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General Review

Machine Learning Approach to Detect Cardiac Arrhythmias in ECG Signals: A Survey

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A B S T R A C T

Cardiac arrhythmia is a condition when the heart rate is irregular either the beat is too slow or too fast. It occurs due to improper electrical impulses that coordinates the heart beats. Sudden cardiac death may occurs due to some dangerous arrhythmias conditions. Hence the main objective of the electrocardiogram (ECG) analysis is to detect the life-threatening arrhythmias accurately for appropriate treatment in order to save life. Since the last decades, several methods were reported for automatic ECG beat classifications. In this work, we present a systematic review of the current state-of-the-art methods used to detect cardiac arrhythmia using on ECG signals. It includes the signal decomposition, feature extraction and machine learning approaches used for automatic detection and decision making process. The articles covers the pre-processing, detection of QRS complex, feature extraction and classification of ECG beats. Based on the past studies, it is understood that the automated approach using computer-aided decision making process is highly required for real-time detection of cardiac arrhythmias. The advantages and limitations of different methods are discussed and also the future scopes is highlighted in the process of effective detection of cardiac arrhythmias. This study could be beneficial for researchers to analyze the existing state-of-art techniques used in detection of arrhythmia conditions.

1. Background

Cardiovascular disease (CVDs) is the leading cause of death worldwide which counts about 31% of all global deaths. The heart is a muscular organ cone shaped that contracts at regular interval to supply the blood to the different organs of the body [1,7–9]. The heart attack occurs due to the blockage in coronary artery that supply the blood and oxygen to the heart itself as shown in Fig. 1. Unhealthy diet, hypertension, smoking, and other life style changes are the main cause of CVDs. According to the key statistics of world health organization (WHO), 7.4 million were killed due to heart attack in 2015 and most of these death occurs in low- and middle-income countries [2–4]. In India, the death rate of due to CVDs is about 272 per 100 000. India would lose $237 billion loss of productivity with the current burden of CVDs [5]. It is predicted that 90% of CVDs can be prevented with proper health care [6]. Therefore a comprehensive stratification protocol is necessary at

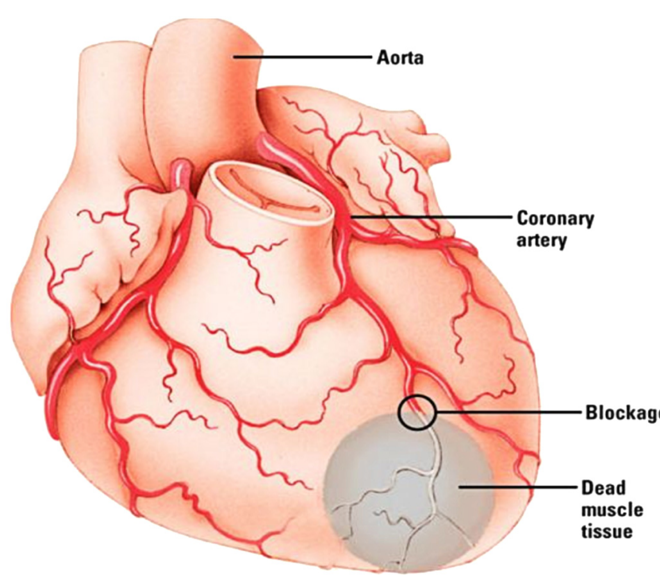

Fig. 1. Myocardial ischemia or heart attack (edited from [2]).

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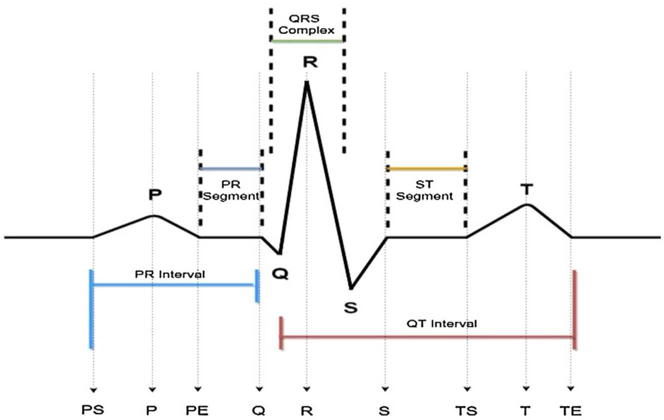

Fig. 2. The normal ECG signal (edited from [10]).

national level for the effective management of risk factors associated with CVDs.

2. Methods

2.1. The ECG waveform

The tracings of the electrical activity of heart is called ECG waveform which is a key diagnostic tool used to assess the health conditions of heart. A typical ECG tracing consists of P-wave, a QRS complex, and T-wave in each cardiac cycle is shown in Fig. 2. The abnormal heart rhythms are called arrhythmias, which occurs due to changes in normal sequence of electrical impulses of heart [11–13]. Arrhythmias may occur in the upper and lower heart chambers, but arrhythmias of ventricles can be the life-threatening events.

2.2. Types of arrhythmias

The normal heart rhythm is called sinus rhythm in which the triggering impulses from the SA node propagates throughout the four chambers of the heart in a coordinated manner. The four common types of arrhythmia: extra beats, supraventricular tachycardia, ventricular arrhythmias, and bradyarrhythmias [14–16]. The ECG signals of different cardiac arrhythmia conditions are represented in Fig. 3. Some of the known types of arrhythmias are:

Normal sinus rhythm (*NSR*): Representation of normal heart rhythm originates from the sinus node. Generally, regular heart rate may vary depending on autonomic inputs to the sinus node.

Premature (*extra*) *beats:* It is the most common type of arrhythmia having no symptoms and is harmless. Persons will feel a fluttering in the chest or a feeling of missed heartbeat. It consists premature atrial contractions (PACs) and premature ventricular contractions (PVCs).

Supraventricular arrhythmias: This is a condition starts in the atria with fast heart rates. Different types of supraventricular arrhythmias are atrial fibrillation (AF), atrial flutter, paroxysmal supraventricular tachycardia (PSVT), and Wolff-Parkinson-White syndrome.

Ventricular arrhythmias: the types of VAs are Ventricular flutter, Ventricular tachycardia (VT), Ventricular fibrillation (VF). This life-threatening conditions of the must be treated urgently with defibrillator shock to save life.

Sinus node dysfunction: Problems with the heart's sinus node leads to a slow heart rhythm. People with this type of arrhythmia may need a pacemaker.

Heart block: This condition may occur in the AV node or HIS-Purkinje system due to complete blockage in the conduction pathway. The heartbeat becomes slow and irregular, may require a pacemaker to treat. The conduction abnormality mainly occurs in the left or right side of the ventricles called the right bundle branch block (RBBB) or left bundle branch block (LBBB).

2.3. Noises in ECG signal and its filtering approach

The ECG signal is very sensitive to the noise due to its low frequency-band having frequency range of 0.5-150 Hz [17]. The signal characteristics changes during recording due to the interference of different source of artifacts [18–20]. The common noises are baseline wander, power line interference, and muscular noise [21] and these noise can be removed with appropriate filters as represented in Fig. 4. The pre-processing step is used to eliminate the noisy signal in order to enhance the signal information. Some of the common used methods are mathematical morphology [22] adaptive filtering [23] and weighted averaging filter [24] and independent component analysis [25]. The filtering and smoothing techniques are applied in pre-processing stage to attenuate P and T waves as well as noise [26,27].

2.4. Literature search

Survey of different methods used for detection and classification of ECG beats are reported in the literature is presented in this paper. We conducted a systematic search of articles from 1999 to 2019. Relevant articles were obtained through a search of articles cited in IEEE, Science direct, and PubMed etc. databases using different keywords. The review covers the pre-processing stage, peak detection, feature extraction and classification of ECG beats. The pre-processing stage highlights the use of filters used to remove the noises present during the recording of ECG signals. Different transform techniques is used in detecting the precise R-peaks and QRS complex in ECG signals also presented. Different feature extraction, features selection and classification techniques used for classifying ECG beats using machine learning and deep learning techniques also have been presented.

2.5. ECG database

MIT-BIH arrhythmias database: The database comprises of 48-records of 2-channel ECG signals of 30-min duration obtained from 47 subjects between 1975 and 1979 at the BIH Arrhythmia Laboratory. Twenty-three recordings were selected randomly from a set of 4000 ECG records from subjects of inpatients and outpatients at Boston's Beth Israel Hospital, remaining 25 were selected from the same set having clinically arrhythmias. Twenty-five men of age 32 to 89 years, and twenty-two women aged 23-89 years were selected. The database consists of 116,137 numbers of QRS complexes. The ECG signals were sampled at 360 samples per second with 11-bit resolution over a 10 mV range and band pass-filtered at 0.1-100 Hz. It was verified by independent cardiologist to annotate for both timing and beat class information. The different beats that include Normal beat (N), LBBB, RBBB, atrial premature beats (APB), and premature ventricular complex (PVC) of recorded signals, which are summarized in Table 1.

AAMI standard: The MIT-BIH heartbeat types are combined according to Association for the Advancement of Medical Instrumentation (AAMI) recommendation [24]. It emphasizes the problem of classifying ventricular ectopic beats (VEBs) from the non-ventricular ectopic beats. The following five types of heartbeat is classified according to AAMI standard:

i. N (Normal beat)
ii. S (supraventricular ectopic beats (SVEBs))
iii. V (ventricular ectopic beats (VEBs))

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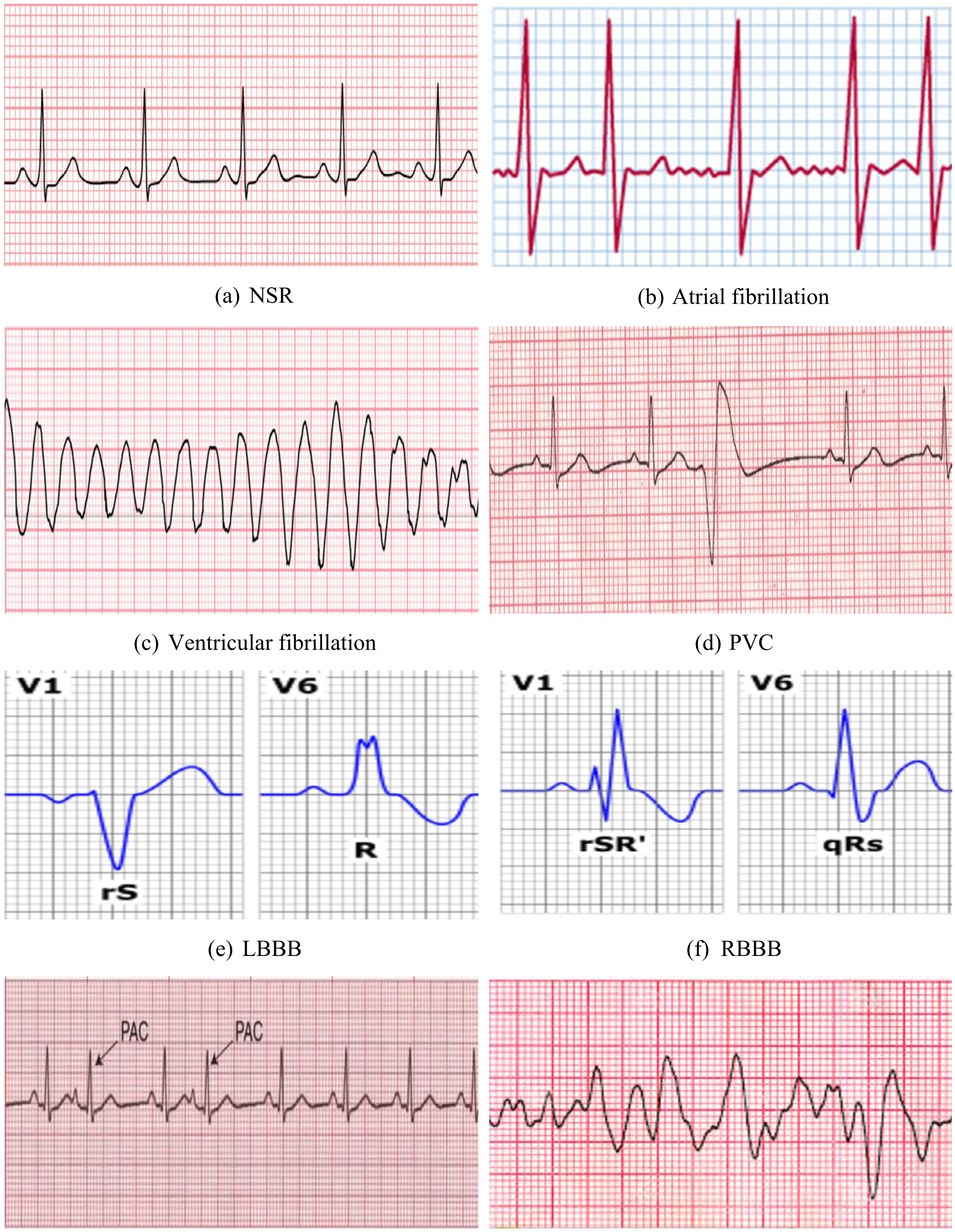

(a) NSR (b) Atrial fibrillation

(c) Ventricular fibrillation (d) PVC

(e) LBBB (f) RBBB

(g) PAC (h) Ventricular tachycardia

Fig. 3. Types of cardiac arrhythmias (edited from [13]).

iv. F (fusion beats)
v. Q (unclassified beats, including paced beats)

3. Result analysis

3.1. An overview of ECG signal analysis

Over the last four decades, the analysis of ECG signal is one of the key research interest in biomedical signal processing. The computer-aided diagnosis system become a reliable tool by the clinician for interpreting the cardiac disease more accurately. It is used in routine and long term monitoring of ECG signals in intensive coronary care unit (ICCU) or processing large amount of data as in Holter records [25]. Identification of arrhythmias is very troublesome in long time monitoring of ECG records acquired by a Holter machine. Two different approaches based on supervised and unsupervised learning are used in the process of automatic diagnosis of cardiac diseases. There is a possibility of error in the ECG recording due to monotonicity and fatigue of the operator hence computational techniques is needed for automatic classification [28]. In an automatic system, the ECG signals are processed in following steps: pre-processing steps; peak detection; feature extraction; and classification [29,96]. In pre-processing stage, the ECG signal are enhanced further by eliminating power line, motion

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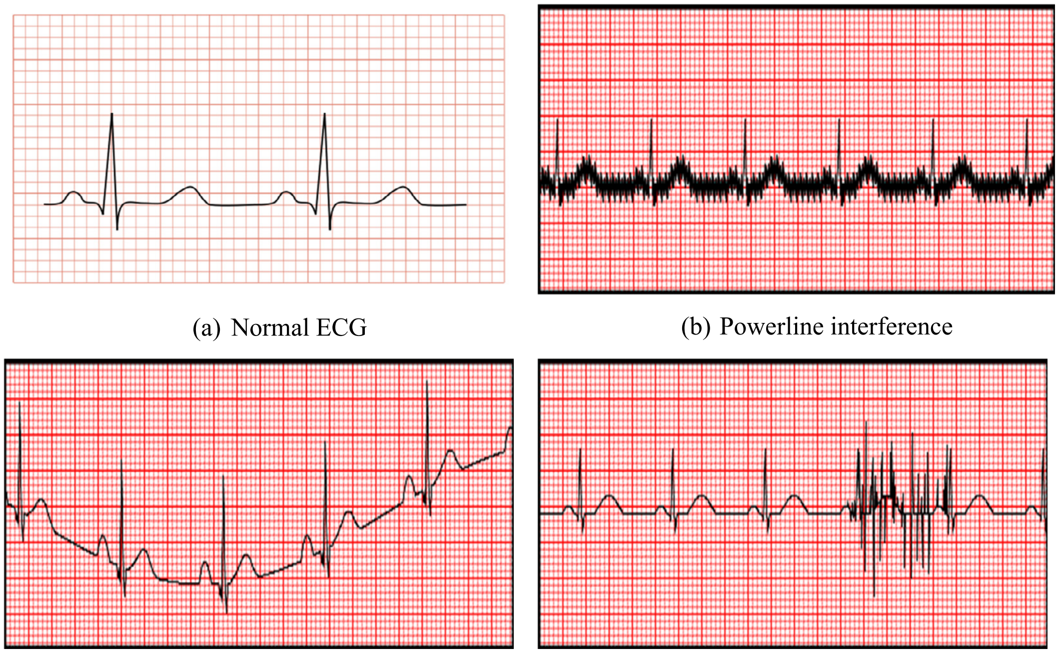

(a) Normal ECG (b) Powerline interference

(c) Baseline wander (d) Muscle artifacts

Fig. 4. Types of artifacts in ECG signal (edited from [17]).

Table 1
Distribution of ECG records for different arrhythmias of MIT-BIH database.

Type	Records
Normal beats	100, 101, 103, 105, 108, 112, 113, 114, 115, 117, 121, 122, 123, 202, 205, 219, 230, 234.
LBBB beats	109, 111, 207, 214.
RBBB beats	118, 124, 212, 231.
PVC beats	106, 116, 119, 200, 201, 203, 208, 213, 221, 228, 233.
APB beats	209, 220, 222, 223, 232.

artifacts and instrumentation noises by the use of adaptive filters [26,27].

3.2. Detection of R-peaks and QRS complex

The energy of heart beats is mainly located in the QRS complex of the ECG waveform, hence accurate detection of this complex has a vital role in ECG analysis [30]. Since last decades, a number of techniques have been reported for automatic classification of cardiac arrhythmias. In time-domain technique, various features are extracted from each beat that consists of duration, amplitude of different waves, area and morphology of QRS complex in order to detect arrhythmia beats [31]. An example of detection of R-peaks and QRS complex is shown in Fig. 5. In 1980, a minicomputer system has designed to classify normal beats, supraventricular ectopic and ventricular ectopic beats using time-domain features like RR interval, width of QRS complex and slopes of various segments [32]. The robust time-varying signal analysis based on wavelet has been widely used in QRS detection. The discrete wavelet transform (DWT) that decomposes a signal into different frequency components with coefficients that represent the adequate information of the original signal and have been applied successfully in delineating the ECG signals [33,34]. Merah et al. [35] designed a robust method based on stationary wavelet transform (SWT) that detects R-peaks and QRS complex reliably, also delineates the ECG signals accurately. In 1990, Dokur et al. [36] combined Fourier and wavelet features to classify 10 types of ECG beats using genetic algorithms based neural network and the success rate was 97%. Lanata et al.

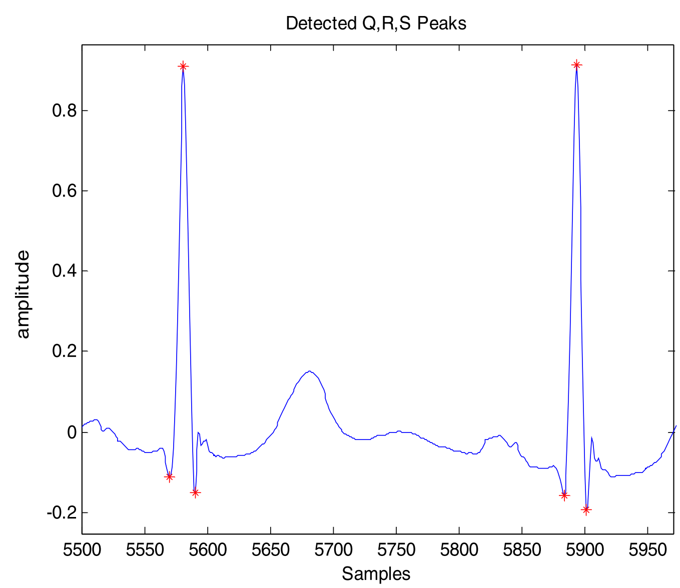

Fig. 5. Detection of R-peaks and QRS complex in ECG signal.

[37] used the parameters of higher order spectra to identify the common multiple cardiac arrhythmias. Jung and Kim [38] proposed an automatic method to detect premature ventricular contractions (PVCs) based on wavelet transform. Jovic and Bogunovic [39] proposed an efficient method to classify cardiac disorders using statistical, geometric, and non-linear HRV features.

The computation of QRS duration starts with detecting the QRS onset and offset points which starts from the R-peaks. Locating a proper fiducial point could determine the accurate QRS complex in ECG signal. Manriquez and Zhang [40] reported a robust algorithm for detecting QRS onset and offset points in ECG signal by computing indicators by covering the envelope of QRS complex, but the detection rate was only 67.5%. Thereafter, numerous algorithms are used for QRS detection based on digital filters and non-linear transforms in order to extract the feature components

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Table 2
Comparison of different methods used for QRS complex detection.

Literature	DB	TP	FP	FN	Se (%)	Pp (%)	DER (%)
Pan et al. [41]	109809	109532	507	277	99.75	99.54	0.71
Banerjee et al. [48]	19098	19022	76	40	99.6	99.5	0.61
Bouaziz et al. [49]	109586	109354	232	140	99.87	99.79	0.34
Hamilton & Tompkins [52]	109267	108927	248	340	99.69	99.77	0.54
Zidelmal et al. [53]	109494	109101	193	393	99.64	99.82	0.54
Afonso et al. [54]	90909	90535	406	374	99.59	99.56	0.86
Arzeno et al. [55]	109456	107344	884	2112	98.07	99.59	2.79
Choi et al. 2010 [56]	109336	109,118	218	376	99.66	99.80	0.54
Chen et al. [57]	102654	102195	459	529	99.55	99.49	0.98
Karimipour et al. [58]	116253	115,945	308	192	99.81	99.70	0.49
Sahoo et al. [59]	109666	110351	315	144	99.87	99.69	0.42

[41,42]. A multi-scale QRS detector using discrete wavelet transform detected the QRS complex, P and T-wave with an accuracy of 99.8% even in the presence of baseline drift and noises [44]. Martinez et al. [45] used wavelet transform approach for delineating the QRS complex and also identified the P and T wave peaks. This method attained more than 99.8% of sensitivity and specificity in ECG records from MIT-BIH Arrhythmia Database, but the accuracy was not evaluated. A multiresolution wavelet transform based system with a set of optimum coefficients achieved an accuracy of 95% and 92% in detecting QRS complex, QT interval and T duration respectively. The main drawbacks was the use of manual process for evaluation [46]. The concept of dominant rescaled wavelet coefficients (DRWC) was also used efficiently to magnify QRS complex and to reduce the effects of other peaks [47]. Banerjee et al. [48] archived sensitivity and specificity more than 99.8% in detecting R-peaks by using multiresolution WT along with adaptive thresholding, however the detection accuracy was not evaluated [48]. The multiresolution wavelet analysis based on the power spectrum of decomposed signals is used for selecting detail coefficient corresponding to parameters $\lambda 1$ and $\lambda 2$ frequency band of the QRS complex. Best performance was achieved with global sensitivity of 99.87% with an error rate of 0.34%, which is higher in case of arrhythmia detection [49]. In 2016, Junior et al. [50] used redundant DWT approach and obtained a detection accuracy of 99.32% in detecting QRS complex but the peaks of P and T waves was not evaluated. The fiducial point detection accuracy has been improved using polygonal approximation [51]. But they did not evaluate the peaks of waves and accuracy of the methods. The wavelet detail coefficients used to discriminate the energy levels of normal and abnormal beats based on the power spectrum of QRS complexes [52]. The decomposition of ECG signals by the filter banks produces more than 99% detection sensitivity with better computationally efficiency [55]. Choi et al. [56] developed a combine approach using low-pass filter and irregular R-R interval check-up for better beat segmentation in ECG signals. Though sensitivity of detection was 99.66% but the detection error rate was higher about 0.54%. The first-order derivative with adaptive thresholding detects the QRS complexes effectively with high accuracy at faster rate [58].

In a recent article, Sahoo et al. [59] detected the QRS complex with a sensitivity of 99.87% with detection error rate of 0.42 by using DWT. Comparison of different methods published in literature in detecting QRS complex detection is presented in Table 2. The empirical mode decomposition (EMD) based approach effectively removes the baseline wander in ECG signals [60] hence used for delineating ECG signals. The combined approach based on EMD and DWT provides better time resolution in de-nosing the ECG [61]. Promising results has been achieved in detecting R-peaks using EMD technique along with digital filters [62]. Rabbani et al. [63] presented a combined approach based on Hilbert and wavelet transforms along with adaptive thresholding for better detection accuracy in detecting R-peaks but they did not evaluate the results qualitatively. An EMD based nonlinear transform technique achieved more than 99% both sensitivity and specificity in detecting the QRS complex [64]. Lu et al. [65] proposed a novel scheme based on integrating with EMD and support vector machines (SVMs) classifier. The dominant features were selected with genetic algorithm to achieve better classification accuracy with reduced dimensionality of features. The articles lack the evaluation process to find the classification accuracy.

3.3. Machine learning approach for detection of ECG beats

Since last decades, large number methods have been reported in literature for the classification of cardiac arrhythmias using machine learning techniques [43]. Some of these approaches are based on SVMs and artificial neural networks (ANNs). An optimized block-based NN classifier achieved the classification accuracy of 97% using Hermit function coefficient and temporal features extracted from the ECG signals [66]. The cross wavelet transform (XWT) based method achieved an accuracy of 97.6% for classifying normal and abnormal cardiac beats [67]. Similarly the DWT and dimensionality reduction methods achieved an accuracy of 96.92% and 98.78% in SVM-RBF and NN respectively in classifying five classes of arrhythmias [44]. Martis et al. [68] obtained classification accuracy of 94.52% in NN classifier using HOS cumulants features extracted with principal component analysis. In all these study the advantages of feature reduction process has not been highlighted.

The Hilbert transforms proved to be an effective approach in extracting discriminative features in ECG beat classification. It has the ability to distinguish dominant peaks among other peaks in ECG signal that have a significant effect in detecting R wave [69]. The Hilbert-Huang transform (HHT) embedded with wavelet analysis is used effectively in detecting weak ECG signal with high computing efficiency by removing undesirable intrinsic mode functions (IMFs) in sifting process [70]. The Hilbert transform along with adaptive thresholding also effectively used for QRS complex detection [71]. In a novel approach, the Hilbert transform and the adaptive threshold technique along with principal component analysis (PCA) found to be an efficient method in detecting QRS complex in the ECG signal [72]. The R-peaks was detected with high accuracy rate of 99.87% less error rate of 0.8%. The Hilbert transform with variable threshold and slope reversal method produces a notable result in PTB-DB database signals [73]. The DWT along with Hilbert transform and adaptive thresholding technique has been used successfully to detect precise R-peaks in ECG signal. An improved half-soft threshold based on the lifting wavelet and Hilbert transform is applied to enhance the QRS complexes of ECG signals. The R-peak detect with an error rate of only 0.27% [74]. Madeiro et al. [75] presented an innovative approach of QRS detection that combines the first-derivative, Hilbert transform, wavelet transforms and adaptive thresholding methods. They achieved the average sensitivity of 99.15% and positive predictability of 99.18%. The computation complexity of the combined approaches has not

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been calculated in these studies which is the main task in detection the arrhythmia beats.

Recently, EMD and VMD have been used successfully in denoising and detecting the cardiac arrhythmia conditions [76,77]. Mitra et al. [78] proposed a three stage technique based on stationary wavelet transform for noise reduction, and classification to detect premature ventricular contraction (PVC) conditions. Huang et al. [79] introduced the empirical mode decomposition to analyze non-linear and non-stationarity in ECG signals. The time-frequency domain features of EMD modes in the ECG signal is helpful for classifying the ECG betas. Dragomiretskiy and Zosso [80] proposed the variational mode decomposition (VMD) model which is an alternative to the EMD process for signal analysis. This technique is more robust than the EMD for sampling and de-noising the non-stationary signal like ECG. Maji et al. [81] proposed the VMD technique for detecting ventricular QRS complex in ECG signal using frequency domain features. The intelligent methods have been widely used in classifying ECG beats. The hybrid features along with neural networks has shown efficiency in discriminate normal and arrhythmia beats with an accuracy of 99.75% [82]. The Hermite transform has been used for successful analysis and classification of ECG beats [83]. The feature reduction methods also have been used widely to reduce the signal dimensions and to improve the performance of classifiers in classification of ECG beats [84,85]. Osowski et al. [87] used SVM classifiers to classify 13 types of heart rhythm and achieved a high classification accuracy by the use of HOS and the Hermite characterization of QRS complex. Neural networks are one of the powerful classifier used with ECG arrhythmia classification [86]. In recent works, four types of ECG beats were classified with accuracy of 96.94% based on a combined effort of statistical feature with neural network classifier [88].

Evaluation of time-frequency domain based features is required for classification in ECG beats more accurately. Martis et al. [60] achieved an accuracy of 93.48% using morphological and time features and classified for five types of ECG beats by LS-SVM classifier. C. Kamath [89] obtained classification accuracy higher than 95% based on teager energy functions in classifying five types of ECG beats in an NN classifier. The main disadvantages was that only two non-linear features were considered for the evaluations. In 2008, Asl et al., [90] used heart rate variability (HRV) features with discriminant analysis (DA) for dimensional reduction. Six types of arrhythmias beats were classified with an accuracy of 98.94% using SVM classifier with reduced processing time. A main disadvantage was that it cannot detect LBBB and RBBB arrhythmia beats. The biorthogonal spline wavelet based features achieved an accuracy of 95.65% in classifying four types of ECG beats with SVM classifier [91]. The multiscale wavelet based time interval temporal features were classified into three class of ECG beats with an accuracy of 95.2% using NN Classifier [92]. In a recent work, an optimized block-based NN classifier used classify the arrhythmia conditions with an accuracy of 97% using extracted Hermit function coefficient and temporal features [66]. Therefore the NN based classification methods were applied successfully in ECG beat detection but the accuracy rate was below 99%.

In a recent report, two feature extraction approaches based on ensemble-EMD and EMD are used to classify five types of heartbeats: normal, premature ventricular contraction, atrial premature contraction, LBBB and RBBB [93]. It achieved good performance with accuracy of 99.20% using sequential minimal optimization-SVM classifier. An automated classification system using optimized diverse features was classified with *k*-nearest neighbor algorithm of heartbeat with sensitivity of 85.59%, and specificity of 99.56% respectively for recognizing five types of ECG but the accuracy rate was not calculated in the study [94].

In a feature reduction approach based probabilistic neural network (PNN) used effectively to classify eight types of ECG beats with an accuracy of 99.71% [97]. The dimensionality reduced features based on PCA, LDA and ICA along with SVM, NN and PNN classifiers found to be efficient in automated classification of ECG beats [95]. It achieved an accuracy of 99.97% in ten-fold cross validation scheme [98]. The multi-resolution wavelet analysis and thresholding has been used to reduce noise in ECG signal. The distance metric for NN classification accuracy was achieved with value of 95.14% and 81.83%, for Mahalanobis distance and Euclidean distance respectively [99]. A novel method based on morphological and statistical features shows an accuracy of 99.70% in class-oriented scheme and 96.15% in the subject-oriented scheme in classifying cardiac beats [100]. The linear and nonlinear features of ECG signals classified with in approach based on support vector machine and radial basis function. A high accuracy rate of 98.91% was obtained in classifying five types of beats hence found effective enough in detecting arrhythmia conditions [101]. Kamath C. [102] obtained classification accuracy of 93.5 using NN classifier in classifying five types of heartbeats using complexity measures. Li and Jhou [103] used wavelet packet entropy features and classified the ECG beats with an accuracy of 94.61% using random forests classifier. The dimensional reduction process may be associated in the approach to improve the beat detection.

In an automatic process, Jovic et al. [105] classified nine different types of cardiac rhythms using three classification algorithms (SVM, Ada Boosted C4.5, and Random Forest) in a time-domain features. The total classification accuracy was very less, roughly 85% on a20 s window length. Recently decision tree classifiers are applied successfully to classify biomedical signals. The random forest based classifier achieved the best performance with classification accuracy of 96.67% using *k*-fold cross-validation in classifying EMG signals [106]. Park and Kang [107] achieved an accuracy of 94.6% using the QRS complex and P wave features of ECG signals in decision tree classifier that may be useful in Holter monitoring. The morphological and heartbeat interval features of ECG signal used effectively for classifying supraventricular ectopic beats (SVEB) and ventricular ectopic beats (VEB) with an accuracy of 95.9% and 99.2% respectively [108]. A block based NN classifier based system used in classifying VEB and SVEB condition and achieved an average accuracy of 98.10%, 96.6% respectively using Hermite transform and time interval based features [109]. Kim et al. reported an extreme learning method to detect six types of ECG beats. The performance was very effective with an average accuracy of 98.72% with a short learning time using PCA and RR intervals features [110]. Llamedo and Martinez [111] presented a patient-adaptable algorithm for automatic classification of ECG heartbeat. It includes RR interval series and morphological descriptors derived from the wavelet transform. The algorithm gained a mean improvement of 6.9% in accuracy, 6.5% in global sensitivity and of 8.9% in global positive predictive value. Li et al. [112] used a parallel general regression NN to classify the heartbeat according to the AAMI in long-term ECG analysis and obtain an accuracy of 95%.

Few recent articles have been reported the implementation of different feature extraction and machine learning techniques for classification of ECG beats with better accuracy rate. Sahoo et al. [114] reported an accuracy of 99.89% in classifying six types of ECG beats by using DWT and EMD based features and radial basis function NN classifier. Nguyen et al. [115] reported an algorithm for detecting shockable rhythms using SVM model and obtained average accuracy of 95.9%. Raj et al. [116] presented a computerized decisive system using composite dictionary (CD) which consists of the stockwell, sine and cosine analytical functions for an efficient representation of ECG signals. The CD approach decomposed the ECG signal into stationary and non-stationary components with high detection accuracy of 99.21%. Yang et al. [117] reported a novel system using principal component analysis network (PCANet) for feature extraction and classified the feature set with a linear

Table 3
Comparison of proposed methodology with some existing method.

Literature	Features	Classifier	Types of ECG beats	Accuracy (%)
Sahoo et al. [59]	DWT + Temporal + Morphological	SVM	4	98.39
Ince et al. [64]	DWT + PCA	MDPSO	5	95.58
Martis et al. [98]	WT + PCA, LDA, ICA	SVM	5	99.28
Shadmand et al. [66]	Hermit function	NN	5	97.00
Martis et al. [68]	Cumulant + PCA	NN	5	94.52
Gulera et al. [88]	Statistical features	NN	4	96.94
Kamath C. [89]	Teager energy function features	NN	5	95
Asl et al. [90]	Heart rate variability	SVM	4	97.65
Fei S.W. [91]	Time intervals	SVM	5	95.65
Inana et al. [92]	WT and timing interval	NN	3	95.2
Banerjee et al. [99]	Mahalanobis distance	NN	-	95.14
Elhaj et al. [101]	Linear and non-linear	NN	5	98.91
Chazal et al. [108]	Morphology + heart beat interval	LDA	5	85.9
Tsipouras et al. [119]	RR-interval	Fuzzy System	4	96
Park et al. [107]	QRS complex, P wave	Decision tree	2	94.6
Llamedo & Martinez [111]	RR interval and its derivative	LD	3	98
Li et al. [112]	Eight heartbeat features	NN	5	95
Sahoo et al. [114]	EMD based features	RBF-NN	5	99.89
Nguyen et al. [115]	Count2 and VF-filter Leakage Measure	SVM	3	95.9
Raj et al. [116]	A set of five features	SVM	16	99.21
Yang et al. [117]	PCA Net	SVM	5	97.77
Rai et al. [118]	Multiresolution DWT	MPNN	2	99.07
Raj et al. [119]	DOST	PSO tuned SVM	16	99.18
Khalaf et al. [120]	Statistical features	SVM	5	98.60
Oh et al. [123]	CNN and LSTM	Deep learning	5	98.10
Sannino & Pietro [127]	RR intervals	Deep learning	2	99.68
Isin et al. [128]	DNN	Deep learning framework	2	92
Mathew et al. [129]	Simple features	Deep belief networks	2	95.57

SVM method with accuracy of 97.77% in identified five types of heart beats. The main advantage os the approach that it was able to classification of skewed and noisy heartbeats. Rai et al. [118] presented a hybrid technique that consist of feature extraction using multiresolution DWT and classification with multilayer-PNN in detecting only LBBB and RBBB types of arrhythmias. The system achieved overall accuracy of 99.07% with an error rate of 0.62%, the main disadvantage of this method was that only two beats are classified with higher error rate than the earlier approaches. The discrete orthogonal stockwell transform (DOST) based method is used efficiently for extraction of time-frequency features and classified with SVM classier. The optimized feature set achieved an overall accuracy of 99.18% in classifying sixteen classes of cardiac arrhythmias [119]. Khalaf et al. [120] proposed a CAD system based on PCA reduction process using spectral correlation and statistical features and classified with linear SVM classifier. They achieved an accuracy of 98.60% in raw spectral correlation in classifying five beat types. The usage of geometry based features may be emphasized for improving the accuracy.

Recently, powerful tools based on artificial intelligence and deep learning has been used for solving the very complex signals like ECG [104,125,131]. It helps in design of real-time classification of ECG signals and eliminates the burden of training a deep convolutional neural network (CNN). Kiranyaz et al. [121] implemented 1-D CNNs in order to fuse the feature extraction and classification process. The better efficiency has been achieved both in speed and computation achieved which can be benefited in long term ECG records such as Holter registers in ICU.

A deep learning approach for active classification of ECG signals has been reported that uses stacked denoising autoencoders (SDAEs) with sparsity constraint. Entropy and Breaking-Ties (BT) ranking criteria has been applied to each test beat and found significant improvements in accuracy and faster online retraining compared to state-of-the-art methods [122]. Oh et al. [123] presented an automated system which achieved an accuracy of 98.10% by combining the CNN and long short-term memory (LSTM) for detecting five types of heartbeats. The main contribution from this work is that ECG segments of variable length have been used in steady of features. Acharya et al. [113] developed an automatic method to detect myocardial infarction by implementing a convolutional neural network (CNN) algorithm and obtained an average accuracy of 95.22% without extracting the features from ECG signals. A new model for deep bidirectional recurrent neural networks (RNNs) architecture which is a type of recurrent neural networks (RNNs) architecture has been successfully used in classifying five types ECG beats with high success rate of 99.39% [124]. In a study, Acharya et al. [126] presented a model based on 9-layer deep CNN for classifying five different types of heart beats efficiently with accuracy of 94.03%. The CNN approach was trained with highly imbalanced data that quickly identified different types of arrhythmic beats. Sannino and Pietro [127] proposed deep learning approach developed by using Tensor Flow and Google deep learning library and able to achieve an overall accuracy of 99.83% in classifying ECG beat using. They have emphasized on the involvement of physicians in the development process for real-time application of ECG monitoring system. Isin et al. [128] obtained an accuracy of 92% in classifying ECG beats using deep learning. A novel method based on deep learning approach using restricted Boltzmann machine (RBM) and deep belief networks (DBN) has been applied for classification of ventricular and supraventricular heart beats [129]. A combined approach detected the supraventricular ectopic beats with accuracy of 95.57%. The method has potential for applications in other bio-signals which may be tested in future scope. In a very recent automated computer-aided system, an 11-layer deep CNN model has been used successfully for diagnosis of congestive heart failure. The best accuracy of 98.97% and sensitivity of 98.87% was obtained in this approach [130]. The long-term ECG signal is monitored by Holter machine to detect arrhythmic signals automatically. For this purpose a convolutional auto-encoder (CAE) is used to reduce the signal size and a Long-short term memory (LSTM) for classifying the signal. The main contributions of the study was improved detection accuracy of over 99.0% and reduction in training time of the deep LSTM network. From the above literature survey we have found that since last decades different methods based of standard classifiers and deep learning approaches has been used effectively for classification of arrhythmia beats and the feature sets and the classifiers used in the works has been summarized in Table 3.

4. Conclusions

In this review article we have surveyed different methods that have been used in detecting R-peaks, QRS complex and classifying cardiac arrhythmias in ECG signals. Semi-automated and automated methods using computer aided diagnosis system using machine learning and deep learning have been presented. The standard classifiers such as neural network and SVM are found to be effective for arrhythmia detection and the accuracy rate was more than 99% using morphological and time-frequency based features. Recent study shows that the deep learning techniques are efficient than the standard classifiers in terms of accuracy and computational complexity which are very essential in life saving in real-time applications. From the literature survey, we found that every researcher has implemented the ECG signals from MIT-BIH database. Therefore the research community must focus on developing new databases for the validation of the process.

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Author contributions

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.

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The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

CRediT authorship contribution statement

S. Sahoo: Conceptualization, Data curation, Formal analysis, Writing - original draft, Writing - review & editing, Validation. **M. Dash:** Conceptualization, Formal analysis, Writing - original draft, Writing - review & editing, Validation. **S. Behera:** Conceptualization, Formal analysis, Validation. **S. Sabut:** Conceptualization, Data curation, Formal analysis, Writing - original draft, Writing - review & editing, Validation.

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