Computer-aided Arrhythmia Diagnosis with Bio-signal Processing: A Survey of Trends and Techniques

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Signals obtained from a patient, i.e., bio-signals, are utilized to analyze the health of patient. One such bio-signal of paramount importance is the electrocardiogram (ECG), which represents the functioning of the heart. Any abnormal behavior in the ECG signal is an indicative measure of a malfunctioning of the heart, termed an *arrhythmia condition*. Due to the involved complexities such as lack of human expertise and high probability to misdiagnose, long-term monitoring based on computer-aided diagnosis (CADiag) is preferred. There exist various CADiag techniques for arrhythmia diagnosis with their own benefits and limitations. In this work, we classify the arrhythmia detection approaches that make use of CADiag based on the utilized technique. A vast number of techniques useful for arrhythmia detection, their performances, the involved complexities, and comparison among different variants of same technique and across different techniques are discussed. The comparison of different techniques in terms of their performance for arrhythmia detection and its suitability for hardware implementation toward body-wearable devices is discussed in this work.

CCS Concepts: • **Mathematics of computing → Time series analysis**; • **Computing methodologies →** *Classification and regression trees*; *Neural networks*; *Feature selection*;

Additional Key Words and Phrases: Electrocardiogram (ECG), arrhythmia detection, computer-aided diagnosis, health-care, machine learning, neural networks, support-vector machine

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1 INTRODUCTION

Following the recent trends in health-monitoring devices and heterogeneous integration techniques, a large number of body-wearable devices in different forms such as wristbands nda smart watches that capture bio-signals are rapidly proliferating in the market. Bio-signals are the non-stationary signals representing the electrical output from the corresponding organ, captured by one or more sensors. Disparate techniques and devices are often utilized to acquire different kinds

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of bio-signals. Analysis of the bio-signal aids to monitor and assess the functionality of the corresponding organ.

Most of these bio-signals are deterministic and follow a pattern. For instance, a deterministic behavior can be seen in the depicted pseudo-random electrocardiogram (ECG) signal in Figure 1. Any malfunctioning in an organ can be mostly observed as an anomaly in the corresponding bio-signal. Some examples of anomalies in an ECG signal is illustrated in Figure 3. An anomaly in a signal can be defined as a sequence or part of signal that does not obey with the behavior of the rest of the signal (Chandola et al. 2009). Further, an in-depth analysis of anomaly in the bio-signal, such as morphological distortions and temporal variations, help to derive conclusions and measures to nullify the cause of the anomaly. Hence, there is an emerging need to study a wide range of state-of-the-art techniques for bio-signal analysis and evaluate their pros and cons. Though various bio-signals can be obtained from a patient for analysis, we confine this article to anomaly detection in ECG signals due to the various reasons mentioned above.

According to cardiovascular disease (CVD) statistics from the World Health Organization (WHO) (WHO 2015), CVDs are the major cause of death globally. Additionally, anomaly detection in bio-signals obtained from the heart, i.e., arrhythmia detection, has drawn significant attention among researchers and practitioners. Cardiac diseases may be diagnosed by invasive and non-invasive techniques. *Cardiac auscultation* (Braunwald et al. 2011), i.e., listening to the heartbeat with the aid of stethoscope, is used by physicians to diagnose CVDs. The efficiency of cardiac auscultation is often hindered due to lack of ability to hear or interpret the heartbeats by a physician and is prone to human errors or inaccuracies (de Medeiros et al. 2011). ECG is a non-invasive and efficient technique that represents the electrical activity of heart. Electrocardiogram signals are useful to analyze and diagnose CVDs (Goldeberger et al. 2012; de Medeiros et al. 2011). It is widely used to monitor patients' cardiovascular activities. Any deviation from the usual heart rhythm (60–100 beats per minute) is termed as *arrhythmia*, including disturbances in the heart rate, regularity or conduction of the cardiac electrical impulse (Thaler 2015). In addition to CVDs, analysis of arrhythmia also helps in deriving conclusions about the lifestyle of the patient. For instance, a high-frequency cardiac rhythm disturbance indicates that a person is suffering from sleep disorders (Migliorini et al. 2011).

Capturing ECG signals for arrhythmia detection often demands special equipment and clinical setup along with expertise. At a large scale, this is not possible, especially in developing or under-developed countries, where the availability of medical experts, clinics, and medical devices is meager. This fueled the need for automatic, low-cost, real-time, and efficient physiological monitoring that can be used in the home or under ambulatory settings alike. This gradually led to arrhythmia detection and health diagnosis by computer-aided diagnosis (CADiag) systems.

1.1 Challenges in Arrhythmia Detection

The major challenges in arrhythmia detection that are vital to consider when designing a CADiag system are listed below:

- The symptoms of the arrhythmia might not show up at all or might not show up during the ECG signal capturing period (Ceylan and Özbay 2007).
- To improve the quality of diagnostics, ECG signals might need to be captured or monitored over several hours using devices like a Holter monitor, which is not always feasible.
- ECG signal properties (such as time period, amplitude, and so on) vary from person to person and depend on different factors such as age, gender, physical conditions, and lifestyle. As such, there exist no generalized framework and standards that are valid for all patients. This is one of the reasons why CADiag arrhythmia detection systems perform well on the

training data but has reduced performance when tested on different patients (Joshi et al. 2009; Ceylan and Özbay 2007).

- Variations in the ECG signal morphology for the same person with time, physical state (such as running, walking, and sleeping), and so on.
- The volume of data to be considered for ECG signal analysis is large; hence there is a higher probability of having false diagnosis of arrhythmia.
- The noise components from an electrical interface such as electrodes and mechanical disturbances (changes in the connection of electrodes on patient's skin) or interference from other nodes can result in morphological variations and discrepancies in captured ECG signal (Adams and Choi 2012; Yaghouby et al. 2009).
- Some other components of noise that contribute to a false diagnosis of arrhythmia are biological ones, such as a patient's muscle movements, which generate high-frequency noise; chest activity due to respiration, which may provoke baseline wandering, and signal interference from other organs.

1.2 Contributions of This Work

Despite the above-mentioned challenges, arrhythmia detection is possible by closely observing and learning the patterns in ECG signals. There exist distinct ways to detect arrhythmias, each of them with their own merits and demerits. In this work, we try to systematically list and analyze notable works for ECG signal analysis from both the perspectives of performance and suitability to emerging body-wearable devices. The main contributions of this work are outlined below:

- A comprehensive overview and analysis of different ECG pre-processing techniques along with their comparison.
- ECG arrhythmia detection is presented in a categorized manner based on the technique used in CADiag.
- Various arrhythmia detection techniques ranging from traditional to advanced methods like machine learning are analyzed.
- A comparison of different variants of a technique and among various techniques is presented along with their achieved performance.
- Last, a tradeoff analysis between arrhythmia detection techniques' performance and resource is presented, which is of great help for researchers to choose the technique depending on their requirements.
- In addition, hardware analysis w.r.t. the performance and resource utilization is presented.

1.3 Distinction to Other Surveys

To the best of our knowledge, this is the first survey on ECG arrhythmia analysis that covers a broader range of topics in terms of arrhythmia detection algorithms (both traditional statistical method based as well as advanced machine-learning based) and analyzes arrhythmia detection performance and overheads across different techniques as well as the variants of these techniques. Furthermore, this work also presents hardware implementation analysis based on performance and resource consumption, which is non-trivial for the design of future and current wearable and fitness tracking devices or to determine which of the techniques is best suited to be deployed on embedded devices such as smart phones for given power and performance budgets. This would be of great help for both researchers and developers to identify a subset that fits the requirements of their use cases. There are a few short survey papers such as da S. Luz et al. (2016), Jambukia et al. (2015), Dewangan and Shukla (2015), and Sahoo et al. (2011). In da S. Luz et al. (2016), ECG arrhythmia classification based on techniques is presented with primary focus on the performance

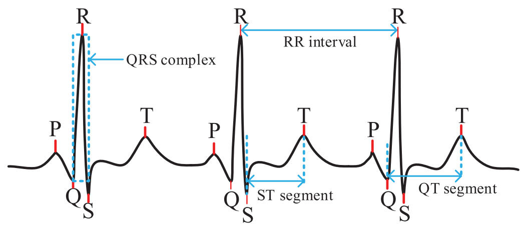

Fig. 1. A pseudo-ECG signal and its components.

evaluation for a given technique. As such, no analysis of the processing overheads, requirements, or suitability of an ECG arrhythmia detection technique to system or implementation resources is presented. This leaves the user with a void when evaluating algorithms for a given power or area constraints or determining the algorithm based on the complexity. Though a compact review of ECG classification is presented in Jambukia et al. (2015), it is mostly confined to machine-learning techniques and focuses mainly on neural networks and Support Vector Machines (SVMs). However, no intriguing comparisons and analysis (in terms of implementations) among different techniques are mentioned. A review that is confined to a specific type of arrhythmia is provided in Sahoo et al. (2011). Our article differs from the existing ones w.r.t. its coverage of a wide range of topics regarding ECG signals, arrhythmias, pre-processing of ECG signals, and different arrhythmia detection techniques. In addition, this work provides guidelines to users for selecting the appropriate arrhythmia detection technique that fits their requirements in terms of performance, power, or area budget.

1.4 Organization of This Article

The rest of this article is organized as follows. We introduce the ECG signal and its characteristics in Section 2. Different arrhythmias and their features are presented in Section 3. Possible techniques employed for extracting different components of an ECG signal is presented in Section 5. Further, we present different arrhythmia detection techniques in a grouped and compact form along with an analysis of individual techniques in Section 6. An in-depth analysis of CADiag-based arrhythmia detection and comparison among various techniques is presented in Section 7. Analysis of other bio-signals is provided in Section 8 with final conclusions presented in Section 9.

2 ECG SIGNAL CHARACTERISTICS

ECG is a time-series signal with a few millivolts of amplitude and a frequency of 0.01–250Hz (Webster 2010). An ECG signal comprises five major components, namely P, Q, R, S, and T. The R component can be easily differentiated from others due to its large amplitude compared to other components. A pseudo-random ECG signal is shown in Figure 1. The terminology used in this article for referring to ECG signal properties is provided below:

Component: A component of an ECG signal refers to the P, Q, R, S, and T peaks.
Feature: Features of ECG refer to its inherent characteristics such as time period, amplitude, and width. For instance, the RR interval can be seen as a feature; similarly, the width of the QRS complex or the amplitude of the R peak.
Heartbeat: A heartbeat is an ECG signal starting from the present P component to the succeeding P component (1 cycle).

We describe the utilized medical terms (in the box) followed by how different components of the ECG signal are generated.

For a better understanding, we present the basic architecture and composition of the heart and the used taxonomy here. The heart comprises four chambers, two upper atria (chambers that receive the blood) and two lower ventricles (chambers that discharge the blood). The upper atria and lower ventricles are linked through atrio-ventricular valves. Description of other terms used in this article are given below.

— *Chambers* in a heart refers to ventricles and atria.
— The *atrium* is the singular form of atria.
— *Valves* in a heart separate the chambers, i.e., one valve lies in between each atrium and ventricle.
— *Sino-atrial node* refers to the group of cells located in the wall of the right atrium, capable of producing the action potential (electrical impulse) that travels through the heart, resulting in the contraction of the heart.
— *Atrio-ventricular node* is responsible for the coordination of the electrical conduction system with the upper portion of the heart, i.e., the sino-atrial node's action potential is passed to the lower part of the heart through the atrio-ventricular nodes.
— *Depolarization* (in biology) refers to a shift in the charge distribution in the cell. Depolarization results in a less-negative charge.
— *Atrial depolarization* refers to the depolarization process in the atrium chambers, resulting in the P component in the ECG.
— *Cardiac cycle* refers to the sequence of mechanical and electrical events happening in the heart that repeats with every heartbeat. It includes two phases: relaxation (diastole) and contraction (systole).
— *Systole* is the contraction of the cardiac muscles in response to electrochemical stimulus in the heart.
— *Diastole* refers to the part of the cardiac cycle during which the blood is filled into the heart. This phenomenon is observed as the physical relaxation of the chambers of heart.
— *Ventricular diastole* is the period during which the ventricles fill the blood and are relaxing.
— *Fusion beats* occur due to simultaneous action of impulses generated from different sources acting on the same region of the heart. If this phenomenon occurs in the ventricular chambers, then it is termed *ventricular fusion beat* and, similarly, an atrial fusion beat is the result of colliding impulses in the atrial chambers.

The state of the heart is generally reflected in the morphology of the ECG signal and the heart rate. Different components of the ECG signal originate from different parts of the heart, as discussed below (Zheng et al. 2013; Braunwald et al. 2011).

— *P component* is formed during atrial depolarization when the electrical wave propagates from the sino-atrial (SA) node to the atrio-ventricular node, spreading from the right atrium to the left atrium (Wagner and Marriott 2013).
— *QRS complex* is formed due to the depolarization of the right and left ventricles. Due to the higher mass of the ventricles compared to the atria, the amplitude of the QRS complex is larger.
— *T component* is formed during the repolarization phase of the ventricles. The ST segments reflect the time period for ventricles to repolarize after depolarization. During the normal state, the ST segment is isoelectric. The period post T component or wave is called the relative refractory period.

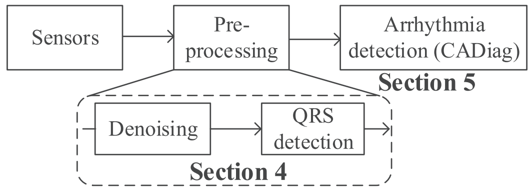

Fig. 2. ECG arrhythmia detection procedure.

While making a diagnosis, most of the medical experts take into account the following features: the relative positions of the components, magnitudes, morphology, and other derived interval features such as the PR interval, the PR segment, the width of the QRS complex, the QT interval, and the ST segment (Chakroborty 2013; Braunwald et al. 2011). As such, the volume of required data for an efficient ECG analysis is enormous. The possibility for a medical analyst to miss (or misread) the vital information is high (Ceylan and Özbay 2007). Arrhythmia detection with the aid of CADiag is performed in two steps, shown in Figure 2 and described below:

(1) Extraction of components in ECG signal.
(2) Analysis of features for the extracted components for arrhythmia detection.

Before discussing the pre-processing and arrhythmia detection, we provide a brief overview of some kinds of arrhythmias in next section.

3 ARRHYTHMIAS IN ECG

The heart rate, i.e., the rhythm of the heartbeat, can be normal, fast, or slow. Heart rate together with other morphological characteristics (including spatio-temporal relations between different components) are taken into account to diagnose an arrhythmia. Any false diagnosis followed by treatment can be fatal. An overview of different arrhythmias is presented in this section. It needs to be noted that the details are provided considering a normal healthy adult. The diagnostic features may vary with age, gender, and race. An illustration of arrhythmias is given in Figure 3.

Figure 3 depicts different kinds of arrhythmias, and a summary of the arrhythmias is listed in Table 1. Some of the common arrhythmias that are widely researched are ventricular fibrillation (VF) and premature ventricular contractions (PVCs), whose characteristics are described below. VF is one of the most commonly identified arrhythmias responsible for sudden cardiac arrests. It is often challenging to perform accurate detection of VFs in an ECG signal. Ventricular fibrillation and ventricular tachycardia look similar in an ECG signal, and an efficient classification leads to better treatment and improves survival rate of the patient (Joo et al. 2010). Asystole is the medical condition where there is no cardiac electrical activity, and medical practitioners use this condition to certify clinical death.

Ventricular Premature Beats (VPB) or PVC results in premature contraction of ventricles during the ventricular diastole (Ayub and Saini 2011). The morphology of PVC changes from person to person and with activity, and hence no specific characteristics exist (Goldberger and et al. 2000). PVC could be identified from ECG with one or more of the following symptoms (Shan-xiao et al. 2010):

— P component is misplaced or not present in the ECG signal.
— The QRS complex is widened and distorted with duration greater than or equal to 0.12 seconds and looks bizarre.
— The directions of the T-wave and QRS complex are paradoxical (opposite in direction).
— There might exist a complete compensation pause.

Consecutive PVCs could result in cardiac arrests and can be fatal.

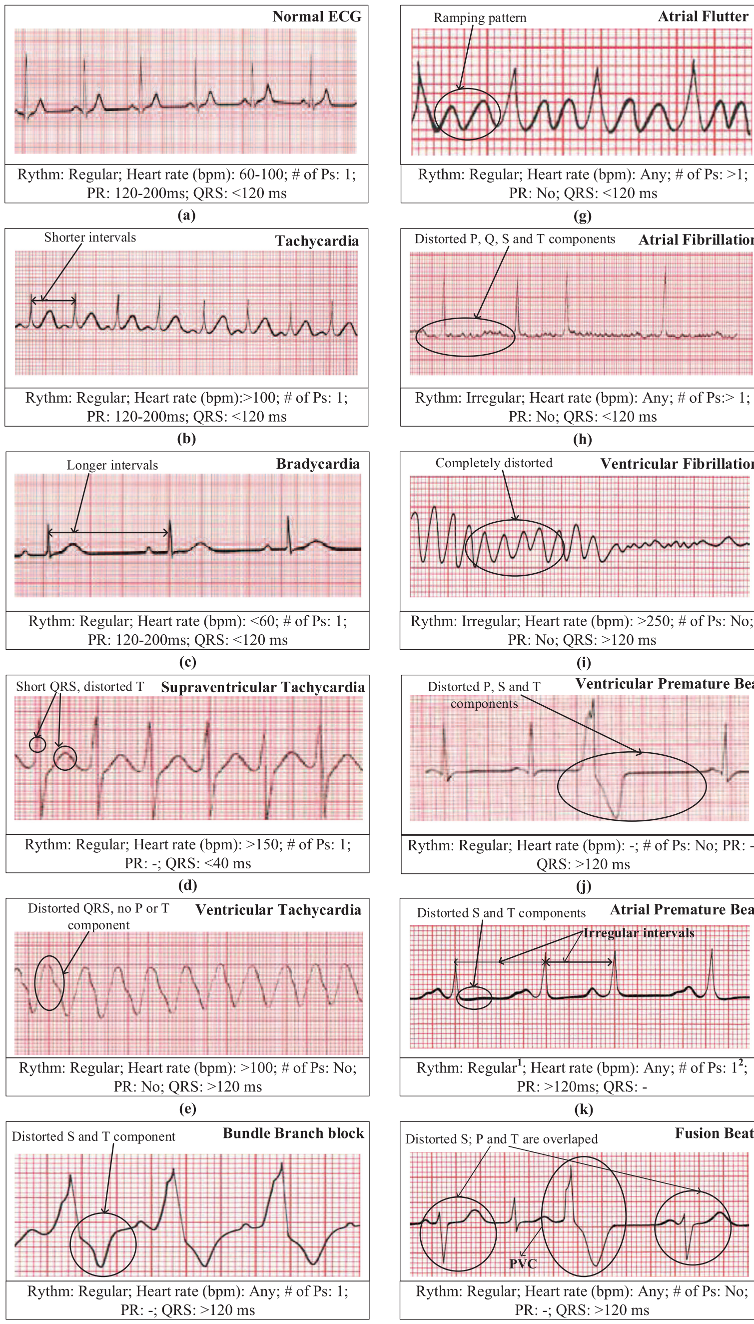

Fig. 3. An illustration of different arrhythmias (Thaler 2015): (a) normal ECG; (b) tachycardia; (c) bradycardia; (d) supraventricular tachycardia; (e) ventricular tachycardia; (f) bundle branch block; (g) atrial flutter; (h) atrial fibrillation; (i) ventricular fibrillation; (j) ventricular premature beat; (k) atrial premature beat[1,2]; (l) fusion beat.

Table 1. Arrhythmias and Their Characteristics

Arrhythmia	Rhythm	Heart rate (bpm)	# of P components	PR (ms)	QRS (ms)
Normal	Regular	60–100	1	120–200	<120
Bradycardia	Regular	<60	1	120–200	<120
Tachycardia	Regular	>100	1	120–200	<120
Supraventricular tachycardia (SVT)	Regular	>150	1	—	<40
Ventricular tachycardia (VT)	Regular	>100	No	No	>120
Ventricular fibrillation (VF)	Irregular	>250	No	No	>120
Atrial fibrillation (AF)	Irregular	Any	>1	No	<120
Bundle branch block (BBB)	Regular	Any	1	—	>120
Atrial Premature Beat (APB)	Regular[a]	—	1[b]	>120	—
Atrial flutter	Regular	Any	>1	No	<120

[a]The rhythm is regular but can as well be irregular depending on the sub-category of APB.
[b]P waves may be present or distorted, depending on the sub-category.

4 ECG DATASETS AND EVALUATION METRICS

4.1 ECG Database for Evaluation

Although ECG signals are captured in a non-invasive manner, to adhere the ethical aspects, most of the works use the ECG signals from existing database records. The most commonly used databases for evaluating the ECG signals are the following: MIT-BIH database (Moody and Mark 2001), Creighton University Ventricular Tachycardia database (FM et al. 1986), PhysioNet (Goldberger et al. 2000), American Heart Association (AHA) database (ECRI 2003), UCI Arrhythmia dataset (Dheeru and Karra Taniskidou 2017), and European ST-T ECG database (Taddei et al. 1992). Each of these databases has a large number of records with some of them being clearly annotated. Most of these datasets are available in PhysioNet (Goldberger et al. 2000). For instance, the UCI Arrhythmia database (Dheeru and Karra Taniskidou 2017) has around 450 well annotated records, and the MIT-BIH database (Moody and Mark 2001) has a large number of records (>1,000) that covers all the different kinds of arrhythmias. Furthermore, there exists an option to download the tool and create a dataset for the required arrhythmia(s) with a desired amount of time in Goldberger et al. (2000).

4.2 Evaluation Metrics

The parameters used for evaluating arrhythmia detection performance are accuracy, sensitivity, and specificity. Accuracy is defined as the total number of true values (positives and negatives) among the total number of samples. Sensitivity is the ratio of the number of true positives to the total number of samples classified as positive (total number of true positives and false negatives). Specificity measures the amount of negatives that are correctly identified. This can also be defined as the percentage of normal beats identified as normal.

5 COMPONENT EXTRACTION IN AN ECG SIGNAL

Component extraction has to be performed for ECG analysis. The components in an ECG signal are extracted by employing different techniques. The QRS complex is the most widely extracted component, based on which other components could be extracted. QRS extraction techniques involve two major steps: *QRS enhancement* followed by *QRS detection*. Enhancement is applied for

QRS complex with respect to other features such as P and T components. Some research works term this as *pre-processing*.

One of the oldest techniques for ECG component detection with low computational complexity is amplitude thresholding (Morizet-Mahoudeaux et al. 1981). The major drawback is its inability to remove noise. Thresholding with first-order derivatives has been tested (Okada 1979) and is proven to effectively remove artifacts (Zhang et al. 2007), but it fails to remove high-frequency noise. Some research works have applied the first-order derivative combined with a second-order derivative of an ECG signal, succeeded by thresholding (Ahlstrom and Tompkins 1983); however, the signal noises are not completely filtered. Digital filters are applied for QRS detection with effective noise removal. The most widely used QRS detection technique, that by Pan and Tompkins (1985), uses a band-pass filter followed by first derivative and threshold. Some other techniques include Hidden Markov model (Cost and Cano 1989), matched filters (Kaplan 1990), Fast Fourier transform (FFT) (Tsai et al. 1990), QRS enhancement in filter banks (Afonso et al. 1995), Hermitian transform (Lagerholm et al. 2000), the zero crossing technique by Köhler et al. (2003), wavelet transform (Alesanco et al. 2003), discrete wavelet transform (DWT) (Prasad and Sahambi 2003), wavelet transform succeeded by neural networks (Shyu et al. 2004), principle component analysis (PCA) (Jiang et al. 2005), mathematical morphology–based filtering by Yongli and Huilong (2005), empirical mode decomposition (EMD) (Tang et al. 2008), Hilbert transform (Arzeno et al. 2008), and EMD followed by singularity and thresholding (Xing and Huang 2008).

Detecting R waves with a fixed threshold is less complex in ECG signals, especially when the ECG signal has a normal morphology (Elgendi et al. 2014). In case of arrhythmias, and noise effects, adaptive threshold-based component detection has proven to be efficient with less probability of misdiagnosis (Elgendi et al. 2014; Rabbani et al. 2011; Madeiro et al. 2007; Köhler et al. 2003). The Hilbert transform aids in differentiating the dominant peaks from other peaks, i.e., it finds the R peaks effectively; however, they tend to fail if the R peaks have low amplitudes (Köhler et al. 2003). According to Rodriguez et al. (2015a), a combination of Hilbert transform and the adaptive threshold has a significant effect on the detection of QRS. Some of the widely used QRS detection techniques are summarized in Table 2.

Analysis and Summary of QRS Detection Techniques

By observing different QRS detection techniques, we could deduce the following:

— Simple thresholding technique is not accurate for QRS detection, especially in the presence of noise.
— Noises like baseline wandering and artifacts impact the effectiveness of QRS detection.
— Adaptive thresholding with the aid of derivatives (and filters), such as the Pan-Tompkins technique (Pan and Tompkins 1985), improves QRS detection capabilities. Even the recent works on QRS detection employ adaptive thresholding.
— Transformation techniques with adaptive thresholding like DWT, although requiring more computations than simple adaptive thresholding, are relatively more accurate for QRS detection and suitable for high accurate detection systems.
— From the hardware implementation perspective, algorithms like the Pan-Tompkins algorithm and DWT can be adopted relatively well due to their low complex computations and use of standard hardware components.
— The pre-processing (QRS) detection is computationally expensive compared to the arrhythmia detection in many of the proposed works and determines the overall accuracy of arrhythmia detection.

As the major focus is on arrhythmia detection and, furthermore, as very limited works focus solely on QRS detection, we provide the arrhythmia detection performance for various techniques

Table 2. QRS Detection in an ECG Signal

Technique	Process	Note	Source
Amplitude threshold and derivative	Amplitude threshold succeeded by the first derivative	Fails to remove high-frequency noise	(Rodriguez et al. 2015a; Thakor et al. 1990; Morizet-Mahoudeaux et al. 1981)
	First derivative of ECG and the threshold	Reduces baseline drifts and motion artifacts	(Rodriguez et al. 2015a), (Okada 1979)
	First derivative combined with the second derivative of ECG, followed by the threshold		(Ahlstrom and Tompkins 1983)
Digital filters and threshold	Bandpass filter on ECG followed by its first derivative and adaptive threshold	Can increase SNR	(Pan and Tompkins 1985)
Mathematical morphology filtering and threshold	Mathematical morphology filtering followed by a threshold		(Yongli and Huilong 2005)
Hilbert-Huang transform and threshold	Empirical mode decomposition (EMD) filtering	Filters out noise, improve SNR	(Tang et al. 2008; Arzeno et al. 2008)
Filter banks		Significantly improves SNR for Gaussian noise and muscle noise compared to median or mean averaging	(Afonso et al. 1999; Afonso et al. 1995)
Wavelet transform	Wavelet transform with adaptive threshold	SNR can be improved by selecting coefficients with the largest amplitude	(Alesanco et al. 2003)
Matched filters	Correlation between input ECG and one or more samples ventricular complexes		(Kaplan 1990)
Syntactic method		Sensitive to noise	(Trahanias and Skordalakis 1990)
Structural analysis	Wavelet transform to ECG followed by neural networks	Neural networks are highly sensitive to noise (Clifford et al. 2006)	(Shyu et al. 2004)
	Wavelet transform and adaptive threshold	Reduces probability of missing QRS complex	(Elgendi et al. 2014; Burte and Ghongade 2012; Rabbani et al. 2011; Madeiro et al. 2007; Xu and Liu 2005; Köhler et al. 2003; Li et al. 1995)
Hidden Markov Model		Sensitive to heart rate variation, baseline wander and noise	(Cost and Cano 1989)
Singularity method	Applied EMD filtering to an ECG and finding singularity of signal and thresholding	Sensitive to noise	(Ayat et al. 2009; Xing and Huang 2008)
Zero-crossing technique		Sensitive to noise	(Köhler et al. 2003)

rather than QRS detection here. In the next section, we present the arrhythmia detection techniques that fit CADiag.

6 DETECTION TECHNIQUES

Arrhythmia detection can be performed using morphological features as well as the ECG temporal properties such as time period (Dinakarrao and Jantsch 2018; Arif et al. 2009; Bortolan et al. 2005). In this work, we classify arrhythmia detection techniques as traditional and machine-learning-based approaches. Irrespective of the technique, the data used for arrhythmia detection are the morphological and/or temporal properties of the ECG signal. However, the considered morphology or temporal properties might change.

6.1 Traditional Methods for Arrhythmia Detection

One of the primary and efficient methods for arrhythmia detection (especially sinus arrhythmia) is heart rate variability (HRV) analysis. HRV analysis can be carried out in the time domain and frequency domain by performing traditional operations such as correlations and standard deviations on the derived statistical metrics such as the mean and the the variance of the ECG signal features. We review some of the most notable works.

6.1.1 Arrhythmia Detection by Analyzing Derived Time Domain Metrics. Analysis of derived statistical metrics of ECG signal such as variation in the mean of RR intervals, QRS widths, and so on, could be effective for arrhythmia detection. The main advantages of such approaches are the low complex computations and that analysis is performed directly on the signal. Time-domain analysis helps in assessing the severity of arrhythmia.

Arrhythmia detection using time-domain metrics can be classified in two ways: statistical and geometrical metrics-based analysis. In statistical metrics-based analysis, ECG signal features are directly extracted and analyzed to detect arrhythmia, whereas geometric metric-based methods mostly make use of techniques like histogram analysis, and so on, for arrhythmia detection; say, for instance, based on how often a component occurs in a window, arrhythmia could be estimated.

Conventional Statistical Metrics-based Arrhythmia Detection. Statistical metrics-based HRV analysis for arrhythmia detection makes use of metrics like duration of successive RR intervals and the corresponding derived statistical metrics (Electrophysiology 1996). Based on the variations in the RR intervals, multiple statistical parameters such as root mean square difference between RR intervals and the standard deviation of average duration intervals are derived, and arrhythmias are detected. In this case, the intervals between adjacent complexes or RR components represent the rate norm. Some of the basic statistical indicators of HRV are given in Table 3. Variations in these parameters indicate the presence of an arrhythmia.

Conventional Geometrical Metrics-based Arrhythmia Detection. HRV analysis to detect arrhythmia can as well be carried out using geometric metrics. Geometric metrics are derived by construction of the distribution density functions of RR intervals (histogram), and analysis of the parameters of its forms are widely used for geometric analysis of HRV, which include Mo (Mode) and Amo (amplitude mode) MxDMn (variation range), described in Table 4.

The main advantage of geometric metric-based methods is its insensitivity to the analytical quality of series RR intervals. However, it requires a reasonable amount of RR intervals to be recorded and considered (at least 20 minutes). The geometrical method of HRV analysis is uninformative in the presence of arrhythmias. Some other methods include minimum-distance classifiers (Chakroborty and Patil 2014). A drawback of arrhythmia detection using traditional time-domain metric-based methods is that the analysis for classification is performed on original (raw

Table 3. Basic Statistical Parameters for HRV Analysis

Parameter	Definition	Estimation
PNN50(%)	Adjacent RR intervals that differ by more than 50ms	Determined primarily by the influence of changes in the contractions of the heart muscles
RMSSD	Root mean square difference between RR intervals of neighboring beats	A measure of HRV between adjacent cycles
SDNN	Standard deviation of the average duration intervals	Integral indicator of the HRV as a whole
SDANN	Standard deviation of the mean of RR intervals calculated every 5 min	It is a measure of the HRV for large number of cycles

Table 4. Basic Geometric Parameters for HRV Analysis

Parameter	Definition
Mode (Mo)	Most often recurring value in a dynamic series (cardio interval value and peaks)
Variation range	Degree of variation of RR-interval values in the investigated dynamic row

or partially pre-processed) data, which have a larger dimensionality and comprises irrelevant or non-useful data for analysis (Strauss et al. 2001).

6.1.2 Arrhythmia Detection with Frequency Domain Metrics. Analysis of ECG signal with derived frequency-domain metrics is an alternative for arrhythmia detection. In this method, frequency properties of the signal are studied (Electrophysiology 1996). The frequency composition of the heart rate can be represented in a graph with power distribution vs. frequency, i.e., power spectral density (PSD), by which it is possible to judge the severity of frequency components in the range of very low frequency (VLF: <0.04Hz), low frequency (LF: 0.04–0.15Hz), and high frequency (HF: 0.15–0.4Hz). Total power in different bands and normalized total powers are used to evaluate the performance.

Classical methods of spectral analysis are widely used for arrhythmia detection because of the ease of algorithms used (in most cases, FFT), high processing speed, the reliability of the analysis results, and ease of implementation with standard hardware units. The advantages of employing methods such as FFT are their simplicity and high computational speeds. However, they suffer from statistical instability in the results.

Autocorrelation-based Arrhythmia Detection. Calculation and construction of the autocorrelation function of the RR intervals aim to study the internal structure as a random process. Calculation and construction of the autocorrelation function (ACF) of the dynamic series of RRintervals aim to study the internal structure of this number as a random process. The correlation coefficient after the first shift is small (typically less than 1), as respiratory waves are big. If there exists a domination of slow wave components, then the correlation coefficient C1 is slightly smaller than 1, and subsequent developments lead to a gradual decrease in the coefficient value. The ACF provides an indication of the latent periodicity of heart rhythm (Jekova 2000).

Autocorrelation functions (ACF95 and ACF99) (Jekova 2000; Chen et al. 1987) are used to analyze the periodicity within the ECG signal and the power spectrum (Lee et al. 2016). A linear regression of ACF peaks is carried out to detect arrhythmias. Based on the detected period and the regression errors, normal sinus rhythms and VFs are classified. However, the performance and accuracy achieved with this technique are questionable as VFs might have cosinelike shape (Amann et al. 2005).

Arrhythmia Detection Using Correlation Coefficients. In contrast to other techniques, in Hsia et al. (1986), an ECG analysis for arrhythmia diagnosis was performed with a gamma camera that has the capability to diagnose radionuclide ventriculography. Each beat is assigned with the measured RR interval and waveform analysis of the underlying rhythm. To overcome the baseline wandering effects, a new correlation coefficient-based arithmetic is utilized in Hsia et al. (1986). Prior to ST segment analysis, averaging of normal beats is performed to improve the signal-to-noise ratio (SNR). The ST level and slope measurements are automatically computed by averaging the signal data for arrhythmia detection.

6.1.3 Graphical Analysis for Arrhythmia Detection. The graphical analysis could as well be performed for detecting arrhythmias. One such method is Scatterogram (Suyama et al. 1993). Scatterogram provides a graphic image of a plurality of adjacent pairs of RR intervals in a 2D coordinate system. This graph provides information about the nature and patterns of a rhythm. The scatterograms are plotted with R-R$_n$ on the abscissa and the R-R$_{n+1}$ on the ordinate axis. Here R-R$_n$ represents the nth RR interval value. A bisector is formed at the center based on the formed set of points. The shift point of bisector to the left indicates that the values of RR intervals are shorter than the previous cycles and a right shift indicates the opposite condition. In practice, the length of the cloud, width, and area are major indicators used to analyze a scatterogram.

6.1.4 Arrhythmia Detection with Filtering. In addition to the use of filters for pre-processing, filters could also be employed for arrhythmia detection, and a few are discussed here.

Spectral Analysis for Arrhythmia Detection with Kalman Filter Identifier. Spectral analysis is used to study various types of cardiac arrhythmias. The time-varying RR-interval spectra could be filtered using the Kalman filter, and any disturbances that are observed beyond the filtering indicate arrhythmia. The amplitude of disturbance could be used to deduce arrhythmia (Szilagyi 1998).

Discrete Wavelet Transform Coefficients Threshold. The DWT is one of the most widely used techniques for extracting the features of an ECG signal (Sahoo et al. 2015; Selvakumar et al. 2007). Feature extraction is one of the important applications of wavelet transforms (de Chazal et al. 2004). The morphological features such as the QRS complex and R-peaks can be used for classification of normal and arrhythmia pattern in an ECG signal. These can be extracted using DWT.

Similarly, in Amann et al. (2005), a WT-based ECG arrhythmia classification is proposed. Ventricular fibrillation is detected using discrete wavelet transform in two steps. DWT with 12 scales and a Daubechies wavelet is applied to find QRS complexes; the threshold is set to 0.14max in Amann et al. (2005). If the value of the signal in the third scale crosses a threshold, then the corresponindg ECG part is considered a QRS complex. If more than two and fewer than 40 QRS complexes are found within an 8s window, then "no VF" is diagnosed.

Performances of different traditional techniques described above are provided in Table 5. The accuracy and other performance indicate the accuracy of arrhythmia detection and classification from normal ECG signal. The methods listed in Table 5 are able to detect normal beats, hence not explicitly mentioned, unless needed.

Analysis and Summary on Arrhythmia Detection by Traditional Methods

The following conclusions can be derived from the above-discussed works:

— Frequency-domain-based ECG signal analysis helps in deriving conclusions about arrhythmia based on the energy spectrum and related parameters. Frequency-domain analysis is robust compared to time-domain metrics-based analysis but requires relatively more computations or operations.

Table 5. Arrhythmia Detection Using Traditional Methods (Grouped According to Class of Arrhythmia)

Technique	Performance parameters			Detected	References
	Accuracy	Specificity	Sensitivity		
Threshold crossing (Thakor et al. 1990)	77.20–83.60%	77.50–84.40%	75.00–75.10%	VF	(Amann et al. 2005)
		75.00%	98.00%		(Jekova 2000)
Spectral analysis (SPEC)	93.80%	99.90%	29.10%		(Amann et al. 2005)
		93.00%	79.00%		(Jekova 2000)
Complexity measure algo.	89.2%	92.00%	59.20%		(Amann et al. 2005)
		75.00%	66.00%		(Jekova 2000)
Standard exponential algo.	79.00%	81.70%	50.10%		(Amann et al. 2005)
Modified exponential algo.	81.30%	84.10%	51.20%		(Amann et al. 2005)
Signal comparison algo.	96.20%	98.50%	71.20%		(Amann et al. 2005)
Autocorrelation (ACF_{95})		32.00%	78.00%		(Jekova 2000)
	49.00%	49.00%	49.60%		(Amann et al. 2005)
Autocorrelation (ACF_{99})	37.90%	35.00%	69.20%		(Amann et al. 2005)
Tompkins algorithm	45.00%	40.60%	92.50%		(Amann et al. 2005)
Wavelet transform and filtering	93.50%	99.70%	26.70%		(Amann et al. 2005)
Li algorithm (based on wavelet analysis)	86.60%	93.90%	9.00%		(Amann et al. 2005)
VF Filter algo.	93.00–93.10%	99.90–100.00%	18.80–19.60%		(Amann et al. 2005)
		91.00%	94.00%		(Jekova 2000)
	68.00%			16 arrhythmias	(Güvenir et al. 1997)
DWT			90.54–93.24%	SVT, VT, VF, V. Flutter	(Selvakumar et al. 2007)
Regularity measurement dubbed blanking variability	95.00%			VF, VT	(Clarkson et al. 1995)
Bi-spectral analysis		83.3–100.00%	81.8–100.00%	AF, VT, VF	(Khadra et al. 2005)
Teager Energy operator (TEO)			99.00%	PVC	(Sharmila and Reddy 2014)

- However, these methods lack stability and are sensitive to noise and artifacts, and the amount of data required to obtain or derive the metrics is large.
- As there are no standard values available for the mentioned parameters, it needs to be calculated for the patient and is not efficient, especially when there exists a large number of irregularities or very few irregularities in the ECG signal.
- Methods like auto-correlation and filtering, which are widely used for determining time periods and noise removal, could also be used for arrhythmia detection, as they outperform some of the traditional metric-based arrhythmia detection techniques.
- Based on achieved performance in arrhythmia detection using the derived metrics, it could be observed that the traditional methods including filtering and auto-correlation are inefficient in terms of performance and are fatal, especially in health-care applications.
- The performance with traditional methods have a large variation, indicating that these techniques are more prone to noise and other kind of fluctuations.
- Additionally, most of these methods focus on detecting very few or single arrhythmia(s). This inidcates that metric-based methods are not a generic potential arrhythmia detector.

However, with the advancements achieved in machine learning (ML), sophisticated and efficient techniques for arrhythmia detection is made possible with ML.

6.2 Application of Machine Learning for Arrhythmia Detection

Signal analysis or data analysis can be automated to make the analysis more efficient and faster with the aid of machine learning. Machine learning is widely employed in various applications (Pagani et al. 2019), and bio-signal analysis is no exception. Machine learning in the context of bio-signal analysis and arrhythmia detection is well researched. We present some of the existing major contributions here. Please note that the details of ML techniques are not presented, but their application in the context of arrhythmia detection is discussed.

6.2.1 Arrhythmia Detection with Neural Networks. Artificial neural networks (ANN) (Anderson 1995; Lippmann 1987) are inspired by the mammalian brain architecture. A basic neural network comprises at least three kinds of layers: an input layer, one or more hidden layers, and an output layer. In a fully connected neural network, all nodes in a succeeding layer are connected to all the nodes in the preceding layer. Each node has input, on which the activation function is applied to obtain outputs. Different layers could have different activation functions. Numerous variants of neural networks exist and the notable works in the context of arrhythmia detection is presented below (Wess et al. 2017; Ince et al. 2009; Jiang and Kong 2007).

Feedforward Artificial Neural Network (FfANN). ANN are one of the most widely used techniques to detect and classify arrhythmias. A vast amount of techniques using feedforward ANN with variations has been published (Adams and Choi 2012). Feedforward neural networks (FfNN) are a class of ANNs with the dataflow always from the input layer toward the output layer, i.e., only in forward direction. For arrhythmia detection, the ANN is often preceded by the pre-processing stage. Noises and ectopic beats are removed in the pre-processing stage. Depending on the type of arrhythmia to be detected, corresponding features are used as input for the neural network. To detect a wide range of arrhythmias, training the neural network with morphology and the features of ECG is the best option.

One of the first known works on arrhythmia detection is by Devine and Macfarlane (1993), in which feedforward ANNs are used to detect left ventricular strain by detecting the ST segment abnormalities of the ECG. Hu et al. (1993) proposed the use of ANN for QRS detection and classification. Mult-layer perceptron (MLP) is used to model the background noise and amplify the QRS complex toward enhanced beat detection and classification.

As mentioned, FfANNs are applied in arrhythmia detection, and some of the recent works are presented below. For predicting ventricular tachycardia, ANN trained with statistically derived metrics such as RR interval, meanNN, SDNN, RMSDD, and pNN50 (refer to Table 3) is proposed in Joo et al. (2010). The major hurdle in this methodology is that handling the amount of data to derive these metrics is difficult. In Asl and Setarehdan (2006), a combination of linear and nonlinear features of ECG, especially HRV, is provided as input for ANN for ECG classification. Time domain and frequency domain-based nonlinear methods are applied in Asl and Setarehdan (2006) to extract the features of ECG and are fed to ANN classifier for ECG arrhythmia detection. The implementation in Asl and Setarehdan (2006) detects and classifies up to five different arrhythmias. This implementation can be effective even when the training dataset is small. This architecture utilizes the features of the ECG and HRV metrics to derive conclusions on arrhythmias. This makes the system prone to noise if the neural network does not offset the effects of noise.

In Inan et al. (2006), the wavelet and timing features of the ECG data are used to train the neural network for classification purpose. Dyadic wavelet transform with quadratic spline wavelet is employed with RR-interval ratios for enhanced PVC detection. This implementation is efficient for PVC detection; however, the resources and computations needed are high. Similarly, the DWT coefficients are fed to the ANN for classifying arrhythmias in Arumugam et al. (2009), and up to three arrhythmias can be detected. The amount of information to be derived from the ECG signal for arrhythmia detection is smaller.

Increasing the number of layers leads to improved performance, and as such arrhythmia detection with multiple layers is as well utilized. A multi-layer feedforward neural network with back propagation learning is proposed in Adams and Choi (2012) that classifies up to 6 classes (1 normal and 5 arrhythmias). It achieved an error of 1.4% over the entire analyzed data. This multi-layer approach though achieves decent accuracy, the number of inputs needed is high, which leads to a large number of computations. To overcome the problem of having a large number of inputs for the neural network, a reduced set of ECG features (from 17 to 4) using linear discriminant analysis (LDA) is fed to FfNN for arrhythmia detection, as proposed in Lee et al. (2005). This technique outperforms PCA-based feature reduction-based implementation. This can detect SVTs, PVCs, VFs, and normal rhythms. This enjoys the benefit of a smaller number of inputs, i.e., small NN architecture, but demands efficient and careful pre-processing, especially LDA.

In addition to temporal features, morphological features could as well be utilized for arrhythmia detection. Morphological features such as average heart rate and energy contained in different bands (33.3–100Hz, 66.7–100Hz), the correlation dimension factor, are used as inputs for the ANN and with the aid of a fuzzy equivalence classifier, arrhythmia detection is proposed in Acharya et al. (2003). Data storage, i.e., memory, is one of the bottlenecks for arrhythmia detection using ECG morphology. A cascade feedforward (FF) network with *trainbfg* training algorithm was implemented in Ayub and Saini (2011) that achieves 99.9% accuracy with low memory requirements. A radial basis function NN (RBFNN) for detecting five different arrhythmias is proposed in Rai et al. (2012).

Modular Feedforward Neural Network. To facilitate reusability and replicability of the neural networks, especially on hardware, modular FF neural networks are proposed. A modular neural network for classifying the ECG signal as normal and abnormal, i.e., arrhythmia detection is proposed in Jadhav et al. (2010a). Some of the missing attributes from the database (Lichman 2013) are replaced by the approximated or closest column value of the concerned class. Although the missing data are restored, there is a large scope to improve the learning methodology in neural networks. A modular generalized FF neural network (GFNN) trained with static back propagation algorithm to classify ECG as normal and arrhythmia is proposed in Jadhav et al. (2010b).

Block-based Neural Network. To enjoy the benefits of block-based architectural design, parallel processing, and modular structures in FPGAs, block-based neural networks are introduced. A block-based neural network (BbNN) (Moon and Kong 2001) is a two-dimensional (2D) array of neural network blocks with flexible configurations and structures (varying the number of input and outputs and so on) and integer weights. This can be implemented with less complexity on digital hardware such as FPGAs and ASICs. In general, the BbNNs are trained using evolutionary algorithms such as generic algorithms (GA). Hermite basis functions are one of the efficient feature extraction methods for ECG signals (de Chazal et al. 2004). The coefficients of Hermite expansions characterize the morphology of ECG signal, i.e., the shape of QRS complex. A BbNN with morphological features and temporal properties of ECG, i.e., Hermite expansion coefficients and RR intervals as inputs is proposed for arrhythmia detection and classification in Jewajinda and Chongstitvatana (2010) and Jiang and Kong (2007). However, in Jewajinda and Chongstitvatana (2010), an online updating mechanism for weights is incorporated. A multi-threaded training mechanism for a 4×4 BbNN is implemented in Nambiar et al. (2012).

Cartesian Genetic Programming Evolved Artificial Neural Network (CGPANN). Simple ANNs are limited in their precision and are often ambushed in local minima (Nambiar et al. 2012; Moon and Kong 2001). To address this, a Cartesian genetic programming–(CGP) based artificial neural network (CGPANN) is proposed in Ahmad and Khan (2012). In contrast to genetic programming, in CGP, the nodes and connections are arranged in form of a 2D graph. The number of nodes, connectivity, number of inputs and outputs per node, and height and width of the graph are the tunable parameters. In CGP, the genotype is an array of pre-specified length representing the node inputs, output genes, and activation functions. To form a CGPANN, the nodes of a CGP are replaced by neurons having nonlinear activation functions and weighted connections. ECG morphological features such as P-R interval, QRS width, R-peak amplitude, and other similar factors are used as an input for training and testing the CGPANN. The work in Ahmad and Khan (2012) uses CGPANN detects and classifies up to four arrhythmias. The classes of arrhythmias it can detect is smaller compared to the involved computational complexity and resources utilized.

Auto-Associative Neural Network. In neural networks, the overlap of data or properties and labels lead to different classification accuracies. Another drawback of neural networks is their long training time. To overcome the interaction of data with other classes, auto-associative neural network (AANN) is proposed. AANN learns in a non-discriminative manner. Non-discriminative learning helps in reducing the off-line training time. In contrast to the standard NN-based approaches (supervised learning), input data need not be accompanied with class labels or targets in AANN. In AANN, for each class, a separate AANN was trained, and weights of those networks are preserved for testing purpose. As such, an individual AANN has to be trained or designed to detect a particular arrhythmia with ECG features and morphology as the input. This could be efficient but resource intensive. An AANN-based arrhythmia detection is proposed in Chakroborty (2013).

Probabilistic Neural Network. Although back-propagation algorithms though utilize heuristics to discover underlying class, they suffer from computational delays, false minima, and lower classification accuracy. To surmount the drawbacks of back-propagation, a feedforward neural network forming the basis from Bayesian theory is introduced and termed as probabilistic neural net (PNN). This is as well employed for arrhythmia detection (Ghongade et al. 2014). Authors utilize 10 statistical characteristics for classifying 10 classes of heartbeats (arrhythmias): PSD, energy of the signal, amplitude of the R-peak, RR-interval duration, mean, distance between Q and S components, area under the QRS complex, R-S slope, the area under autocorrelation curve, and the singular value decomposition (SVD) value. Each beat is represented by these 10 features. This technique provides good accuracy with negligible training time. However, MLP-BPNN enjoys the benefits of consistency in training and with reduced iterations during testing. An identical work that is also based on Bayesian theory and logistic regression for arrhythmia detection is proposed in Gao et al. (2005).

Adaptive Wavelet Network. An extension of probabilistic neural networks is adaptive wavelet networks (AWN). In AWN, adaptive wavelets are used to derive the correlations based on which the classification is performed. An AWN-based ECG anomaly detection is proposed in Lin et al. (2005). It consists of two stages: wavelet layer and an adaptive PNN. Features of the heartbeat are extracted in the wavelet layer using Morelet wavelets. These wavelet coefficients represent the similarity measure of the signal and the wavelet under different dilation and translation parameters. This layer is robust in detection but not capable of recognition. This is followed by probabilistic neural network layer(s) for recognition of the beats, i.e., normal, arrhythmias. In architecture, it is composed of wavelet nodes, followed by a hidden summation and output layers. The inputs can be binary or continuous signals (Specht 1988). It performs well under dynamic conditions with supervised or unsupervised learning.

Wavelet Neural Network. Wavelets can be seen as a matching function to identify a set of patterns. A wavelet neural network (WNN) is proposed in Ceylan and Özbay (2011) with wavelets as the activation functions. Morlet and Mexican hat wavelet functions are widely selected for experimenting, and ANN with Mexican hat wavelet function outperforms Morlet activation function-based ANN in terms of classification accuracy (Ceylan and Özbay 2011). In Ceylan and Özbay (2011), ECG signals are first filtered using low-pass and high-pass filters. The RR intervals are provided as inputs and training data for the NN. This work can classify bundle branch blocks (BBB) and normal beats. It is stated that with the increase in a number of beats used for training, the accuracy can be improved. Though the wavelet functions can be fine-tuned, the number of arrhythmias that could be detected are dependent on the wavelet properties in the hidden nodes.

Sparsely Connected RBF Neural Network. The activation functions used in previously mentioned techniques are more generic and can be applied widely. Using a Gaussian distribution function when the input follows a Gaussian distribution yields better results (Husain and Fatt 2007). Additionally, fully connected neural networks demand more computations. A sparsely connected radial basis function neural network (RBFNN) is proposed in Husain and Fatt (2007). In contrast to fully connected RBFNN, sparsely connected RBFNN has fewer connections. This lowers the computation costs, and an increase in classification accuracy is observed. By providing the features of the ECG signal, arrhythmia detection can be performed.

Elman Neural Network. In all the previously described neural network architectures, there exists no information on context nor previous state. Elman network consists of an additional delay element facilitating the previous state of the hidden layer(s) as input to decide or calculate the succeeding feed-forward mapping process (Shukri et al. 2012). This state information helps to detect continuous irregular patterns with better accuracy. An Elman neural network implementation for ECG arrhythmia detection is proposed in Mohamad et al. (2013). In Mohamad et al. (2013), for ECG anomaly detection, there is a three-step process: pre-processing, processing, and classification is followed. For pre-processing, median filter and moving average filters are used to remove high-frequency noises, smooth the signal and eliminate the jagged edges. This is followed by principal component analysis for reducing the features to save the computation costs. The reduced feature set is provided as input to the Elman neural network to detect arrhythmias. The major bottleneck in the Elman neural networks is the memory requirements, especially when the number of states to remember are high.

Performances of different neural network implementations for arrhythmia detection and classification is presented in Table 6. The accuracy determines the accuracy of classification of different arrhythmias compared to normal heartbeats.

Analysis on Arrhythmia Detection Using Neural Networks
Neural networks are one of the widely employed machine-learning techniques for different applications, including ECG arrhythmia detection. Based on the presented works and the achieved performances for arrhythmia detection using neural networks, we derive the following conclusions:

— Artificial neural networks (ANN MLP, or FfNN) with back-propagation learning is the most commonly used and achieved good accuracy for arrhythmia detection but is efficient only if the number of kinds of arrhythmias to detect are small.
— For better suitability to hardware platforms such as FPGA, block-based neural networks are widely deployed due to its modular structure.
— Sparsely connected neural networks can be used as an alternative when the system has been constrained on the number of computations that can be performed or energy efficiency is one of the optimization goals.

Table 6. Arrhythmia Detection Using Neural Networks and Their Variants (Grouped According to Neural Network Variant)

Technique	Performance parameters			Detected	References
	Accuracy	Specificity	Sensitivity		
FfNN(ANN MLP)	98.60%			5 different arrhythmias	(Adams and Choi 2012)
	56.00-100.00%			6 different arrhythmias	(Jadhav et al. 2010c)
	88.10%	89.70%	86.70%	Normal, abnormal	(Leutheuser et al. 2014)
	88.24%			16 different arrhythmias	(Raut and Dudul 2008)
	66.00%	72.00%	58.00%	VT	(Hoher et al. 1995)
	76.60%	71.40%	82.90%	VT	(Joo et al. 2010)
	98.53-99.98%	99.15-100.00%	90.00-100.00%	PVC, AF, VF, heart block	(Asl and Setarehdan 2006)
		82.10%	80.70%	PVC	(Bortolan et al. 2005)
	82.35%	89.13%	68.18%	Normal, abnormal	(Jadhav et al. 2010b)
	90.40±9.6%	90.20±9.8%	90.30±9.7%	Normal and abnormal	(Ramirez et al. 2010)
	98.80%	99.70%	98.84%	Tachycardia, LBBB, RBBB, PVC	(Rai et al. 2012)
Discrete wavelet with ANN	96.50%			PB, APB	(Sarkaleh 2012)
Wavelet decomposition with FfNN			86.67−100%	VT, VF, V. Flutter	(Arumugam et al. 2009)
Cascade FfNN	99.90%			Fusion beats, VPB, unclassified	(Ayub and Saini 2011)
FCM-PCA-NN	99.09%			10 different arrhythmias	(Ceylan and Özbay 2007)
Modular ANN	82.22%	82.76%	81.25%	Normal, abnormal	(Jadhav et al. 2010a)
BbNN	97.50-98.80%	98.80-99.40%	74.90-94.30%	Ventricular, SV ectopic beats	(Jiang and Kong 2007)
	99.64%			Normal, abnormal	(Nambiar et al. 2012)
Auto-associative NN	95.62-99.35%			LBBB, RBBB, PVC, APC	(Chakroborty 2013)
RBFNN	64.87±0.53%	40±2%	70±3%	Normal, abnormal	(Gao et al. 2005)
	99.60%	99.90%	99.60%	Tachycardia, LBBB, RBBB, PVC	(Rai et al. 2012)
Sparsely connected RBFNN			75-100%	AF, Malignant ventricular entropy	(Husain and Fatt 2007)
Bayesian ANN	80.69±1.67%	15±2%	76±4%	Normal, abnormal	(Gao et al. 2005)
Probabilistic ANN	98.10%	99.78%	98.10%	10 different arrhythmias	(Ghongade et al. 2014)
Adaptive wavelet NN	>90.00%			5 different arrhythmias	(Lin et al. 2005)
Elman NN	>95.00%		87.50-99.90%	Cardiomyopathy, LBBB, RBBB	(Mohamad et al. 2013)
Genetic ANN		84.10%		6 different arrhythmias	(Waseem et al. 2011)
Quadratic NN	98.16%	97.60%	97.05%	APC, PVC	(Rodriguez et al. 2015b)

—Neural networks perform well when the number of arrhythmia types to detect and classify is smaller in number, say, five to six types.
—Neural networks outperform traditional techniques but are computationally complex.
—Techniques such as approximations can be deployed for improved hardware efficiency but can cost the accuracy of detection, which is crucial for health-care applications.

6.2.2 Arrhythmia Detection with SVM. SVMs are used for classification and regression analysis. An SVM builds a model based on the input data with labels such that it could be classified as clear as possible (as provided in labels). Here the label indicates the class or a group to which the input data belongs. Every new input is mapped to the corresponding category. SVMs operate on vectors rather than individual points, making them robust. We review most significant SVM-based arrhythmia detection works here.

Similarly to neural networks, features and morphological components are used as inputs for SVM. In Faziludeen and Sabiq (2013), an SVM-based classification is performed to differentiate normal rhythms from PVCs and (left) bundle branch blocks. The classification phase is with one-against-one (OAO) multi-class SVM. As OAO technique is employed and the number of output classes are three (normal, PVC, and BBB), three SVMs are designed, and a final grouping (classification) is done using the maximum voting technique as in Milgram et al. (2006). As using three SVMs is computationally intensive, it is non-trivial to evaluate its performance against other SVM methods. In Kohli et al. (2010), ECG classification using OAO SVM, one-against-all (OAA) and fuzzy decision function–(FDF) based SVMs are employed. The OAO SVM outperforms other two, and FDF performs poorly.

As the amount of input data for the purpose of classification is large and SVMs are computationally expensive, data reduction techniques such as PCA are employed in the preprocessing stage. In Imah et al. (2011), four different arrhythmias are distinguished from normal signals using SVMs. The process comprises data pre-processing, feature extraction, and classification with SVM. With the advancement in data reduction algorithms such as PCA and genetic algorithms, they are employed for processing ECG signals together with classification algorithms such as SVM. In Nasiri et al. (2009), a genetic algorithm is used in combination with SVM classifier for arrhythmia detection. This work is capable of distinguishing four types of arrhythmias. Overall classification accuracy of nearly 93.5% is achieved with SVM-genetic algorithm combination.

Although SVM genetic algorithms are a good learning methodology, the achieved performance is not satisfactory in health-care applications. Hence, a hybrid method of SVM called the holder-SVM detection algorithm is introduced in Joshi et al. (2009), which is designed to take care of the imbalance rampant in bio-signals with a hybrid arrangement of binary and multi-class SVMs. ECG classification is performed as follows: noise patterns are removed, followed by wavelet transform modulus maxima–(WTMM) based local holder exponents (LHE), which captures the hidden information in time series, and a few points with more information are calculated and then selected points are provided as inputs for multi-class SVM for classification. It is efficient in reducing false negative, i.e., patient falsely classifying as normal.

Transformation functions can be realized using simpler functions and as filters in hardware; hence, they are preferable candidates in combination with SVMs. A WT for feature extraction followed by SVM for arrhythmia classification is proposed (She et al. 2010). This method outperforms the ambulatory ECG (AECG) arrhythmia intelligent software (AIAS). It can classify normal beats, atrial premature beats, and premature ventricular beats.

We have presented most of the works on SVMs methodologies with more focus on classification part rather than preprocessing or signal analysis. A multi-resolution support vector machine (MR-SVM) is proposed in Zheng et al. (2013) for arrhythmia detection in ECG. This technique performs

Table 7. Arrhythmia Detection Using SVM (Grouped According to Variant of SVM)

Technique	Performance parameters			Detected	References
	Accuracy	Specificity	Sensitivity		
SVM	99.32%		99.32-99.71%	16 different arrhythmias	(Ye et al. 2012)
	98.91±0.12%	99.71±0.12%	94.91±0.33%	PVC beats	(Lashgari et al. 2013)
	77.00%	84.90%	72.00%	Normal, abnormal	(Leutheuser et al. 2014)
	90.80±1.5%	85.40±2.10%	98.20±1.20%	Normal, abnormal	(Ramirez et al. 2010)
OAO SVM	98.46-99.92%	97.80-99.97%	97.57-99.85%	LBBB, PVC	(Faziludeen and Sabiq 2013)
PCA with Linear SVM	92.00-97.50%			RBBB, LBBB, PVC, V. Fusion	(Imah et al. 2011)
MR-SVM	93.00%			normal, abnormal	(Zheng et al. 2013)
Multi-section vector quantization (OAA)	98.13%		97.80%	LBBB, RBBB, APC, PVC	(Chakroborty and Patil 2014)
Multi-section vector quantization (combined)	97.54%		97.86%	LBBB, RBBB, APC, PVC	(Chakroborty and Patil 2014)
PCA with Wavelet SVM	87.25-96.75%			RBBB, LBBB, PVC, V. Fusion	(Imah et al. 2011)
SVM with evolutionary learning	>93.00%			Tachycardia, LBBB, RBBB	(Nasiri et al. 2009)
Continuous wavelet transform with SVM	99.56%			VPC, APC	(She et al. 2010)
SVM with rejection option	89.20%			normal, abnormal	(Uyar and Gurgen 2007)

multi-resolution analysis (MRA) in signal processing and support vector (SVM) in data mining. First, extraction of T wave is carried out with the MRA by decomposing the original signal, i.e., data are transformed into coefficients by employing MRA. Second, these coefficients are fed to SVM for distinguishing normal and abnormal ST segments. A nice comparative study is presented in Ye et al. (2012).

ECG morphological features can also be used as an input for arrhythmia detection using SVMs. An ECG classification method based on dynamics and the morphological features is presented in Ye et al. (2012). Morphological features of the ECG signal are extracted with the aid of Wavelet transform and independent component analysis (ICA). Further, the temporal behavior is evaluated based on the RR-interval information. All this information together is provided to SVM with radial basis function (RBF) to perform classification.

Arrhythmia detection performance of different works that make use of SVM for arrhythmia detection is listed in Table 7.

Analysis on Arrhythmia Detection using SVM

SVMs are employed for the purpose of classification and regression in a variety of applications. SVMs are efficient when the datasets are labeled. Based on the existing works that use SVM for arrhythmia detection and classification, we derive the following conclusions:

— Depending on the kind of arrhythmia, SVM could be modified and trained to classify arrhythmias.

Table 8. Arrhythmia Detection Using Bayesian Classifiers and Its Variants (Grouped According to Variant of Bayesian Classifier)

Technique	Performance parameters			Detected	References
	Accuracy	Specificity	Sensitivity		
Bayesian classifier discriminant	69.38-94.67%			3-6 arrhythmias	(Ahmed et al. 2014)
One-vs.-one error minimization with a Bayesian classifier	70.00-97.11%			3-6 arrhythmias	(Ahmed et al. 2014)
Laplacian Eigen map with a Bayesian classifier	98.85±0.90%	99.95±0.01%	98.97±0.99%	PVC beats	(Lashgari et al. 2013)
Naïve Bayes	70.46±1.11%	19.00±3.00%	59.00±3.00%	Normal, abnormal	(Gao et al. 2005)
	64.90%	74.90%	60.60%	Normal, abnormal	(Leutheuser et al. 2014)
	58.92%	33.14%	50.49%	Normal, abnormal	(Park et al. 2015)
	53.00%			16 arrhythmias	(Raut and Dudul 2008)

- SVMs are more flexible and could be combined with other kind of methods, including statistical methods and regression techniques.
- SVMs can as well be employed together with dimensionality reduction techniques such as PCA for data reduction and pre-processing purpose.
- SVMs are efficient when the training data are labeled and sufficiently large compared to neural networks.
- Different kinds of SVMs, such as OAO, MR-SVM can as well be used for arrhythmia detection. OAO SVM outperforms OAA-based SVM and FDF.
- SVMs are computationally expensive and is resource hungry (especially computing units).
- SVMs outperform neural networks and other techniques when the class of arrhythmias to detect are large.

6.2.3 Arrhythmia Detection with Bayesian Classifiers. The Bayesian classifier is a branch of machine-learning techniques that is effective to perform data classification. This uses probabilistic statistics for classification. The main idea is to obtain the probability that the data belong to a particular class. In general, features of the ECG signal are provided as inputs for Bayesian classifiers.

In Elghazzawi and Geheb (1996), a Bayesian posterior probability-based classifier is proposed for ECG arrhythmia detection and classification. The major features used for classification are the beat width, polarity, ST-area, polarity, correlation coefficient between QRS complex and a window of the same length from the patient, and presence of the P-wave. The classification is performed based on the Bayes posterior probability. The posterior probability curves are derived from the MIT-BIH database and used for classification. Some other variants of Bayesian classifiers, such as Naïve Bayes classifiers and one-vs.-one error minimization Bayesian discriminant, are employed for arrhythmia detection. The performance of Bayesian classifiers in arrhythmia detection is presented in Table 8.

Analysis on Arrhythmia Detection using Bayesian Classifier

Bayesian classifiers are helpful for classification of data, even when the data are not associated with labels. Based on some of the presented existing works that use Bayesian classifiers for arrhythmia classification, we can derive the following conclusions:

— Bayesian learning could be applied for arrhythmia detection when there are no labels associated with data or the amount of training data is very little.
— Naïve Bayes, though less complex compared to other discussed Bayes techniques, has relatively lower accuracy.
— Bayesian learning associated with Laplacian could be more effective to accurately detect PVCs, which many of the CAD methods fail to detect and classify accurately.
— Bayesian classifiers can also be used even if the arrhythmias to be detected are unseen.
— However, the performance of Bayesian classifiers for arrhythmia detection is not as effective as neural networks or SVM-based methods. Furthermore, the hardware implementation also incurs higher overheads due to involved computational complexity.

6.2.4 Clustering and Neighboring-based Classification. Among machine-learning techniques, clustering and nearest-neighbor techniques can be termed as relatively low complex techniques. Clustering is the process of grouping the data and to detect the outliers. Clustering is as well employed for arrhythmia detection. Similarly, one more low-complex technique to perform classification is to use the distance metrics. This method involves calculation of distance metrics such as Euclidean between the beats present in the databases. Based on the distance from different classes, the class with least distance is assigned to the beat. This technique is a one-against-all scheme and is computationally expensive (Chakroborty and Patil 2014).

Simple K-nearest-Neighbor Classifier. A simple K-nearest-neighbor (SKNN) classifier can be employed by forming the clusters in the training phase and depending on the nearest-neighbor value, the class or kind of arrhythmia could be determined. This involves calculation of Euclidean distances. The technique was employed in Arif et al. (2009) and Yeh et al. (2009) for the six types of beats, namely left and right bundle branch blocks (BBB), paced beats, PVC, APB, and normal beats.

SSA K-means Clustering. In addition to time-domain metrics as input for clustering, spectral data can as well be used for clustering purposes. To detect arrhythmias, a combination of classical single-spectrum analysis (SSA) with k-means clustering can be employed (Uus and Liatsis 2011). It employs a semi-supervised approach k-means clustering, where the library of patterns is serially annotated by clinicians.

Kernel Difference weighted k-nearest-neighbor classifier (KDF-WKNN). A kernel difference weighted k-nearest-neighbor classifier (KDF-WKNN) is proposed for ECG anomaly diagnosis in Zuo et al. (2008). In contrast to the classical KNN, a weighted k-nearest neighbors is employed with least-squares optimization in KDF-WKNN. This is succeeded by Lagrangian multiplier for computing the weights. In case of any missing attributes, techniques like PCA could be employed to reconstruct the data.

The performance of KNNs and clustering is outlined in Table 9.

Analysis on Arrhythmia Detection using Clustering and Distance Classifiers

Techniques like clustering, distance-based classifiers, and so on, can be implemented for classification purposes. Based on the observed performances with clustering and distance classifiers in different works, we could derive the following:

— Clustering and nearest-neighbor techniques, when integrated with fuzzy logic, outperforms simple clustering and nearest-neighbor techniques.
— Similarly to neural networks, the nearest-neighbor and clustering techniques are effective when the number of differenc types of arrhythmias is smaller. Compared to neural networks, these techniques achieve lower specificity and sensitivity.

Table 9. Arrhythmia Detection Using Clustering and Nearest Neighbor Techniques (Grouped According to Technique)

Technique	Performance parameters			Detected	References
	Accuracy	Specificity	Sensitivity		
K-nearest neighbors	92.80%	93.30%	92.30%	Normal, abnormal	(Leutheuser et al. 2014)
		34.62%	85.84%	5 different arrhythmias	(Owis et al. 2002)
	97.95%	90.49%	85.21%	Normal, abnormal	(Park et al. 2015)
	75.00%			16 different arrhythmias	(Raut and Dudul 2008)
		75.40%	80.90%	PVC	(Bortolan et al. 2005)
Kernel difference weighted k-nearest neighbor	70.66%			15 different arrhythmias	(Zuo et al. 2008)
Prediction by partial matching	99.14%	99.37%	91.74%	AFib, PVC, Sinus Bradycardia	(de Medeiros et al. 2011)

— These techniques are unsupervised, adding the advantage of not having the labeled data, but have higher complexity and the robustness to the variations is small.

6.2.5 Arrhythmia Detection with Fuzzy Logic. Fuzzy logic makes use of many-valued logic for true or false, whereas binary logic uses one or zero for true and false. This use of many-valued logic helps in determining confidence levels of true or false in addition to determining accuracy. Fuzzy logic is adapted in ECG signal analysis as well for arrhythmia detection. A few notable methods are discussed below.

Fuzzy Inference Model. A three step procedure using the fuzzy inference model is proposed in Huang and Chen (2012). Initially, the amplitudes of heartbeats, intervals, slopes, angles, and edge lengths are considered to get 21 heartbeat features. As processing using all the features is computationally expensive, PCA is applied to reduce the state space, and only 6 principal features including QRS duration, QR duration, RS-slope, area under RS, length, and height of QR are selected. Then, the maximum, minimum, and mean values of each heartbeat type are used to construct the initial membership functions of the fuzzy inference model. Using the extracted features, arrhythmia classification on ECG signal is performed.

Fuzzy Neural Network. A neural network with weighted fuzzy membership function (NEWFM) for premature ventricular contraction (PVC) detection is proposed in Lim (2009). The NEWFM classifies normal and PVC beats by the trained bounded sum of weighted fuzzy membership functions (BSWFMs). Eight generalized coefficient features are extracted (from wavelet coefficients d_3 and d_4) by the non-overlap area distribution measurement method (Lim and Gupta 2004) is used to predict PVCs using Haar wavelet transform and NEWFMs (Lim and Gupta 2004).

Fuzzy-hybrid Neural Network. Neural networks and fuzzy-based techniques are widely used in pattern recognition. In Engin (2004), a fuzzy-hybrid neural network is proposed for classification of ECG beats. The fuzzy-hybrid neural network comprises of a fuzzy self-organizing layer to perform initial classification of ECG signals, followed by the multi-layer perceptron (MLP) network, which works as a final classifier. For classification of beats, statistical features of ECG are used.

Fuzzy-Neuro Learning Vector Quantization. To perform classification, a learning vector quantization (LVQ) is used together with the fuzzy-neuro network to overcome the noise and distortion impacts. A fuzzy-neuro learning vector quantization technique for ECG arrhythmia detection on

Table 10. Arrhythmia Detection Using Fuzzy Logic (Grouped According to Variant of Fuzzy Logic)

Technique	Performance parameters			Detected	References
	Accuracy	Specificity	Sensitivity		
Fuzzy C-means with ANN	93.50%	95.30%	99.60%	PVC, RBBB, non-conducted P	(Engin 2004)
NN with weighted fuzzy membership	97.97-99.86%	99.20-99.99%	90.67-99.21%	PVC	(Lim 2009)
Fuzzy neural network	97.20-99.0%	99.20-100.00%	95.00-98.30%	AF, VF, VT	(Wang et al. 2001)
Fuzzy neural network	92.48%			VPC, APB	(Shan-xiao et al. 2010)
Neuro fuzzy approach		81.80%	85.80%	PVC	(Bortolan et al. 2005)
Fuzzy KNN	97.63±0.02%		94.74%	6 different arrhythmias	(Arif et al. 2009)
Pruned Fuzzy KNN	97.32±0.05%		94.58%	6 different arrhythmias	(Arif et al. 2009)
Polar Teager energy with Fuzzy C-means	98.93%		99.85%	PVC, LBBB, RBBB, Tachycardia	(Sutar and Kothari 2015)

FPGA is presented in Jatmiko et al. (2011). Arrhythmia detection is carried out in three steps: pre-processing, feature extraction, and arrhythmia detection (classification). FLVQ utilizes fuzzy theory to form input vector, learn, and decide. This method has advantages of speed and accuracy (Jatmiko et al. 2009).

Fuzzy K-nearest-neighbor Classifier. Fuzzy K-nearest-neighbor classifier is an extension of SKNN. Despite the high classification accuracy, SKNN or FKNN is hindered by the involved time and space complexities. The additional overhead comes in terms of extra memory. This can be overcome by performing pruning on training data. To reduce the complexity, ATRIA, a neighbor search technique (Merkwirth et al. 2000) has been used. Fuzzy *k*-nearest-neighbor classifier enjoys the benefit over SKNN by having a robust and stable decision, i.e., high confidence with the inclusion of higher-level decision process.

Fuzzy C-mean Clustering. A fuzzy C-mean clustering algorithm is proposed in Sutar and Kothari (2015). These processes also employ pre-processing, feature extraction, and classification for arrhythmia detection. For pre-processing, digital filters as in Pan and Tompkins (1985) are employed. Digital filters are preferred over analog filters because of lower design complexity, effective noise removability, and artifacts. For QRS detection, i.e., feature extraction, polar teager energy (PTE), which is based on the entropy of the signal, has been utilized. Employing features that are linearly dependent or related leads to feature vectors with smaller dimension. Hence, a relation between information entropy and mean teager energy is exploited. Based on these features, ECG beat classification using Fuzzy C-mean clustering algorithm is performed. The performance of fuzzy logic in arrhythmia detection is presented in Table 10.

Analysis on Arrhythmia Detection Using Fuzzy Logic

- Fuzzy neural networks are effective when operating in noisy environments and have been proven to achieve higher performance in arrhythmia detection.
- Fuzzy logic can be operated together with methods like SVM and neural networks to achieve good accuracy in arrhythmia detection.

Table 11. Deep Learning-based Arrhythmia Detection (Grouped According to Technique and Architecture)

Technique	Performance parameters			Detected	References
	Accuracy	Specificity	Sensitivity		
CNN (4 conv.+2 FC)	93.53-95.22%	92.83-94.19%	93.71-95.49%	Mycardial infraction	(Acharya et al. 2017b)
DNN (9 hidden layers)	89.07-94.03%			5 arrhythmias	(Acharya et al. 2017c)
DNN (11 hidden layers)	92.5-94.9%	81.44-93.13%	98.09-99.13%	AF, A. Flutter, VF	(Acharya et al. 2017a)
CNN (11 conv. layers)	93.18%	91.04%	95.32%	VT, VF	(Acharya et al. 2018)
DNN (3 conv. + 2 FC)	96.6-99%	98.1-99.5%	64.4-95.9%	5 arrhythmias	(Kiranyaz et al. 2016)
CNN	91.8%			AF	(Shashikumar et al. 2017)
3-layer Restricted Boltzman machine	75-99.5%	73.1-100%		4 arrhythmias	(Taji et al. 2017)
8-layer CNN-LSTM	99.85%	99.84%	99.85%	Coronary artery disease	(Tan et al. 2018)

—Fuzzy logic-based methods perform well for arrhythmia detection. As seen, the accuracy ranges from nearly 92 to 99%, depending on the approach.
—The major drawback with fuzzy logic is that it is not always possible to have multi-valued logic for true and false values.

6.2.6 Deep Learning-based Arrhythmia Detection. Deep learning is also applied in the recent years for the purpose of arrhythmia detection and ECG signal analysis. Various deep learning techniques such as convolutional neural networks (CNNs) (Acharya et al. 2018), belief propagation deep neural networks (DNNs) (Taji et al. 2017), and long-short term memory (LSTM) networks (Tan et al. 2018) are used. The primary advantage with deep learning compared to the traditional (shallow) machine-learning techniques are the robustness to the noise and other artifacts arising during the signal acquisition. Furthermore, large amounts of data (say, the data from all the 12-leads (Oh et al. 2017)) can be used to analyze the signal. Most of the works use large numbers of hidden layers such as 11 in Acharya et al. (2017a) and 9 hidden layers in Acharya et al. (2017c) for arrhythmia detection. The results reported in Table 11 also include the tests where the noise is injected and tested. One can observe, in most of the cases, that the accuracy, sensitivity, and specificity are high, despite the presence of noise. It needs to be noted that all the works are primarily carried out in software (CPU or GPU), as the CNNs are resource intensive. Some of the popular DNN architectures used in arrhythmia detection are listed in Table 11. In addition, CNN-based ECG analysis is also used for other purposes such as sleep apnea detection (Cheng et al. 2017).

Analysis on Arrhythmia Detection Using Deep Learning:

—Deep learning techniques are proven to be effective in combating the noise issues that can arise during the ECG signal acquisition effectively.
—DNN-based arrhythmia detection are deployed primarily on software due to large (hardware) resource consumption of the DNNs.
—DNNs are required to be fed with large amount of samples compared to shallow technique for a better performance.
—LSTM-based DNNs have proven to be efficient for ECG signals, even in the presence of high noise.

— DNNs are more suitable for high-end or CPU/GPU-based systems rather than only-hardware-based computing systems.

6.3 Other Methods for Arrhythmia Detection

In addition to the above-mentioned popular approaches like neural networks, SVMs, clustering, and fuzzy logic, there exist other approaches for arrhythmia detection. An overview of those works in arrhythmia detection is provided in this section.

Hermite coefficients (Jiang and Kong 2007; Osowski et al. 2004; Lagerholm et al. 2000), high-order statistics features (de Lannoy et al. 2012; Osowski et al. 2004), wavelet features (Ince et al. 2009), and wave-form shape features (de Lannoy et al. 2012; Llamedo and Martinez 2011; de Oliveira et al. 2011; Rodriguez et al. 2005; de Chazal and Reilly 2006; de Chazal et al. 2004) are some of the filtering-based approaches used for ECG arrhythmia detection and classification. In these approaches, the inputs whose filtering characteristics are based on the characteristics of normal ECG are filtered. Any abnormality (arrhythmia) can be seen at the outputs, and depending on the characteristics of output, the arrhythmia can be classified. However, the design of the filters is one of the major concerns, as the ECG signal characteristics vary with person and time. Template matching is another approach where the incoming ECG is matched with a template of a normal ECG for diagnosing arrhythmias. Discrete time wrapping–based template matching method is proposed (Huang and Kinsner 2002). In the DTW paradigm, the original training templates need to be stored for comparison. On the same test dataset, a DTW-based distance measure was used to compare the distance with the templates (here the ECG beats) stored in the training corpus. For any unknown test sample, the DTW distances between the test beat and all the training samples from a particular class are determined first. Similarly, an L1-norm-based signal comparison is proposed in Amann et al. (2005). In this technique, the signal comparison algorithm (SCA) compares four pre-defined reference signals (three sinus rhythms containing one PQRST segment and one ventricular fibrillation signal) with the ECG signal. The decision is made based on the residuals in the L1-norm. This technique, though simple, requires highly efficient and accurate reference signals for comparison, which is not always possible.

Numerous machine-learning techniques are proposed for classification in ECG, and some of them are self-organizing map (SOM) (Lagerholm et al. 2000), linear discriminant analysis (LDs) (Llamedo and Martinez 2011; de Chazal and Reilly 2006; de Chazal et al. 2004), decision tree (Rodriguez et al. 2005), dynamic Bayesian network (DBN) (de Oliveira et al. 2011), conditional random field (CRF) (de Lannoy et al. 2012), and so on. A Fisher Linear discriminant-based arrhythmia detection is proposed in Elgendi et al. (2008). The RR-interval duration and the PT interval are obtained as the basic features. Using these features, Fisher's Linear Discriminant is applied. The performance of techniques not discussed in the previous sections for arrhythmia detection, and classification is outlined in Table 12.

Analysis on Arrhythmia Detection Using Other Techniques

Based on the above-mentioned techniques for arrhythmia detection, we could deduce the following statements:

— Techniques like regression analysis and linear discriminant analysis achieves higher accuracy in detecting the arrhythmias but have lower specificity and sensitivity compared with some of the machine-learning techniques discussed previously.
— The above-mentioned techniques perform poorly when the types of arrhythmias increases.
— Optimization techniques like ant-colony optimization (ACO) and bee colony algorithms can help to detect and classify a limited number of analysis but are computationally more expensive and might run into convergence issues.

Table 12. Other Methods for Arrhythmia Detection (Grouped According to Technique)

Technique	Performance parameters			Detected	References
	Accuracy	Specificity	Sensitivity		
Space search	71.88-98.00%			3-6 arrhythmias	(Ahmed et al. 2014)
Linear regression	74.60%	82.30%	69.70%	Normal, abnormal	(Leutheuser et al. 2014)
Logistic regression	68.76±0.52%	23±0.02%	58.00±2.00%	Normal, abnormal	(Gao et al. 2005)
Auto-regression with Itakura distance	90.00-100.00%			VF, VT	(Alliche and Mokrani 2003)
Discriminant analysis		88.50%	81.70%	PVC	(Bortolan et al. 2005)
Hidden Markov model			97.25%	Ventricular Ectopic beats	(Cost and Cano 1989)
Hidden Markov modeling with mutual info estimation			99.00%	PVC, SVT, AF	(Lima and Cardoso 2007)
Hidden Markov modeling with maximum likelihood estimation			92.00-99.00%	PVC, SVT, AF	(Lima and Cardoso 2007)
PSO-ACO		93.10%		6 Arrhythmias	(Waseem et al. 2011)
Ant-miner		91.00%		6 Arrhythmias	(Waseem et al. 2011)
Modified Artificial Bee colony algorithm	98.73%			6 different arrhythmias	(Dilmac and Korurek 2013)
Reservoir computing with logistic regression	98.43%	97.75%	84.83%	5 different classes	(Escalona-Morán et al. 2015)
Decision tree	81.39±3.01%	14±0.05%	76.00±8.00%	Normal, abnormal	(Gao et al. 2005)
	92.54%	55.41%		T wave variations	(Hadjem and Abdesselam 2015)
	91.60%	92.30%	90.90%	Normal, abnormal	(Leutheuser et al. 2014)
	65.71%			16 different arrhythmias	(Raut and Dudul 2008)
LDA	93.04-97.21%	95.36-97.22%	90.20-97.18%	AFib, Ventricular bigeminy	(Sarlak et al. 2012)
Wavelet decomposition with LDA	99.48%	99.33%	94.38%	SVT, PVC, VF	(Lee et al. 2005)
Laplacian Eigenmaps with FLDA	99.69±0.25%	84.88±14.69%	99.91±0.12%	PVC beats	(Lashgari et al. 2013)
PSO-LDA		98.80%		6 Arrhythmias	(Waseem et al. 2011)
Wavelet decomposition with PCA	98.74%	97.17%	93.11%	SVT, PVC, VF	(Lee et al. 2005)
Random forest	98.69%	97.14%	86.40%	Normal, abnormal	(Park et al. 2015)
Statistical discriminant analysis	50.00%			16 different arrhythmias	(Raut and Dudul 2008)
Voting feature algorithm	62.00%			16 different arrhythmias	(Raut and Dudul 2008)

As such, it could be seen clearly that the above-mentioned other techniques, although some are less complex, have lower efficiency, which can be critical in health-care applications. Additionally, these techniques also have lower sensitivity and specificity, which could create unnecessary false alarms and might not diagnose the arrhythmia(s).

7 ANALYSIS AND DISCUSSION

In the previous sections, the arrhythmia detection using different techniques and their analysis is presented. Here, we present an overall analysis that not only compares variants of one technique but also provides a comparison across different techniques and suitability of a technique depending on the operational conditions and requirements.

The following is the analysis for different methods discussed previously:

- Statistical metrics-based methods are simpler compared to many of the machine-learning methodologies. These metrics-based methods can be realized effectively even when the available hardware and computing resources are limited. However, these techniques have lower efficiency in terms of performance in arrhythmia detection, and some of the methods operate on the data directly, resulting in a larger state space.
- Machine-learning techniques are widely employed for arrhythmia detection. Machine-learning techniques (in general) outperform most of the discussed traditional techniques for arrhythmia detection.
- Neural networks have gained attention for arrhythmia detection and are widely employed. Neural networks perform arrhythmia detection in an efficient manner, i.e., good performance, and they are suitable for moderate and medium size systems, depending on the variant of neural networks used.
- Neural networks, though efficient, are suitable only when the number of types of arrhythmia to detect are limited (around 5 or 6). However, when the number of types of arrhythmias are large, neural networks is not efficient with respect to resources.
- Support vector machine technique–based classification can be seen as an alternative and perform effectively even when the number of kinds of arrhythmia to detect is large. However, the major drawback of SVMs is their complexity ($O(N^3)$, where N is the size of the input).
- SVMs can be implemented together with other techniques like DWT, FCM, and so on, to achieve higher performances.
- In the case of training data associated with less or no labels (i.e., information of arrhythmia type), Bayesian classifiers can be employed. However, the achieved performance is limited.
- Clustering techniques when integrated with some data labeling techniques could perform well and are of lower complexity compared to SVMs but also do not achieve as high performance as SVMs and neural networks.
- A vast variant of other techniques is as well proposed in the literature. However, the most successful methods are neural networks, SVMs, and their variants, but at the cost of more computations and required resources.
- Deep learning–based analysis techniques are proven to be robust and efficient despite the presence of noises in the received ECG signal. However, they are resource intensive and slower compared to other machine-learning-based techniques.

Though there exist numerous works on arrhythmia detection, some of the challenges still remain unanswered, such as the following: How do we perform ECG signal analysis with a smaller amount of data and independent of the patients' physical state and characteristics (such as food, place, gender, and so on) still remains an unanswered, as most of the works focus on one or few characteristics. Which of the platforms (software or hardware or embedded) are best for arrhythmia detection, especially in the era of mobile devices that have higher processing capabilities? And, most importantly, how reliable and robust are the existing techniques for arrhythmia detection? In addition, deep learning has been shown robustness to the noise impacts and other kinds of artifacts, which is one of the major problems for the ECG analysis. However, the deep learning works are performed on CPU/GPUs or at the software level. The major concern with such implementations is the resource consumption and involved latencies. Hence, there is an emerging need to devise lightweight architectures for performing hardware-based ECG analysis for the future health-care body wearable devices, as the existing hardware implementations (even optimized for image processing) are too big to fit on body-wearable devices. Furthermore, as some other bio-signals can also be analyzed using similar techniques that are useful for arrhythmia detection, can we devise a generic bio-signal analyzer that can be used for analyzing multiple bio-signals (a set of similar bio-signals) are some of the future directions that have to be explored.

8 ANALYSIS OF OTHER BIO-SIGNALS

In addition to the ECG signals, there exist numerous other signals, such as EMG, for muscular analysis, electroencephalography (EEG) to monitor the electrical activity of the brain, galvanic skin response (GSR) for electro-dermal activity, and magnetoencephalogram for neuroimaging purposes. ML techniques are also widely used for such bio-signal analysis. For instance, neural network–based analysis for EEG, GSR, and EMG is proposed in Matsumura et al. (2002), Übeyli (2009), Villarejo et al. (2012), Anusha et al. (2012), Zhang et al. (2016), Oleinikov et al. (2018), and SVM based on Lin et al. (2008), Kumari and Jose (2011), and Altaf and Yoo (2016). For the purpose of brain–computer interfacing, image processing or deep learning techniques such as using CNNs are as well deployed (Park et al. 2018; Lee and Choi 2018). In Anusha et al. (2012), the features of the EEG signal are provided to the neural network for analyzing the EEG and detection of epilepsy and seizure. This is similar to how the ECG signal is processed using neural networks to detect arrhythmias. However, in terms of implementation requirements and signal characteristics, some of the anomalies such as epilepsy shows a symptom nearly 7.5s before the it can be observed clinically (Verma et al. 2010), which indicates that detection using body-wearable devices can alert the patient much further in advance than can be done in some of the arrhythmias. As such, the symptoms and requirements are different. But in terms of analysis for other bio-signals, similar techniques that are used for ECG arrhythmia detection can be employed, but under different requirements in terms of performance (accuracy and timing).

9 CONCLUSION

Arrhythmia detection is one of the most widely researched topics. There exist numerous techniques for arrhythmia detection, ranging from simple statistical metrics-based methods to sophisticated machine-learning techniques like neural networks, SVMs, Bayesian classifiers, and so on. Based on the existing works, it has been observed that the machine-learning methods outperform traditional methods in arrhythmia detection. However, the complexity of most of the traditional techniques is much lower compared to the machine-learning techniques. In machine-learning techniques, neural networks and SVMs (including their variants) achieve better performances. However, neural networks are efficient when the number of types of arrhythmia to detect is small (5 or 6), whereas SVMs and their variants are efficient even when the number of types of arrhythmias to classify is large but of higher complexity. Additionally, SVMs can be effectively utilized when the amount of data is large and can as well be utilized together with data reduction techniques such as PCAs. Last, Bayesian classifiers, though not efficient compared to neural networks and SVMs, are preferred especially when there exist no labels for the data.

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