-	-
MIT-BIH Long term	7	14-22h	-	-
MIT-BIH Long-term ST	86	21-24h	250Hz	-
MIT-BIH Malignant Ventricular arrhythmia	22	30min	-	-
MIT-BIH normal sinus rhythm	18	-	-	26-45-M 20-50-F
Creighton University Ventricular Tachycardia	35	8min	250Hz	-
American Heart Association (AHA)	80	30min	250Hz	-

The MIT-BIH database beats are classified in to AHA annotation beats: N, V, F, O, E, P, and Q as given in Table 2 and the same are classified in to AAMI beats: N, S, V, F, and Q as given in Table 3. Only, the beats of MIT-BIH arrhythmia database are given in physionet data bank. These beats are classified in to AHA (N-93412, V-7130,

F-1785, O-665, E-106, P-7028, Q-33) beats and AAMI (N-91296, S-2781, V-7236, F-803, Q-8043) beats respectively. Apart from the MIT-BIH beats mentioned in Table 4 for AAMI Normal beat, the beats which are not classified as S, V, F and Q considered as Normal beat [3]. The annotations of beats of remaining database given in Table 1 are given in .dat file. However, the .dat file is not able to open.

Table.2. MIT-BIH beat classification in to AHA annotation beats

AHA beat	MIT-BIH beats
N	Normal beat, Left bundle branch block beat, Right bundle branch block beat, Atrial premature beat, Aberrated atrial premature beat, Nodal (junctional) premature beat, Supraventricular premature beat, Atrial escape beat, Nodal (junctional) escape beat.
V	Premature ventricular contraction
F	Fusion of ventricular and normal beat, Fusion of paced and normal beat
O	Ventricular flutter wave, Non-conducted P-wave (blocked APB)
E	Ventricular escape beat
P	Paced beat
Q	Unclassifiable beat

Table 3. MIT-BIH beat classification in to AAMI annotation beats [2]

AAMI beat	MIT-BIH beats
N	Normal beat, Left bundle branch block beat, Right bundle branch block beat, Nodal (junctional) escape beat, Atrial escape beat.
S	Atrial premature beat, Aberrated atrial premature beat, Nodal (junctional) premature beat, Supraventricular premature beat
V	Premature ventricular contraction, Ventricular escape beat
F	Fusion of ventricular and normal beat
Q	Paced beat, Fusion of paced and normal beat, Unclassifiable beat

Table 4. MIT-BIH database beats classified in to AAMI classified beats

Database	# records	N	S	V	F	Q
American Heart Association (AHA)	155	319125	0	32745	1266	0
MIT-BIH supraventricular Arrhythmia	78	162271	12195	9940	23	79
European ST-T	90	784568	1095	4467	354	0
MIT-BIH ST change	18	46215	798	319	0	0
MIT-BIH long-term database	7	594672	1499	63584	2785	0
Long-term ST	86	6422003	30905	37894	0	0
St. Petersburg Inst. of Card. Tech. (INCART)	75	153651	1959	20005	219	0

III. FEATURE EXTRACTION AND FEATURE SELECTION

There is no limit for the features to extract from ECG to classify the beats into different types of abnormal beats. In previous work, the authors used different features for beat classification. However, those can be categorized into temporal, morphological, spectral and statistical features. Some of them are explained here.

A. *Features*

Temporal features are pre RR interval [2-8], RR interval [2][4][6-14], post RR interval [4][15], average RR interval [2][5-8], average of RR for last 10 beats [2][8][9][12], average of RR in last minute [15], average of RR in last 20 minutes [7][15], QRS complex [2][4-6][9-13][16-23], difference RR interval [4] as given in equation (1)

$$RR_v(n) = \sum_{j=-1}^{1} |dRR(n-j)| \qquad (1)$$

Where dRR = RR(n) – RR(n-1), minimum and maximum of QRS [6], amplitude between Q & R and slope of QR [24], amplitude between R & S and RS slope [11][22], Q-peak [21], T-wave duration [4] [6][2], QT duration [11], slope of ST [11][22], S-peak [21], p-wave flag [2][4], P-wave duration and PR interval [20].

Morphological features extracted are 10 uniformly samples amplitude values between QRS onset and offset and their normalized samples [4][6], 9 uniformly samples between QRS offset and T-wave offset and their normalized samples [4], 64 & 128 samples centered on R-peak [24], 10 uniformly samples between R-peak-50ms to R-peak+100ms and their normalized samples [4], 8 uniformly samples between R-peak +150ms to R-peak+500ms and their normalized samples [4], two absolutely greater values of QRS complex, their relative potions & three- T-wave attains between four absolute values[4], mean beat period represented by 300 uniformly distributed samples [9][12], modulation of amplitude envelope of beat and AM bandwidth [25], modulation of instantaneous frequency of IMFs (Intrinsic Mode Functions) and FM bandwidth [25].

Statistical features: Kurtosis and skewness [26], the ratio of sum of Eigen of 5 PCA coefficients and sum of Eigen of all PCA coefficients [18], QRS mean wavelet scale in 1st principal component [7], threshold crossing count and threshold crossing sample count [27], standard exponential and modified exponential [27], mean absolute value [27], sample entropy [27], mean of Teager Energy Operator functions in time domain and frequency domain [21], different order moments based indexes, histogram mean, variance, standard deviation and skewness [2], signal quality indexes (SQI) of peak detectors [26], kurtosis SQI is given by equation 2 and skewness SQI is given by equation 3 [26].

$$kSQI = E\{X-\mu\}^4/\sigma^4 \qquad (2)$$

$$sSQI = E\{X-\mu\}^3/\sigma^3 \qquad (3)$$

Where, "X' represents and considered as signal vector of random number variable, μ represents the mean of "X", σ represents the standard deviation of "X" as well as $E\{X-\mu\}$ represents the mean value of $X-\mu$. Spectral features: zero crossing position and maximum amplitude position of WT autocorrelation function [15], relative power in (5-15Hz) (pSQI) and in baseline (1-40Hz) (basSQI) given by equations 4 & 5 respectively [18], FFT (magnitude & phase) of 64 & 128 -samples centered on R-peak [24], 1st minimum position of WT ACF (Auto Correlation Function) in 1st principal component and 1st maximum in QRST complex CCF (Cross Correlation Function) over the WT-scale 3 of two-primary components [7], ventricular fibrillation filter residue and peak amplitude frequency (0.5-9Hz) [27], frequency content between 0 & min (20F, 100Hz) and 0.7 & 1.4F [27], median frequency [27], Lempel-Ziv complexity measure normalized value [27], phase – space reconstruction [27],

Hilbert transform Area, Power, and extrema of WT scales 2,3,4,& 5 [2], each sample average frequency from ST signal [8], the difference in absolute area and maximal CCF coefficients [13].

$$pSQI = \frac{\int_{5Hz}^{15Hz} P(f)df}{\int_{5Hz}^{40Hz} P(f)df} \quad (4)$$

$$basSQI = \frac{\int_{1Hz}^{40Hz} P(f)df}{\int_{0Hz}^{40Hz} P(f)df} \quad (5)$$

B. *Feature extraction methods*

The above-explained features are extracted by using the following methods.

Pan-Tompkins algorithm [8][13][16]

This is the fundamental method of QRS detection. the QRS complex is the key region of heart rhythm. From QRS complex, we can find R-peaks, QRS onset & offset, QRS duration and their relevant morphological features. Pan-Tompkins algorithm requires two thresholds,

THR1 = NPK + 0.25 (SPK − NPK). and
THR2 = THR1/2.
SPK = 0.125 PEAK + 0.875 SPK
NPK = 0.125 PEAK + 0.875 NPK

The thresholds are updated for each segment. The peaks above the THR1 & THR2 is detected as R-peak. To detect the missing beats ie., RR exceeds 166% of RR_{avg}, search back algorithm is applied using THR/2 threshold.

In the paper [16], the author modified slightly the Pan-Tompkins algorithm for detecting R-peaks. In this algorithm, only one threshold is used, and it is fixed given as follows.

PEAK = Maximum (Peak)
NPK = Minimum (Peak)
SPK = 0.125 PEAK + 0.875 SPK
THR = NPK + 0.25 (SPK − NPK).

However, the minimum and maximum peak are found initially using peak detector. In addition, search back algorithm is applied for 116% of RR_{avg} and threshold is THR/8. RR_{avg} is calculated as given in equation 6.

$$RR_{Avg} = \begin{cases} \frac{1}{n-1}\sum_{i=0}^{n-2} RR_{(n-i)}, & 2 \le n \le 7 \\ \frac{1}{8}\sum_{i=0}^{7} RR_{(n-i)}, & n \ge 8 \end{cases} \quad (6)$$

Wavelet Transform (WT) [2][4] [15-16] [19]

In general, the Continuous Wavelet-Transform (CWT) analysis of signal s(t) is given by equation 7. There is several mother wavelets used for the feature extraction from ECG. In paper [16], un-decimated wavelet transforms (UWT) sym5 by soft-thresholding and single range is utilized for denoising the wavelets, peak detection, as sym5 which accords the complex functions of QRS with a ECG over the opposite wavelet series. The advantage of UWT is its shift invariant and less sensitive to noise.

$$W_s s(b) = 1/\sqrt{s} \int_{-\infty}^{\infty} s(t)\Psi\left(\frac{t-b}{s}\right) dt, \; s > 0 \quad (7)$$

In paper [4], DWT was applied by discretizing the time0scaling function as map by utilizing hydraulic sampling equivalents, where, b = l for l∈ Z and s = 2k, as the author interested to keep only the time accuracy be high. In addition, a derivation of filter-out function (Quadratic-Spline) was used as the model of prototype. Scale 4 [15] of WT is proffered to present the absolute maxima and zero-crossings of ECG. A fourth order Haar wavelet-based DWT processor [19] is designed for beat detection. W4 coefficient without the low-frequency component was preferred for beat detection as the baseline drift can be eliminated in W4 coefficient. Quadratic spline wavelet was used in [2] for efficient developments as a filtering networks. Since the Dy WT (Dyadic WT) [23] evaluated by utilizing a wavelet function which is the primary derivative of a smoothing filters which exhibits the local maxima at various successive scale factors at presence of transients (QRS-complex).

Teager energy algorithm [10][21]

The preprocessed ECG is applied to LPF with a cutoff frequency of 2Hz to separate QRS complex, which is further applied to find Polarized Teager Energy (PTE). The PTE is very effective to computation; TE offers the discrete time sequence is measured as follows,

$$E[n] = \{x[n]\}2 - \{x[n+1]\}\{x[n-1]\}. \quad (8)$$

Let Δ = {x[n + 1]}{x[n − 1]}. Then from above (Eqn.8) that there can be furnishing the four flexible functions as specified below,

(a) Δ > {x[n]}2, x[n] > 0
(b) Δ <{x[n]}2, x[n] > 0
(c) Δ >{x[n]}2, x[n] < 0
(d) Δ < {x[n]}2, x[n] > 0

Where (a) and (b) are treated as positive signal which consists of R. peak values, whereas (c) & (d) treated as negative signals which consists of S wave. Because, as per morphology of S & R signals, function (a) is indefinitely true for peak of R (due to E[n]<0), and (d) is in-definitely true for peak of S (due to E[n]>0). TE may affect the definite positive of peak R. Thus, the representation of R and S coordinates, E[n] are to be polarized by using functions of (b) & (c) as,

$$E'[n] = -E[n], \; x(n) < 0$$
$$+E[n], \; x(n) \ge 0 \quad (9)$$

Where, E′[n] is preferred as PTE, the applied domain rule for searching the R peak zone as follows,

If E′[n] ≥ Eth → R-peak zone
If E′[n] < Eth → none

Where Eth is known as adaptive threshold which is updated by

$$Eth = \sigma\delta * PEAK + (1 - \sigma)\, Eth$$

Where σ is treated as "forget-coefficient factor". The new of every value of threshold is described from current prediction of PTE peak and preceding the running values of threshold with a weighting factor δ is used for describing the peak value of adjusted threshold. When the Teager Energy Operator (TEO) [21] is due to multi sources, TE is negative instead of positive which indicates the affects in impulse production and furnishing the conductive path for deviated from regular sinus rhythms.

Differentiation with reduced sampling rate and threshold [22]The reduced sampling rate [22] eliminates the noises due to high-frequency functions and the differentiation maintains the maximum amplitude at the same positions as the original signal. the threshold to find the R-peaks is given by

$$L_{thr} = \frac{\sum_{i=0}^{M} Acc(i)*i}{\sum_{i=0}^{M} Acc(i)} \quad (10)$$

Where, Acc(i) is the accumulated local peaks.

Difference operation method (DOM) [11] [22]

After removing noise, the QRS detection using DOM is as follows.

1. Find the difference signal $x_d = x(n) – x(n-1)$.
2. apply LPF with cutoff frequency of 100Hz to suppress low amplitude but high frequency variations. the filtered signal is x_{df}.
3. apply thresholds to x_{df}

$$\widehat{x_{df}} = \begin{cases} 0, \ if \ 0 < x_{df} < T_1 \ or \ T_2 < x_{df} < 0 \\ x_{df}, \ if \ x_{df} \geq T_1 \ or \ x_{df} \leq T_2 \end{cases} \quad (12)$$

where $T1 = 2M_{Vp}$ and $T2 = 2M_{Vn}$. M_{Vp} and M_{Vn} denote the mean values of all positive and negative waveform amplitudes.

4. from the step 3, separate the signal in to positive part and negative parts x_{df}^{+} and x_{df}^{-}.
5. measure the time difference between the positions of two adjascent nonzero positive extreme points.
6. if the time difference (i-1,i) ≤ (0.14sec or 50 samples), select i^{th} positive extreme. if the time difference (i-1,i) > (0.14 sec or 50 samples), select both extremes. Repeat same for negative extremes.
7. if the time difference between selected extremes ≤ (0.14sec or 50 samples), the exreme pair is correct otherwise wrong pair and that pair should be deleted. the final positive extremes are R-peaks.
8. Q & S: Q_n = min (R-20samples:R) and S_n = min(R:R+20samples).
9. for abnormal ECG, Q_{abn} = min (R-80samples:R) and S_{abn} = min(R:R+80samples).
10. Q: if $Q_n = Q_{abn}$, Q is selected. otherwise, if $M_{vqq} > V_{q1} + T_v$, $Q = Q_{abn}$, where M_{vqq} = max mag(Q_n : Q_{abn}), V_{q1} = mag(Q_n) and T_v = 0.18mV. otherwise, if $V_{q2} > V_{q1}$, $Q = Q_n$, else $Q = Q_{abn}$.
11. S: if $S_n = S_{abn}$, S is selected. otherwise, if $V_{s2} > V_{s1}$, $S = S_n$, else $S = S_{abn}$.

Hilbert Transform (HT) [21][25]

The Hilbert Transform (HT) is employed for differentiating the ECG signals, the peaks values are indicated that the time occurrence of original R-peaks [21]. The bandwidth features of ECG are extracted from intrinsic mode functions (IMF) [25]. The IMFs are derived by Empirical Mode decomposition (EMD) of segmented beats. The EMD is a process of decomposition of ECG betas of 500ms around R-peaks in to sum of IMFs. where the IMF has two characteristics: (i) the several counts of zero-crossing & peaks as both either as equal or utmost, it may varies by one; and (ii) the averaging of local positive/negative envelope peaks are zero.

$$B_{AM}^2 = \frac{1}{E}\int \left(\frac{dA(t)}{dt}\right)^2 dt \ \ and \ B_{FM}^2 = \frac{1}{E}\int \left(\frac{d\varphi(t)}{dt} - \langle w \rangle\right)^2 A^2(t)dt \quad (13)$$

Where E is the signal energy and ⟨ω⟩ is the mean frequency of an IMF. A(t) and ϕ(t) are the amplitude and the instantaneous phase of analytic IMF. The analytic IMF c(t) can be represented as

$$z(t) = c(t) + jcH(t) = A(t)\, e^{j\phi(t)} \quad (14)$$

where cH(t) is the Hilbert transform of c(t).

Steepest & sharp edges evaluation using adaptive threshold [14]

The steepest & sharp edges indicate the QRS complex in ECG. Therefore, the algorithm used for the detection of QRS complex is as follows.

1. Find SUM = abs(2Si - Si-TPL - Si+TPL) if sign(Si - Si-TPL) = sign(Si - Si+TPL).
2. the Initial value of adaptive threshold AT is AT0 = 0.2 mV. QRS is found if SUM > AT_0.
3. AT = 0.7 SUM, except for peak < 0.4mV && SUM > 0.3mV when AT = 0.6 SUM.
4. AT does not change for 200ms to avoid high amplitude T-waves.
5. AT decreases linearly to succeed in 0.2 of its initial value. this continues until AT drops to 0.2mV.
6. The true beats are found by DIST (minimum delay between two successive true beats).
7. Initial DIST = 200ms, later DIST = QT_interval = $0.4 * \sqrt{mRR}$, where mRR = (7 RR_{mean}+ RR_{min}) / 8, where RR_{mean} is the average of latest four RR intervals and RR_{min} is the shortest RR in latest four.

Linear interpolation & second derivative of ECG (slope detection technique) [21]

After finding the R-peaks using Hilbert transform with adaptive threshold, Q & S peaks are found by using linear interpolation and second derivative of ECG [21].

Stockwell Transform [8]

Stockwell Transform is a time-frequency domain method and is given by

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{-2\pi^2 m^2/n^2}\, e^{i2\pi mj/N} \quad (15)$$

This transform is used to extract the morphological features of ECG. the algorithm is as follows.

1. Select the window of -250ms to +250ms (180 samples) around R-peak.
2. Apply ST for the selected segment.
3. Select information in the 3-20Hz band as the QRS energy and least HF & LF noise laid in this band.
4. Obtain morphological features from each sample by averaging its frequency.

Apart from this there are some open source software like ecgpuwave [2][9][6][12] and epimited and wqrs [18] available on [28] which will exact all time domain and frequency domain features.

C. *Feature selection*

Feature selection is used for reducing the computational burden to the classifier. Some of the feature selection techniques used are sequential floating (forward & backward) [2][4],

Principal component analysis (PCA) [9][12], Filter type [27], t-test and scatter plot [21], Bacteria Foraging Optimization (BFO) [8], information gain criterion [6]. The SFFS algorithm is the sequential forward selection (SFS) algorithm is accepted by a sequential backward selection (SBS) algorithm. This SFFS iterates based on number of iterates for all models, which is ranging from single feature model, registered simple performances are exhibited for every model size. The every iteration is started with an SFS step from a model size higher than 2 features based on every step range of SFS. An SBS step is repeated when the attractiveness of the model attains lower than the registered model size as small. This way algorithm of program goes forward and backward (like floating) looking out at every step for the trail of most performance. Several examples of filtering schemes for feature extraction methods consisting based (on correlation criteria, maximum separability fishing criterion), formal test statistics ($\chi 2$ -test, F-test, t-test), the primary component analysis, mutual information methods (minimum redundancy maxima relevance-mRMR criteria), classified wavelet trees, self-organized trees and/or fuzzy clustering, etc. The Fisher criteria and correlation are easily and fast computing, but never disclose the mutual information over the features (apart from linear correlation functions). Moreover, the mRMR criteria maximizing the mutual information over the outcome and feature distribution with the minimizing factor as redundancy in between features accords to Eqn. (16).,

$$\max_{x^{(j)}} \left\{ \frac{1}{|S|} \sum_{x^{(j)} \in S} MI\left(x^{(j)}, y\right) - 1S2xj,xk \in SMI(xj,xk) \right. \quad (16)$$

Where MI(*x, y*) accounts for the mutual information among variables *x* and *y*, and |*S*| represents the size of the feature set.

The features selection using BFO removes redundant and irrelevant features. The advantages of BFO compare to other methods are: it can deal with complex search spaces where minimum knowledge is available, and it converges quickly to reach a global minimum solution. The information gain criterion selects the features by calculating the difference between the unconditional entropy associated with the heartbeat-class and the conditional entropy of the heartbeat-class given the value of a feature. This difference indicates the information gained from the heart beat class with the selected feature set. This algorithm can be implemented in feature selection package in WEKA, which is a freely available tool. This procedure repeats by gradually removing 20 least informative features at a time until we observed a decline in performance.

IV. BEAT CLASSIFICATION

The beats taken from different databases are classified in to Normal (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), Fusion of normal and V beat (F) and unknown beat (Q) [2-4][7-8][11][15][24]. These beats are recommended by ANSI/AAMI (Association for Advancements in Medical Instrumentation) EC57:1998 standard. In some of the papers [4][7] AAMI beats are modified as N, S, V', where V' is the combination of F and V beats. There are other classification of beats like normal sinus rhythm (N) Atrial premature beat (A), ventricular premature beat (V), Right Bundle Brach Block (RBBB), paced beat (P), Left Bundle Brach Block (LBBB) [9][10][12][21], N, Premature Ventricular contraction (PVC), PVC/aberrant, BBB, escape beat, A, Aberrant, Fusion of two beats, AV block, tachycardia and bradycardia [13], N & V [26], N & ectopic beat [14][22], N, tachycardia & bradycardia [17]. Apart from these the classification is also done based on arrhythmias like normal & abnormal [16][18][25], normal sinus rhythm, supraventricular arrhythmia, malignant ventricular arrhythmia, Atrial fibrillation frequency estimates around QRS [20], Hypertrophic cardiomyopathy (HCM) patients & non HCM patients [6] and shockable & non shockable arrhythmias and VF vs non VF arrhythmias [27]. There are number of classifiers used to classify the heartbeats in to different classes mentioned above. Some of them classifiers are explained as follows.

Linear discriminate classifier (LDC) is a quadratic discriminate function, which gives maximum posterior probability of the class. if the prior probabilities are considered as same for all classes (ie., covariance matrix is same), Quadratic discriminate classifier is called as LDC [4-5][15][2]. Therefore, LDC quadratic discriminate function is given by equation (17).

$$g_i(x) = \mu_i^T \sum{}^{-1} x - \frac{1}{2} \mu_i^T \sum{}^{-1} \mu_i + \log\left(P(w_i)\right) \quad (17)$$

where, $g_i(x)$ is the maximum posterior probability, x is the classification rule to the class i, μ_i is the mean vector, $P(w_i)$ is the prior probability of the i^{th} class and $\sum$ can be estimated as the weighted sample covariance given by equation (18).

$$\sum = \frac{\sum_{i=1}^{C} w_i \sum_{m=1}^{M_i} (x_m - \mu_i)(x_m - \mu_i)^T}{\sum_{i=1}^{C} w_i M_i} \quad (18)$$

where C is the no: of classes and w_i are the weighting coefficients.

Feature repetition profiling [16], similar concept as pattern matching used in Internet-packet processing. The data in each heartbeat is analyzed and search for repetitions to extract an ECG pattern for any individual. Like the packet-processing technique where abnormalities are reflected as a long-distorted tail with additional humps on the normal distribution curve scaled with a factor of the number of counters 2*n*, abnormal ECG beats of the ECG profiling curve will be seen where humps exist on the tail of the bell-shaped curve.

Decision tree [13-14][17][22], is used for abnormal ECG classification based on threshold comparison. In [17], the long-term observation is treated as the baseline reference, indicating the trend of heart beat rate (HBR) drift under normal status. The decision tree for beat classification in to normal and abnormal beats is given in [13]. In [22], the decision rule for classifying sinus and ectopic beats is given by euq (19) *abs*(*kM* **QRS*[*k*, *n*] – *RQRS*[*k*, *n*]) > 0.25 *RQRS*[*k*, *n*] (19)
then this *QRS*(*k*) is not sinus complex and belongs to the set of potential EB.

Where, $RQRS(k) = \frac{\sum_{i=n}^{i=n+L} Acc(k)}{L}$ (20)

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Here *Acc*(*k*) is the accumulator used for segment *k*, *n* is the ongoing index of the analyzed signal; *L* = 5 for AHA recordings, and *L* = 7 for MIT-BIH recordings.
And, $k_M = k_{patMAX} / k_{sigMAX}$. Here $k_{patMAX} = \max(RQRS'[n]^2)$, *n* = (0÷79), stands for the maximum of the *k*-th squared reference derivative *RQRS'* and k_{sigMAX} = max (RQRS'[n]QRS[n+q]), *q* = (0÷79).

The linear **Support vector machine (SVM)** [6][8-9][12][18][27] classification approach consists of looking for a separation between the two classes by means of an optimal hyperplane that maximizes the separating margin. In the nonlinear case, the two classes are first mapped with a kernel method in a higher dimensional feature space, $\Phi(\boldsymbol{X})$. The membership decision rule is based on the function *sign*[$f(\boldsymbol{x})$], where $f(\boldsymbol{x})$ represents the discriminate function associated with the hyperplane in the transformed space and is defined as $f(\boldsymbol{x}) = \boldsymbol{w}^* \Phi(\boldsymbol{x}) + b^*$[6][18][27]. The optimal hyperplane defined by the weight vector $\boldsymbol{w}^*$ and the bias b^* is the one that minimizes a cost function that expresses a combination of two criteria: margin maximization and error minimization. there are many active learning methods to classify using nonlinear SVM classifier: Random selection (R), Margin sampling (MS), Posterior Probability Sampling (PPS) and Query by Committee (QBC). Among these methods, MS active learning is best [9] for classification which quickly selects the most informative samples. Therefore, only the MS active learning algorithm is given here.

1) Initialization
Step 1: contemplate the initial training set L, composed of n-labeled samples of T completely different categories.
Step 2: contemplate the educational set U, composed of m (m>>n) unlabeled samples.
Step 3: Set Ns the number of samples to add at every iteration of the active learning process.
2) MS active learning process
Step 1: Train a SVM classifier with the training set L, while estimating its free parameters by cross validation (CV).
Step 2: For each sample uj (j = 1, 2, . . ., m) of the learning set U, compute the maximum number of votes VMAX,j and the minimum discriminative function value $f_{MIN,j}$ as follows:
a) Calculate the discriminate function values fj for each binary SVM classifier.
b) Count the number of votes of each class vj .
c) Identify the class $\omega_{MAX,j}$ with the maximum number of votes V_{MAX},j. Let f_{MIN},j be the minimum absolute value of the discriminative function associated with w_{MAX},j .
Step 3: Select and label the Ns samples exhibiting the minimum values of V_{MAX},j (and, if necessary, of f_{MIN},j).
Step 4: Add the Ns selected samples to the coaching set L and take away them from U.
3) Convergence check: Return to Phase 2, if the predefined convergence condition is not satisfied (e.g., the total number of samples to add to the training set is not yet reached).

For multi-classification of ECG beats, the most popular strategies used are: one-against-all (OAA) and the one-against-one (OAO). OAA is more complex but involves reduced number of binary decompositions and OAO requires a shorter training time. In [8][12], OAA strategy was used, which is as follows.

1. Let Ω = {*w*1, *w*2, . . ., *wT* } be the set of *T* possible labels (information classes) associated with the ECG beats that we desire to classify.
2. First, an ensemble of *T* (parallel) SVM classifiers is trained.
3. Each category aims at determination a binary classification drawback outlined by the discrimination between one information class $\omega i (i = 1, 2, \ldots, T)$ against all others (i.e., $\Omega - \{wi\}$).
4. Then, within the classification part, the "winner-takes-all" rule is used to decide which label to assign to each beat. This means that the winning category is that the one that corresponds to the SVM classifier of the ensemble that shows the best output (discriminant operate value).

Bayesian Maximum likelihood-based classifier [20], is a supervised learning technique. Using a feature vector y, of dimension N_y, the Bayes ML classifier calculates and ranks the likelihood $p(y|C_q)$ of the feature vector conditioned on each of the considered classes C_q , which are assumed here to follow multivariate Gaussian distributions. Considering N_q possible classes, the likelihood of feature vector in class Cq is given by

$$p(y|C_q) = \frac{1}{(2\pi)^{\frac{N_q}{2}} |\sum q|^{\frac{1}{2}}} e^{-\left(\frac{1}{2}\right)(y-\mu_q)^T \sum \bar{q}^1 (y-\mu_q)} \quad (20)$$

for q = 1, 2,…N_q , where μ_q and $\sum q$ are the Gaussian mean and covariance for class C_q . the classifier output C* is the class that maximizes the log-likelihood, C* = arg $\max_q$ log $p(y|C_q)$.

Fuzzy C-means clustering algorithm [10] was used to finding the cluster centre for every class. Classification of beat formed as steps are specified below,

1. Accepting the feature vector Ii (for an ECG beat) from the ECG of the subject.
$$I_i = \begin{bmatrix} I_{i1} \\ I_{i2} \end{bmatrix} = \begin{bmatrix} MTE \\ S \end{bmatrix}$$
where, MTE is mean teager energy and S is the information entropy.
2. Finding the Euclidean distance over the cluster center and feature vector of every class. Findings the cluster centers based on respective Eqn. (21),
$$v_i^t = \sum_{j=1}^{N} \left(u_{ij}^{t-1}\right)^m x_j / \sum_{j=1}^{N} \left(u_{ij}^{t-1}\right)^m, \ 1 \le i \le C \quad (21)$$
where, u_{ij} is the membership matrix, updated by equation (22) and update cluster center until $\|U^{(t)} - U^{(t-1)}\| < \in$ (a small error).
$$u_{ij}^t = 1 / \sum_{k=1}^{C} \left(\frac{\|x_j - v_i^t\|}{\|x_j - v_k^t\|}\right)^{\left(\frac{2}{m}-1\right)}, \ 1 \le i \le C, \ 1 \le j \le N \quad (22)$$
3. The outcome Euclidean distance with minimum values over its classes, then the feature vector will be reorganized as corresponded heartbeat case,
4. Follow steps (1)–(3) for all test vectors.

Random Forest classifier [6], is an classifier operated based on collection of several decision trees data, decision is forwarded based on respective major vote over all trees.

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1-D conventional NN (CNN) back propagation used in [24] has 32 and 16 neurons on the first- and second-hidden CNN layers and ten neurons on the hidden MLP layer. In [21], by training the feed forward NN with 2 input, 15 hidden layer and 5 output layer NN, heart beat is detected in to normal or arrhythmic (PVC, paced, LBBB or RBBB).

MLPs with a single hidden layer of 25 neurons were used in [2] and trained with a learn rate of 0.25 and a momentum of 0.03 to avoid being stuck into local minima. Parallel general regression NN [11] is a branch of the radial basis function neural network where only the smoothing parameter requires optimization, used to classify the AAMI beats.

Artificial Bee Colony (ABC) algorithm based on least squares SVM classifier [25] is used to classify two classes, normal and abnormal ECG beats. The SVMs classify data by separating them with hyperplanes; it consists of an objective function that minimizes the classification flaw and maximizes the hyper-plane gap simultaneously. The decision function for (LSSVM) two-class problem is formulated as equation (23).

$$f(x) = sign[\sum_{i=1}^{N} a_i y_i K(x, x_i) + b] \quad (23)$$

Where, $K(x, x_i) = g^T(x)g(x_i) = e^{-\frac{\|x-x_i\|^2}{2\sigma^2}}$. Optimization of kernel width parameter (σ) and regularization parameter (γ) was done by ABC algorithm, which is a nature-inspired algorithm that has fast optimization capability owing to its fast convergence.

Patient adaptable algorithm was used in [7], which is the combination of LDC and expectation maximization clustering (EMC). Here, LDC computes the labels for each heartbeat. Then, for every cluster, the algorithm tests if any label obtains a qualified majority, meaning that the most represented label exceeds the α percent of the cluster population. In case this label exists, it is assigned to the whole cluster, superseding the LDC labels. If the qualified majority isn't reached, the uncertainty is taken into account to be too high to modify the labels, therefore an thus the LDC labels stay unchanged. Subject adaptable algorithm was used in [3].

Switching Kalman filter approach proposed in [26] has the advantage of automatic rejection of noisy heartbeats or unknown morphologies. Therefore, in a first instance, the heartbeat classification will not consider the heartbeats classified as X-factor, proposed by Quinn et al.

V. DISCUSSION AND CONCLUSION

There is a tremendous increase in death rate due to cardiac diseases in India from past few decades. In this direction, different proposals were made to develop an automatic heart beat classification, which help in the automatic diagnosis of heart diseases for early diagnosis. In this review, different methods are presented for developing an optimal ECG diagnostic system. The datasets used in previous work are given in section II. Most of these datasets are free to download from physionet database ATM. Even though the database has many records, the previous authors selected only few records, which do not have motion artifacts, and which can be classified easily in to AAMI beats. As the AAMI beats are standard beats, most of the authors classified the heart beats in to AAMI beats. But, some of the authors had classified in to AAMI-II beats, where V and F beats are combined and denoted as V'. However, no author had explained to find the AAMI beats quantitatively. However, they classified the AAMI beats by training the classifier with the manually annotated beats given in Physionet database. The features extracted for beat classification using different methods are explained in section III. Later, feature selection had done using different feature ranking methods explained in the same section for reducing the feature-set to train the classifier, thereby, reduces the classifier-training time and increases the classification speed. Finally, different classification methods are explained in section IV. The classification using repetition-based packet processing technique [16] results a negligible classification error 2.58%. with the limitation of Gaussian assumption using LDC classifier used in [4] with many features not fulfilling the requirements, the classifier had shown the sensitivity (*S*) and positive predictivity (*P*+) for the supraventricular class are of 77% and 39%, and for the ventricular class (though better) are of 81% and 87%. SVM using MS active learning method [9] had shown better accuracy than full SVM classifier. It was also suggested that the accuracy of this method could be increased by the wavelets and higher order statistical features. Using PCA analysis to the wavelet transform of ECG leads [15], had shown better accuracy for normal and ventricular beats, but for supraventricular beats, the accuracy was poor. The signal quality and reduction of false alarm was done [18] using SVM classifier and achieved good results for ectopic beats, tachycardia rhythms, atrial fibrillation, and on sinus rhythm. However, the same algorithm could not be used alone for FA suppression in ICU context. Bayesian ML classifier with estimated parameters of IMM-KF and SMCMC methods [20] had shown 98% average accuracy. Since feature set is small, it does not perform well when tested with abnormal ECG. Fuzzy C-means clustering classifier in [10] resulted 98.93% of S, P^+ and diagnostic accuracy. In [6], it was shown that random forest method and SVM classifier attained better performance for classifying HCM and non-HCM subjects. The I-D CNN [24] had shown better performance in the detection of VEB and SVEB. The main advantage of this method was, it requires only 1-D convolutions. Therefore, it is convenient to implement in hardware. The classification accuracy achieved [11] was 88% using parallel GRNN for classifying AAMI beats on real holter data. This algorithm was executed in the parallel computational cores of GPU that improved the efficiency by approximately hundred times. The classification using ABC-LSSVM [25] resulted that bandwidth features evaluated for second IMF was found to be the best amongst first three IMFs. The patient adaptable heart beat classification [7] had inability to find marginally represented classes. In [3] subject adaptable heart beat classification was proposed to address the challenge of interperson variations in ECG signals. PSO-SVM classifier [12] attained better classification accuracy by detecting the best subset of features and solving the tricky model selection issue. The BER metric is a suitable figure of merit in SVM algorithms to jointly maximize the values of Se and Sp [27]. The classification accuracy using NN [21] achieved through only two non-linear features, mean of TEO energy in TD and the mean of TEO energy in FD is comparable to that obtained by others using many parameters. Even though number of methods are proposed previously, the work done on beat classification of real time datasets are meager.

As there are some quality issues in acquiring of wireless transmitted ECG signals from real time systems, there is a need to verify the same algorithms explained in this paper on real time system signals ie., which are not from open source database. Even the classification methods explained in section IV were presented with good results for open source database given in section II;

they got those results by excluding some of the datasets, as those datasets were difficult to classify the beats. Therefore, there is a need of study in this direction to overcome this problem. The limitations explained above help further to develop a better diagnostic system.

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