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A survey on ECG analysis

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ABSTRACT

The electrocardiogram (ECG) signal basically corresponds to the electrical activity of the heart. In the literature, the ECG signal has been analyzed and utilized for various purposes, such as measuring the heart rate, examining the rhythm of heartbeats, diagnosing heart abnormalities, emotion recognition and biometric identification. ECG analysis (depending on the type of the analysis) can contain several steps, such as preprocessing, feature extraction, feature selection, feature transformation and classification. Performing each step is crucial for the sake of the related analysis. In addition, the employed success measures and appropriate constitution of the ECG signal database play important roles in the analysis as well. In this work, the literature on ECG analysis, mostly from the last decade, is comprehensively reviewed based on all of the major aspects mentioned above. Each step in ECG analysis is briefly described, and the related studies are provided.

Contents

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1. Introduction

An electrocardiogram (ECG) is simply a recording of the electrical activity generated by the heart [1]. Sample ECG signals associated with a common cardiac cycle are illustrated in Fig. 1 [2,3]. The ECG is an effective non-invasive tool for various biomedical applications such as measuring the heart rate, examining the rhythm of heartbeats, diagnosing heart abnormalities, emotion recognition and biometric identification.

One of the major fields in which ECG analysis is required is the diagnosis of cardiovascular diseases. As reported by the World Health Organization, cardiovascular diseases are the main reason for deaths worldwide. Among the cardiovascular diseases, cardiac arrhythmias are the most common, and as a result, their precise classification has been of great interest in biomedical studies [4]. One of the most effective tools for identifying arrhythmias is ECG signal exploration [5]. The investigation of individual ECG beat characteristic shapes, morphological features, and spectral possessions can provide meaningfully correlated clinical information for the automatic recognition of an ECG pattern. However, automated classification of ECG beats is a difficult problem because the morphological and temporal features of the ECG signals include noteworthy dissimilarities for different patients under different physical circumstances [6]. The main problem for diagnosing heart diseases with ECGs is that an ECG signal can vary for each person, and sometimes different patients have separate ECG morphologies for the same disease. Moreover, two different diseases could have approximately the same properties on an ECG signal. These problems cause some difficulties for the problem of heart disease diagnosis [5,7,8]. To detect abnormalities of the heartbeat, the electrical signal of each heartbeat must be analyzed. Therefore, the process of analyzing long-term ECG records, especially for bedside monitoring or wearable online health care monitoring, can be very troublesome for a person, and it is very time-consuming. Furthermore, some personal errors can occur throughout an ECG analysis due to fatigue, [9] and the interpretation of the signal requires deep knowledge [10]. Therefore, computer-assisted methods that provide automatic ECG analysis are utilized.

The use of ECG analysis in fields other than the diagnosis of cardiovascular diseases has also increased substantially. Many researchers have used ECG signals for emotion recognition, especially for stress level detection in addition to many other signals such as the electroencephalogram, skin temperature, blood pressure, electromyogram, heart rate variability, cortisol levels, and thermal imaging features. Researchers measure ECG signals at different critical moments (stress situations), such as during an oral exam, after a holiday for students, in office environments for office workers, and during a driving task for drivers. The results of these studies reveal that ECG features are useful at distinguishing the characteristics between different mental workloads and stress levels as well [1].

In addition, ECGs are also being used in the field of biometric identification. In biometric recognition, physiological characteristics, such as face, fingerprints, hand geometry, DNA and iris, as well as behavioral characteristics, such as voice, gait, signature and keystroke dynamics, are used for identifying an individual. The biometric systems provide security and restricted access to protected areas [11]. The mentioned characteristics and the features to be used for this purpose must meet the criteria of universality, uniqueness, permanence and robustness to attacks [3,11,12]. Because ECG has features that are unique to an individual, it is being used increasingly by many researchers in this area.

As seen in the examples above, an ECG signal is analyzed and utilized for various purposes and applications. Depending on the application, the analysis contains several steps, such as preprocessing, feature extraction, feature selection, feature transformation and classification. Additionally, the employed success measures and appropriate constitution of the ECG databases play crucial roles

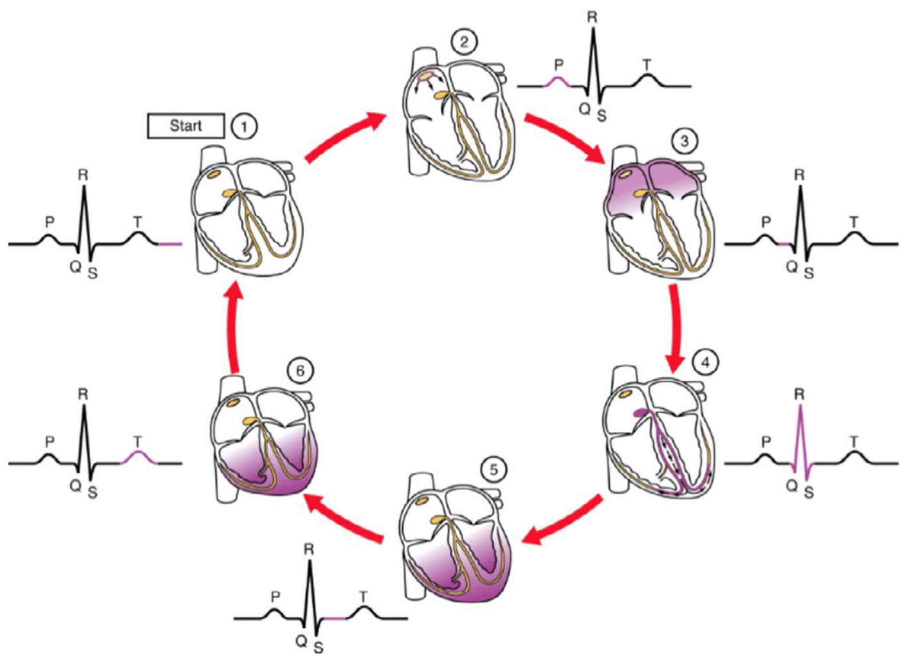

Fig. 1. A sketch of a common cardiac cycle with the associated waves of an ECG signal (one-lead) [2,3].

in the analysis. In this paper, a comprehensive review is conducted for ECG analysis, and the subject is handled considering all the major aspects, including preprocessing, feature extraction, feature selection, feature transformation, classification, application fields, databases and success measures. Although there already exist several review articles in the literature [3,13–15] on this topic, they are limited to only a few of these aspects rather than all. Therefore, this work comes forward as an all-in-one resource that reviews all the aspects of ECG analysis to enable readers to reach the desired information immediately without searching for different articles. Specifically, this work comprises a survey of existing studies on ECG analysis in the literature, mostly from the last decade. For this purpose, we particularly review the articles published in journals indexed by prestigious scientific indices such as Science Citation Index and Science Citation Index-Expanded. To search the relevant studies in the literature, several platforms, such as IEEEXplore, ScienceDirect and Google Scholar, are employed, and various combinations of the keywords "electrocardiogram" and "ECG" together with "classification"; "database"; "QRS"; "feature extraction"; "feature selection" and "preprocessing" are used. In addition; some articles other than ECG analysis are also utilized to introduce certain methodologies briefly.

The remainder of this paper is organized as follows: Sections 2, 3, 4, and 5 include the preprocessing, feature extraction, feature selection and feature transformation techniques applied for ECG analysis together with the associated articles, respectively. In Section 6, widely preferred classifiers mentioned in the literature for analyzing ECG signals are reviewed. In Section 7, various application fields of ECG signals are described. In Sections 8 and 9, the databases and success measures (evaluation metrics) used for quantitative evaluation of ECG analysis are presented, respectively. Finally, a discussion and the conclusions of the paper are given in Sections 10 and 11, respectively.

2. Preprocessing

ECG recordings are usually contaminated by different types of noise and artifacts. In the preprocessing step, the goals are to reduce such noise and artifacts to determine the fiducial points (P, Q, R, S, T (P-onset, P-peaks, P-offset, QRS-onset, QRS-offset, T-onset, T-peaks and T-offset)) and to avoid amplitude and offset effects to compare signals from different patients. Typical types of noise are described briefly and grouped into the following categories [3,16–18]:

a) Power line interference: a signal in the frequency of 50 or 60 Hz, and its bandwidth is below 1 Hz
b) Baseline wander: a low-frequency (0.15 up to 0.3 Hz) noise. This noise results from the patient inhaling and compels a baseline shifting of the ECG signals.
c) Electrode contact noise: noise that results from a deficiency in the contiguity between the electrode and skin, which adequately cuts off the measurement system from the subject.
d) Electrode motion artifacts: artifacts that result from variations in the electrode-skin impedance with electrode motion.
e) Muscle contractions (Electromyography noise): noise that results from the contraction of other muscles apart from the heart.
f) Electrosurgical noise: noise produced from other medical apparatus in the patient care circumstance at frequencies between 100 kHz and 1 MHz
g) Instrumentation noise: noise produced by the electronic equipment utilized in the ECG measurements.

In cardiovascular disease classification, the various noise in varying degrees causes a physician to make wrong assessments about patients and reduces the diagnostic correctness. Hence, ECG signal denoising and preprocessing become a discriminative demand [19]. However, some state-of-the-art methods for automatic arrhythmia identification do not use state-of-the-art preprocessing methods and signal-to-noise ratio enhancement, and the impact of the preprocessing techniques on automatic arrhythmia identification methods is not clear as well [9].

2.1. Filtering

The preprocessing stage uses a filtering block to delete artifact signals from an ECG signal [20]. Usually, an ECG signal is initially bandpass filtered with different frequency ranges before analyzing it. Bandpass filtering is widely used to delete muscle noise, baseline wander, power line interference, and low- and high-frequency noise components and to limit ADC saturation and address antialiasing.

The frequency range of 0.1–100 Hz for the bandpass filtering is most often used [4,21–23]. Other frequency ranges used in bandpass filtering are 1–40 Hz [24–26], 0.5–40 Hz [12,27,28], 1–30 Hz [29,30], 0.4–40 Hz [31], 0.05–40 Hz [32], 0.5–50 Hz [33], 1–120 Hz [34] and 1–100 Hz [35]. Refs. [36] and [37] also used a bandpass filter to remove noise, but they did not specify the frequency ranges of the filter. The output of the bandpass filter proceeds through a moving average filter to smooth the signal [38–41].

Analog low-pass filtering has a noticeable effect on the QRS complex, epsilon, and J-waves but does not alter the repolarization signals [42]. A good low-pass filter can filter out the noise and still leave a large amount of data for further processing [43]. A low-pass filter is designed to remove the high-frequency component in the ECG waveform. Low-pass filters with the cut-off frequency of 11 Hz [36,44], 90 Hz [45], 30 Hz [46,47], 35 Hz [48], 50 Hz [49], 100 Hz [50] and 70 Hz [51] were used to delete high-frequency noise and power line interference. References [52–55] also used a low-pass filter, but they did not specify the cut-off frequency.

Unlike low-pass filters, analog high-pass filters do not attenuate much of the signal. However, analog high-pass filters suffer from phase shifts that affect the first 5–10 harmonics of the signal [42]. The main intention of a high-pass filter in ECG work is to remove the DC offset, which in turn is largely caused by the electrode/gel/body interface [56]. High-pass filters with cut-off frequencies of 0.5 Hz [45,49,51,57], 1 Hz [46,47], 2.2 Hz [55] and 5 Hz [44] were also used to remove baseline wander and for drift suppression. Reference [53] used a high-pass filter to determine the level of high-frequency noise that is available in any beat.

The motivation behind a notch filter is to attenuate several singular frequencies while preserving the others [43]. Notch filters combine both high- and low-pass filters to create a small region of frequencies to be removed. High "quality" notch filters can be created in software that target only 50 or 60 Hz, but the drawback of these filters is that they can create unusual ringing, especially for waveforms with high rates of change [56]. Notch filters centered approximately 50 Hz [45,51] and 60 Hz [32] were used to remove power line interference and suppress DC components. References [46,55,58,59] also used a notch filter for the same purpose.

ECG signals are also filtered with two median filters that have 200 and 600 ms widths to remove the baseline wander [58,59] and the P and T waves [48]. A series of three median filters was used to remove the ECG isoelectric line [60]. The median filters usually have the order of two [54] and fifty [61]. A local median filter is used in [62,63] to decrease the especial effects and arbitrary noise, and two steps of median filtering is used to delete the baseline wandering [4]. An averaging filter helps to assess the polarity of the P and T waves [36]. In that study, the average value of each six-adjacent points was used. Zero-phase filtering provides sharp peaks near QRS complex regions and smooths out fake spikes [39]. Savitsky-Golay filtering or digital smoothing polynomial filtering was also utilized for smoothing the ECG signals at the beginning of the preprocessing stage [64,65]. An adaptive filter was used to reduce power line interference [52]. The adaptive filter achieves performance close to a fixed Kalman filter with an optimally selected noise covariance method [45]. Rahman et al. proposed various adaptive filters based on the normalized signed regressor LMS algorithm, normalized signed LMS algorithm and normalized sign–sign algorithm [66]. The adaptive filter ensures that the signal waveforms are not distorted while the noise is being removed [67]. The performances of abovementioned filters are given comparatively in Table 1. Since only two papers include an SNR improvement of the raw ECG signals, different performance criteria are given in the following table, although the respective values do not indicate the actual contributions of the filters.

Table 1
Performances of the filters used in the preprocessing step.

Filter type (Ref.)	Frequency/Duration	Performance (Criteria)
Bandpass [4]	0.1–100 Hz	99.7% (total accuracy)
Bandpass [21]	0.1–100 Hz	98.3% (average accuracy)
Bandpass [23]	0.1–100 Hz	95.24% (average accuracy)
Bandpass [24]	1–40 Hz	96.42% (identification accuracy)
Bandpass [25]	1–40 Hz	100% (subject identification accuracy)
Bandpass [26]	1–40 Hz	94.8% (correct detection rate)
Bandpass [12]	0.5–40 Hz	2.57% (error rate)
Bandpass [27]	0.5–40 Hz	98.3% (average accuracy)
Bandpass [28]	0.5–40 Hz	100% (subject identification accuracy)
Bandpass [29]	1–30 Hz	99% (accuracy)
Bandpass [30]	1–30 Hz	99.94% (identification accuracy)
Bandpass [31]	0.4–40 Hz	0% (error rate)
Bandpass [32]	0.05–40 Hz	100% (accuracy)
Bandpass [34]	1–120 Hz	95.8% (average accuracy)
Bandpass [35]	1–100 Hz	100% (average accuracy)
Lowpass [36]	11 Hz	98% (average prediction accuracy)
Lowpass [44]	11 Hz	97.01% (overall accuracy)
Lowpass [46]	30 Hz	96.2% (accuracy)
Lowpass [47]	30 Hz	100% (accuracy)
Lowpass [48]	35 Hz	86.6% (average accuracy)
Lowpass [49]	50 Hz	99.6% (average accuracy)
Lowpass [50]	100 Hz	80% (accuracy)
Lowpass [51]	70 Hz	88.84% (global accuracy)
Highpass [49]	0.5 Hz	99.6% (average accuracy)
Highpass [51]	0.5 Hz	88.84% (global accuracy)
Highpass [57]	0.5 Hz	95.3% (detection accuracy)
Highpass [46]	1 Hz	96.2% (accuracy)
Highpass [47]	1 Hz	100% (accuracy)
Highpass [55]	2.2 Hz	92.5% (classification accuracy)
Highpass [44]	5 Hz	97.01% (overall accuracy)
Notch [51]	50 Hz	88.84% (global accuracy)
Notch [32]	60 Hz	100% (accuracy)
Median [58]	200 and 600 ms	93.59% (overall accuracy)
Median [59]	200 and 600 ms	90% (sensitivity)
Median [60]	200 and 600 ms	89.22% (accuracy)
Median [54]	200 and 600 ms	94% (multiway accuracy)
Median [61]	200 and 600 ms	100% (sensitivity)
Median [62]	200 and 600 ms	97.1% (accuracy)
Median [63]	200 and 600 ms	97.41% (average accuracy)
Median [4]	200 and 600 ms	99.7% (total accuracy)
Savitsky-Golay [64]	N/A	96.02% (overall classification accuracy)
Savitsky-Golay [65]	N/A	96.31% (overall classification accuracy)
Adaptive [52]	N/A	100% (positive predictive accuracy)
Sign based normalized adaptive [66]	N/A	25.8473 dB (average SNR improvement)
Adaptive morphological [67]	N/A	65.5% (SNR improvement)

The median filter removes the outliers and shot noise that are independent of the magnitude. The median filtering is less sensitive to the outliers than the mean filter. The median filters are used most often for noise suppression or smoothing, while high-pass filters are typically used for signal enhancement.

One could use a static notch filter, but you would have to reject a wider range of frequencies to accommodate the variability in the main frequency. The adaptive filter follows the main frequency, and thus, the stop band can be much narrower, which retains more of the useful ECG information. The mean amplitude values for the notch-filtered signals were less than those for the raw and adaptive-filtered signals. Adaptive filtering can be a powerful tool for the rejection of narrowband interference in a direct sequence spread spectrum receiver. This finding is exactly the difference between normal and adaptive filters. In a normal filter, the filter coefficient is static, while it dynamically changes in an adaptive filter.

When a priori knowledge of a dynamic process and its statistics is limited, then the use of adaptive filters can offer performance improvements over more conventional parametrically based filter designs [68]. The parameters of an adaptive filter are updated continuously as the data flows through it; therefore, the adaptive filter is strictly a nonlinear system. However, it is common to distinguish linear and nonlinear adaptive filters. A linear adaptive filter is one whose output is a linear combination of the actual input at any moment in time between adaptation operations. A linear adaptive filter system filters a sequence of input data by controlling its adjustable parameters via an adaptive process. The choice of filter structure is a very important part of the system [68]. A nonlinear adaptive filter does not necessarily have a linear relationship between the input and output at any moment in time [68]. A nonlinear adaptive filter has more signal processing capabilities. Since non-linear adaptive filters require more complicated calculations, the actual usage is still most often the linear adaptive filter [69].

2.2. Resampling, digitization and artifact removal

Scientists use resampling or downsampling to preserve the consistency of databases [70] and to reduce the memory requirements and computational cost [71].

After an ECG signal was filtered, it was resampled and digitized with the frequency of 125 Hz [72], 200 Hz [33], 250 Hz [73,74], 257 Hz [75], 360 Hz [21,22,76,77] and 1 kHz [78,79]. Wavelet transform (WT)-based downsampling was also used for this purpose. The discrete WT (DWT) is one of the well-known approaches [6,16,80,81] and depends on the sub-band decomposition and allows the fast computation of the WT [82]. In that paper, DWT is engaged to decompose the noisy ECG signal into wavelet coefficients. A neural network is then applied as the final filtering stage to delete the remaining noise that is "buried" in the DWT coefficients while considering its adaptive learning and fault tolerance features. An effective method is essential to designing a downsampling filter that corresponds to the WT filter [71]. In this study, the parameters are chosen by considering an equivalent filter of the WT.

For denoising and baseline wandering removal, different types of WTs were usually applied to ECG signals. An undecimated WT or stationary WT (SWT) was utilized to obtain a descriptive representation that is both robust to noise and tuned to the morphological components of the waveform features [83–85]. Valuable information can be achieved by using the DWT at different scales [7,31,73,86,87]. To remove different types of noise that contains muscle artifacts and electrode moving artifacts, an advanced signal processing approach, such as the SWT denoising technique, should be used [65]. Baseline wander removal and denoising were achieved by multiresolution WT [41], and the range of the remaining signal was 1.4–45 Hz after the high- and low-frequency noise was removed with multiresolution WT [88]. In their study, all five fiducial points (P, Q, R, S, T) were identified by applying the DWT. Reference [89] decomposed the noisy signal into six levels by using the Daubechies wavelet db4. The denoised signal was recovered by taking the inverse DWT of the resulting coefficients.

2.3. Normalization

Amplitude normalization was used as one of the steps in the preprocessing stage [13,39,90–94]. Amplitude normalization is optional, but it helps when visually comparing signals from different patients [33]. Ref. [52] updated the amplitude to avoid false positives or negatives caused by high-amplitude T waves or low-amplitude R peaks. ECG signals were normalized to avoid amplitude and offset effects [52]. Refs [85,95,96] normalized sample vectors to zero mean and unity standard deviation to decrease the DC offset and disregarded the amplitude variance from signal to signal. ECG signals were also normalized to have unit variance to eliminate the influence of amplitude biases [97]. In another study, ECG signals were normalized by dividing the features of each beat by the arithmetic mean of the last eight normal beat's features [5].

2.4. Others

The cardiac activity mean and the motion artifact noise of an ECG signal were modeled by a Hermite polynomial expansion and principal component analysis [98]. Thus, the resulting coefficients serve as another feature set for classification in the temporal domain. Ref. [99] proposed an Empirical Mode Decomposition that is based on ECG signal enhancement and a QRS detection algorithm. Therefore, the noise was estimated by statistical techniques from the set of decomposed signals, and then, the QRS region was reconstructed from the relevant components of the decomposed signals. Delineation of a regular heartbeat into only two segments has been considered [92]. However, consideration of resampling of each of the basic waves and segments separately could be useful for further improvement of the alignment. This approach could be especially valuable if the alignment of irregular heartbeats is considered. Segmentation and spike removal were also used in the preprocessing step [100]. Ref. [101] applied unit block size optimization, adaptive threshold adjustment, and 4-bit-wise Huffman coding approaches to decrease the processing charge while preserving the quality of the signal.

Before the identification of ECG signals, pre-processing stages such as linear predictive (LP) model estimation and residual error signal computation were also conducted [70]. In LP analysis of the ECG signal, the signal is modeled as a linear combination of its past input signals. The ECG signal can be predicted from the third order linear predictor using the LP coefficients. The residual error signal computation is necessary for the registration of linearly independent ECG features. A Hilbert transform-based peak-finding technique facilitates the determination of the locations of the R-peaks [39,61]. This approach does not require any amplitude threshold and prior knowledge of the past detected R-peaks. In addition to the aforementioned methods, [39] proposed a pre-processor based on a first-order forward derivative and Shannon energy envelope estimation that provides a smooth envelogram of the ECG signal.

Ref. [102] treated a time series as a text document using a bag-of-words representation, and local segments were deduced from the time series as words. First, they continuously slide a window with a pre-defined length along the time series to deduce a group of local segments. Thus, the time series is represented as a histogram of codewords. The task of data mining in physiological signals using a feature selection structure was addressed [103]. Therefore, a reduced set of the input features was obtained while preserving the relevant discriminatory information.

Another preprocessing technique is based on the well-known Pan and Tompkins algorithm, which includes differentiation, squaring, and so on, of the ECG signal [104]. Information about the slope of the QRS is obtained in the derivative stage. The squaring process intensifies the slope of the frequency response curve of the derivative and helps restrict false positives caused by T waves with higher than usual spectral energies. The moving window integrator produces a signal that includes information about both the slope and the width of the QRS complex. In [105], the derivative step is utilized to decline the wandering baseline effect. The integration stage is also used to delete the high-frequency artifacts from the signal, and this step acts as a low-pass filter (Moving Average). The squar-

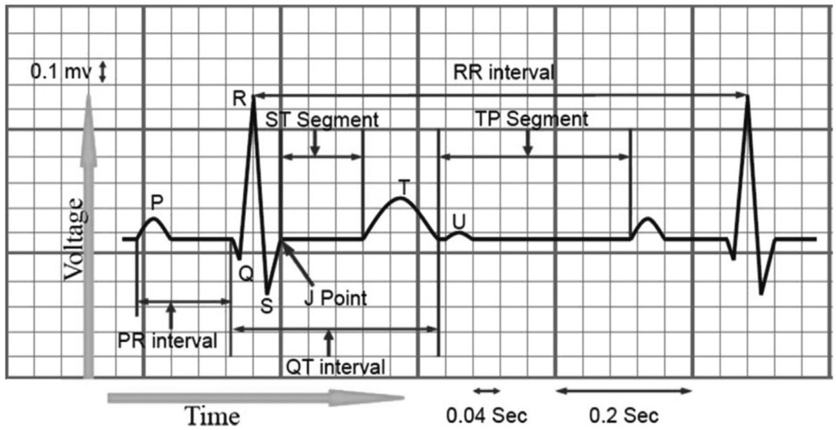

Fig. 2. Standard fiducial points in the ECG (P, Q, R, S, T, and U) together with clinical features (listed in Table 2) [108].

ing stage is utilized to accentuate the R peaks [105]. Other models can be found in [16,36].

3. Feature extraction

Since electrocardiography is an interpretation of the electrical activity of the heart, a correct representation of the ECG signal plays an important role in the proper diagnosis of heart diseases. In the literature, various feature extraction techniques have been proposed to expose the distinctive information from ECG signals for different purposes, such as analysis and classification. Those features can be used individually or in combination with other features. In this work, we categorize ECG features mainly into 5 groups, namely, QRS, statistical, morphological, wavelet and other features.

3.1. P-QRS-T complex features

The P-QRS-T complex features for an ECG signal basically correspond to the locations, durations, amplitudes, and shapes of particular waves or deflections inside the signal [106,107]. Typically, an ECG signal has a total of five major deflections, including P, Q, R, S, and T waves, plus a minor deflection, namely, the U wave, as shown in Fig. 2 [108]. The P wave is a small low-voltage deflection away from the baseline that is caused by the depolarization of the atria prior to atrial contraction as the activation (depolarization) wave-front propagates from the sinoatrial node through the atria. The Q wave is a downward deflection after the P wave. The R wave follows as an upward deflection, and the S wave is a downward deflection following the R wave. Q, R, and S waves together indicate a single event. Hence, they are usually considered to be the QRS complex. The features based on the QRS complex are among the most powerful features for ECG analysis. The QRS-complex is caused by currents that are generated when the ventricles depolarize prior to their contraction. Although atrial repolarization occurs before ventricular depolarization, the latter waveform (i.e., the QRS-complex) has a much greater amplitude, and atrial repolarization is, therefore, not seen on an ECG. The T wave, which follows the S wave, is ventricular repolarization, whereby the cardiac muscle is prepared for the next cycle of the ECG. Finally, the U wave is a small deflection that immediately follows the T wave. The U wave is usually in the same direction as the T wave.

Researchers utilize various attributes of the QRS complex as the features. Some of those attributes are the R wave duration, P+ amplitude, QRS *p*-p amplitude, R wave amplitude, ST amplitude, T+ amplitude, QRS wave area and ST slope. The R wave duration is the time that passes between the beginning and end of the R wave [109]. The P+ amplitude can be defined as the difference between the P point and the other subsequent points where the signal rises again. The QRS *p*-p amplitude is the difference between the R and Q points in the QRS complex in terms of the amplitude. The R wave amplitude can be defined as the height of the R wave from the baseline. The ST amplitude is the difference between the S and T points in terms of the amplitude values. The T+ amplitude can be defined as the difference between the T point and the subsequent point where the signal rises again. The QRS wave area is the area of the region when a rectangle is drawn on the QRS complex using the Q, R and S points [110]. The ST slope is the angle of the line, which can be drawn from the S point to the T point of the QRS complex. Some of the recent studies on ECG analysis that utilize QRS features are [35,40,67,70,76,80,88,89,91,106,107,111–117].

Table 2
Typical lead II ECG features and their normal values in the sinus rhythm at a heart rate of 60 bpm for a healthy male adult [18].

Feature	Normal Value	Normal Limit
P width	110 ms	±20 ms
PR interval	160 ms	±40 ms
QRS width	100 ms	±20 ms
QTc (corrected) interval	400 ms	±40 ms
P amplitude	0.15 mV	±0.05 mV
QRS height	1.5 mV	±0.5 mV
ST level	0 mV	±0.1 mV
T amplitude	0.3 mV	±0.2 mV

In addition, certain intervals within the ECG signal carry meaningful information and are employed as the features. For example, the PR interval is the duration between the beginning of the P wave and the QRS complex of an electrocardiogram. This duration contains signals between the onset of atrial depolarization and the onset of ventricular depolarization [118]. The QT-interval is the time between the onset of ventricular depolarization and the end of ventricular repolarization. The ST-interval is the time between the end of the S-wave and the beginning of the T-wave [119]. The RR interval (or heartbeat interval) is the time between the R peak of a heartbeat and the following heartbeat, which could be its predecessor or successor [9]. The RR-interval features are determined to realize the dynamic characteristics of the ECG signals [120]. Different RR interval features are used in [4,120,121].

Standard values for several QRS complex features of a normal ECG signal and healthy subjects with no cardiac abnormalities are listed in Table 2. The detailed information for these features is provided in [18] as well.

Since the extraction of the QRS features requires detection of the abovementioned fiducial points, various QRS complex detection algorithms are proposed in the literature. Although the most common one is the Pan-Tompkins algorithm [104], QRS detection algorithms can be categorized as derivative [122], digital filters [104,123,124], wavelet transform [125], neural networks [126] and phasor transform [127] based algorithms. In addition, high-order moments are used to detect QRS complexes in [111]. The difference operation method is used to find the fiducial points in [77]. There are also some studies that especially make use of R peak detection, such as [39,86,111,128–133]. In [105], a dynamic threshold based on a finite state machine is used to detect the R peaks. In [93], the techniques based on differentiation are used to detect the fiducial points. In [57,75,120], the Pan-Tompkins algorithm is used as well.

There also are several open-source QRS detectors that can be used by researchers. For example, EP-LIMITED, based on the Hamilton and Tompkins algorithm, and WQRS, based on a length transform, are used in [72]; the Augsburg Biosignal Toolbox is used in [81]; and ECGPUWAVE software is used in [134,135] to detect QRS and recognize the ECG wave boundary and extract the morphological features.

3.2. Statistical features

Statistical features, which are among the widely used features for ECG analysis in recent years, are usually computed using time domain values of ECG signals. Researchers extract statistical attributes such as energy, mean, standard deviation, maximum, minimum, kurtosis and skewness [5,28,40,46,60,62,64,94,100,111,115,116,131,136–141]. These features, in generic terms, provide an effective means of analyzing the level of complexity and the type of distribution that any time-series exhibits. In the case of ECG recordings, these features therefore would help us to discriminate patient-specific and/or disease-specific variations in such a way that better classification performance is attained.

3.3. Morphological features

The use of morphological features is also possible in ECG analysis. In different studies [21,39–41,48,52,54,58,64,65,83,84,89,92,97,129,139,142], morphological features were used to diagnose ECG signals. Refs [7,87] also used morphological features to classify five types of beats. In [121], the authors choose a random matrix in which each column is normalized, and each row is transformed by DCT as the projection matrix to extract the morphological features of the heartbeats.

3.4. Wavelet features

Frequency-based techniques are among the most popular feature extraction techniques for representing ECG signals for classification purposes. ECG signals are intrinsically nonstationary in nature. This property makes WTs an effective tool for the analysis of ECG signals [143] and for frequency-based feature extraction, with its powerful time-frequency localization property [115,144]. The WT is a linear transform that decomposes a signal into components that appear at different scales [6,145]. Time localization of the spectral components can be obtained by wavelet analysis, as this provides the time-frequency representation of the signal. WTs use wavelets (i.e., scaled and shifted versions of a mother wavelet) to decompose the signal into simpler elements. In the initial stage in a WT, the signal is decomposed into its low- (i.e., approximation) and high-frequency (i.e., detail) components. Further levels of decomposition are accomplished over the last approximation component [146]. Alternatively, if the wavelet packet analysis is used, both approximations and details are decomposed at all levels to achieve full sub-band decomposition [147]. The advantage of the WT is that it preserves the temporal locality [6]. For more details on WTs, readers can refer to [146].

Some of the recent studies on ECG analysis that utilize wavelet-based features are [16,91,115,116,148–158]. Continuous WT features [6], Dual Tree Complex WT features [96], tunable Q factor WT features [141], Flexible Analytic WT features [75] and dyadic DWT features [57] are other features.

3.5. Others

In addition to the abovementioned features, there are particular feature extraction techniques for ECG signals in the literature, such as Lyapunov Exponents [22,159], power spectral density-based attributes [115,116,160,161], statistical features [59,162,163], autocorrelation analysis-based features [24,92], and Kolmogorov complexity-based features [94]. Features extracted by the variation in the beat-to-beat interval in ECG signals [52,103,164–167] and genetic algorithms [168] were also used.

4. Feature selection

High dimensionality of the feature space is one of the most important concerns in ECG signal analysis due to several considerations, such as the computational time and classification accuracy. Feature selection is a set of techniques to determine a subset of the relevant features for building robust learning models by removing the most irrelevant and redundant features. The objective of feature selection is threefold: improving the performance of classification, providing a faster and more cost-effective learning process, and providing a better understanding of the underlying process that generates the data [169]. It is well known that the incorporation of feature selection can improve the generalization ability of classifiers [48]. Therefore, feature selection plays a crucial role for not only reducing the feature dimension and computational time but also improving the performance of discrimination or classification of ECG signals.

Feature selection methods are primarily grouped into three categories, called filter, wrapper, and embedded methods [170]. Filter methods evaluate feature relevancies using various scoring schemes independently from a learning model or classifier [171]. These methods are scalable, computationally simple and fast. On the other hand, wrapper methods evaluate features using a specific learning model and search algorithm [172]. Those methods consider feature dependencies and provide interaction between feature subset search and choice of a learning model. However, they are computationally expensive with respect to the filters. In the case of embedded methods, an optimal feature subset search is built into the classifier setup. In other words, feature selection is integrated into the training process of the classifier; therefore, embedded methods are specific to the utilized learning model. In this sense, they are similar to but less computationally intensive than wrappers [171,173]. While the individual employment of the filters or wrappers is more common in the literature, researchers can also utilize the filters and wrappers together within a feature selection scheme. There is a vast amount of work on ECG analysis that employs the abovementioned feature selection methods. In this survey, widely used versions of those methods are grouped as filters, deterministic wrappers, and randomized wrappers, among others. In addition, the studies on ECG signal analysis using feature selection methods are given in these subsections.

4.1. Filters

As mentioned before, filter-based selection methods are general feature selection procedures that rank the features according to a predefined evaluation criterion, which is independent of the classifier. Some studies on filter-based feature selection for ECG signals involve correlation criteria [90,174,175], Fisher score [140], mutual information techniques [163], fuzzy clustering [47,136], information gain-based selection [135], and rough sets-based selection [28].

Correlation criteria is a feature selection algorithm that considers such criteria as the feature's affinity toward a particular class and the feature's correlation with other features [174]. The Fisher score is a feature selection method that assigns a score to each feature according to a Fisher criterion [140]. The Fisher criterion is a discriminant criterion function introduced by Fisher in 1936. Mutual information of two random variables shows the mutual dependence of the variables [170]. When mutual information is used as a feature selection method, these two variables will be a feature and a particular class. A fuzzy c-means algorithm is used for fuzzy clustering-based feature selection. The relative distance among the patterns and cluster prototypes are calculated for the computation of fuzzy memberships in the fuzzy c-means algorithm [136]. The information gain measures the amount of information that the presence or absence of a feature contributes to correct classification about a particular class [135,170]. The rough sets-based feature selection method benefits from rough set theory [28]. This method uses a heuristic function to measure the significance of the unselected features when a forward selection approach is employed.

4.2. Deterministic wrappers

Sequential selection methods are the most widely used deterministic wrappers. These methods measure the contribution of each feature to the classification by adding or removing different numbers of features to/from the original feature set until a better criterion value is attained [176]. In the sequential forward selection method, the selection procedure starts with an empty set initially. Then, at each step, the feature maximizing the criterion function is added to the current set. This operation continues until the desired number of features is selected. In the sequential backward selection method, the selection procedure starts with a complete feature set, and the other steps are the reverse of steps in the sequential forward selection method. Due to the presence of the nesting effect, those two methods can offer only suboptimal results. In generalized versions of those methods, instead of a single feature, n features are used for adding to or removing from the current feature set at each step [177]. The nesting effect is still present. Plus-l takeaway-r (PTA) is another generalization version of these two methods. In PTA, l feature is selected using the sequential forward selection method, and then r features are removed with the sequential backward selection method at each step. Although the nesting effect is reduced with respect to both methods, PTA still provides suboptimal results.

Sequential floating selection methods are extensions to the PTA algorithms that have flexible backtracking capabilities. Sequential Floating Forward Selection (SFFS) starts with an empty set. After each forward step, SFFS performs backward steps as long as the objective function increases. SFFS is like a dynamic version of PTA. In this selection method, l and r parameters float in each step, whereas they are constant in the case of PTA [178]. Thus, in each step of a selection, different numbers of features can be added to or removed from the original set until a better criterion value is attained. This flexible structure causes the feature dimension to float at each step. Sequential floating backward selection (SFBS) starts from the full set. After each backward step, SFBS performs forward steps as long as the objective function increases.

Sequential feature selection method [164], sequential floating feature selection algorithm [34,54,179], *k*NN based sequential forward selection algorithm [59], and forward selection and backward selection SVM with Gaussian RBF kernel [62] are some sample approaches for feature selection on ECG signals.

4.3. Randomized wrappers

Another often-preferred feature selection approach in an ECG signal analysis algorithm is a genetic algorithm (GA)-based selection approach. The GA is a probabilistic search method inspired by the biological evolution process [180]. The principle of GAs is the survival of the fittest solutions among a population of potential solutions for a given problem. Thus, new generations produced by the surviving solutions are expected to provide better approximations to the optimum solution [170]. The solutions correspond to chromosomes that are encoded with an appropriate alphabet. The fitness value of each chromosome is determined by a fitness function. New generations are obtained using genetic operators, crossover and mutation, with certain probabilities on the fittest members of the population. The initial population can be randomly or manually defined. The population size, number of generations, probability of crossover and mutation are defined empirically. In genetic selection, the chromosome length is equal to the dimension of the full feature set. The chromosomes are encoded with a (0, 1) binary alphabet. In a chromosome, the indices that are represented with "1" indicate the selected features, while "0" indicates the unselected features. For example, a chromosome defined as (1 0 1 0 1 1 0 0 0 1) specifies that the features with indices 1, 3, 5, 6, and 10 are selected while the others are unselected. The fitness value that corresponds to a chromosome is usually defined as the classification accuracy obtained with the selected features. Some of the recent studies that utilize GA-based feature selection on ECG analysis are given in [32,44,46,58,139,158].

4.4. Others

In [47,90,174,175], the features are selected according to correlation coefficient-based techniques. A hill-climbing feature selection algorithm [91] and Greedy best first algorithm (selection of the relevant characters in a compressed ECG) [181] techniques are heuristic-based feature selection applications for ECG signal analysis. In addition, there are different types of user-defined feature selection methods, such as character frequencies (selection of relevant characters in compressed ECGs) [182], selection of the first couple of Ics and subset of features [183], multi-class f-score feature selection [184], nonoverlapping area distribution measurement [185], Fuzzy c-means clustering [136], Q− (alfa) algorithm [103], Qualitative feature selection [106], Range-Overlaps Method [107,186] with FPGA [187], kernel-based class separability [137,166], SVMAttributeEval [60], divergence analysis [5] and Student's *t*-test [57]. A disease-specific feature selection method, (one-versus-one (OvO) features ranking stage and a feature search stage wrapped in the same OvO-rule SVM binary classifier) is used in [48].

5. Feature transformation

Since the main goal of feature selection and feature transformation is to reduce the feature dimension, these two terms are often used interchangeably by researchers. However, feature transformation actually achieves this goal by transforming the original space into a lower dimensional subspace, whereas feature selection reduces the dimension by selecting a more discriminative subset among an initial feature set. In other words, feature selection and feature transformation are not equivalent approaches. In this section, well-known feature transformation methods that are employed in ECG analysis are introduced, and the reference studies are mentioned.

5.1. Principal component analysis (PCA)

PCA is one of the well-known methods for feature extraction and dimensionality reduction in signal classification, and it accomplishes a linear mapping of a high-dimensional input vector into a low-dimensional vector whose components are uncorrelated. It also acquires a unique solution by compelling a specific orthogonal structure onto the mapping matrix [188]. PCA computes the principal components as a percentage of the total variability of the data. The first principal component corresponds to the vector that has the highest variability (uncorrelated). The second principal component corresponds to the vector in the next direction that is orthogonal to the first principal component, and so on. Feature transformation using PCA requires computation of the covariance matrix of the data, its eigenvalue-eigenvector decomposition, storing of eigenvectors that correspond to the eigenvalues sorted in descending order and, finally, projection of the data into the new subspace defined by the principal components [16,86,87]. The PCA projects the data into the directions that have the highest variability, which provides a representation of the data with a small number of features. However, these features do not represent the best directions for obtaining the highest possible discrimination to identify different classes [86]. Some of the recent studies on ECG analysis that used PCA for feature dimensionality reduction are given in [21,28,86,87,120,133,140,166,189,190].

5.2. Linear discriminant analysis (LDA)

LDA is a popular dimension reduction method that is used to transform one set of features into another set that is smaller than the original set. In the new feature space, the data distribution can acquire the main idea: maximizing the between-class distance and minimizing the within-class distance [166]. The studies that used LDA are given in [28,86,133,166].

5.3. Independent component analysis (ICA)

Independent component analysis (ICA) is a statistical approach that transforms measured multidimensional random data into features that are statistically independent from one another as much as possible [191]. ICA was originally produced to address problems that are closely related to the cocktail-party problem [192]. It also separates a mixed signal into components. The ICA method assumes that the given measured signal is produced due to linearly mixing the source components [73]. In [73,86], ICA was also applied for the same purposes as in PCA and LDA.

5.4. Others

Reference [193] used SR (spectral regression) and KSR (Kernel-based spectral regression) projection for feature transformation. Another method is FCM (Fuzzy C-mean) clustering [35,194]. Uncorrelated Fuzzy Neighborhood Preserving Analysis (UFNPA) using SVD, and QR decomposition was proposed as a feature projection method that is utilized to derive the discriminant information relevant to the loss of attention that results from drowsiness [195]. Reference [189] used RCC (Rank Correlation Coefficient) and B-splines for feature transformation.

Fang et al. [29] embedded each type of ECG signal into three-dimensional phase space, which includes closely repeating topological patterns. The main advantage of the phase space perspective is that the R-waves do not need to be completely aligned as long as the necessary waveform is contained. There are also different feature transformation methods, such as radial basis function [128], continuous WT [196], heart rate variability [166], and singular value decomposition [57].

6. Classification

In the literature, there are various classifiers that have been utilized for ECG analysis and classification tasks. According to the recent studies reviewed in this paper, these classifiers can be mainly grouped into categories such as artificial neural networks (ANNs), LDA, k nearest neighbor (kNN), support vector machine (SVM), decision tree (DT), and Bayesian classifiers. All of these common approaches and other uncommon approaches are explained in the next subsections.

6.1. Artificial neural networks (ANN)

An ANN is a mathematical model that is inspired by biological neural networks. It includes interconnected artificial neurons, with the interconnections associated with adjustable weights; the neurons consist of input, output and/or hidden layer(s); this approach is one of the widely used pattern classifiers. ANNs aim to solve both linear classification and non-linear classification problems with various network structures and learning algorithms. The neural network structures frequently used in the ECG classification domain are as follows:

a) **Complex-valued ANN:** This ANN is a type of network that consists of complex-valued data, complex-number weights and complex-valued neuron activation functions [197]. Complex-valued ANNs are employed in one of the ECG classification studies [148].
b) **Fuzzy clustering ANN:** In this structure, a fuzzy clustering layer and an ANN layer that consists of a multilayer perceptron work sequentially. While the fuzzy layer performs the initial operations for the classification task, the ANN layer works as a final classifier. Eventually, fuzzy clustering is used to improve the performance of the ANN classifier [136]. The fuzzy clustering ANN has been used in some recent studies [35,136,198].
c) **Recurrent ANN:** This ANN is a neural network structure that has closed loop connections between neurons [199]. This type of ANN can perform highly nonlinear dynamic mappings, and it has been used in many applications, such as spatiotemporal pattern classification, control and optimization [162]. Recurrent ANNs are utilized in some of the ECG classification studies [23,159,162].
d) **Backpropagation neural network (BPNN):** In the backpropagation learning algorithm, the output response of the network is compared to the desired output, and the error value is calculated. Based on this error, the weights of the various layers moving backward from the output layer to the input layer are adjusted. Then, the whole learning process is repeated until the error is minimized. BPNN was employed in some recent studies [16,54,96,158,198].
e) **Probabilistic neural network (PNN):** PNN is a feed-forward neural network that was derived from the Bayesian network and kernel Fisher discriminant analysis. In addition, the training phase of the PNN is known to be faster than many neural network models, such as backpropagation networks [200]. The PNN was used in several recent studies [35,86,133].
f) **Radial basis function neural network (RBFNN):** RBFNNs have a simple structure and training efficiency [83]. This type of ANN uses radial basis functions as activation functions, and the output of the network is a linear combination of radial basis functions

of the inputs. RBFNNs were employed in various recent ECG classification studies [25,28,81,111,128].

g) **Generalized regression neural network (GRNN):** The GRNN is a branch of the radial basis function neural network in which the smoothing parameter requires optimization. It consists of 4 layers, namely, the input layer, pattern layer, summation layer, and output layer. Parallel GRNN, based on a graphics processing unit (GPU), is used in [77] to classify heartbeats.

h) **Neural network models with adaptive activation function (NNAAF):** This approach has the same architecture as the conventional multi-layer perceptron, which consists of input, output, and hidden layer(s). The only key difference is that the hidden layer has adaptive activation functions with free parameters [201].

i) **Learning Vector Quantization (LVQ):** LVQ is close to being a version of the self-organizing map, which is an unsupervised ANN, that is transformed into a supervised network. LVQ usually includes a competitive layer followed by a linear layer. While the competitive layer is used to learn classifying input vectors similar to self-organizing algorithms, the linear layer is used to transform the competitive layer's classes into desired output classes [23].

j) **Time-delayed neural network (TDNN):** The TDNN has a structure that is similar to a classical multi-layer perceptron. The main difference is the existence of time-delayed links [202]. The TDNN was used for ECG classification in one of the recent studies [55].

k) **Block-based neural network (BbNN):** BbNN can be represented by a two-dimensional array of blocks, where each block is a simple processing element. These blocks correspond to a feed-forward ANN with four variable input/output nodes, and they are connected to their four neighboring blocks with a signal flow represented by an incoming or outgoing arrow between those blocks [203]. The BbNN was also applied in some recent studies [7,204].

6.2. Linear discriminant analysis (LDA)

LDA was originally developed in 1936 by Fisher, and it often produces models that obtain higher classification accuracies in comparison with more modern and complex classification methods [205]. It aims to maximize the ratio of the between-class variance to the within-class variance, and it provides the highest possible discrimination between different classes. LDA is utilized in some of the recent ECG classification studies [62,86,106,150,153,166,193].

6.3. k *nearest neighbor (*k*NN)*

*k*NN classifies feature vectors according to the labels of the closest training samples in the feature space. For an unknown feature vector, the distances from this vector to all vectors in the training set are calculated using a distance measure such as the Euclidean distance. Then, an unknown feature vector is assigned to the class in which the closest k samples mostly belong to. Thus, a kind of majority voting approach is applied. The value of *k* is a positive integer and is known to be a strongly influencing factor for the accuracy of the classification. *k*NN has a wide usage in most of the pattern recognition problems and is also employed in some recent ECG classification studies [30,58,59,62,74,114,193].

6.4. Support vector machine (SVM)

SVM is a widely used tool for solving binary classification problems because of its outstanding generalization performance. The main idea of the SVM is to find a maximum margin between the training data and the decision boundary [183]. Support vectors, which are the training samples that are closest to the decision boundary, are used for margin maximization. The SVM can be regarded as either a linear or nonlinear classifier according to the type of its kernel function. While a linear kernel function makes the SVM a linear classifier, other kernel functions, such as Gaussian radial basis, polynomial, and sigmoid, make it a non-linear classifier. The SVM is utilized in most of ECG classification studies [16,44,47,48,57,60,62,63,72,75,79,83,86,87,89,91,94,95,98,114, 120,121,135,139,140,142,145,153,165,183,189,190,193,195, 206–209].

6.5. Decision tree (DT)

DT learning aims to map observations about an item to a conclusion. This conclusion can be either a possible target class label or a target value. According to the difference in this conclusion, DT structures are called classification or regression trees. While the leaves of classification trees represent class labels, the leaves of regression trees represent continuous values. DT is used in some ECG classification studies [81,137,138,195]. In addition to common decision tree approaches, there are some more specific decision tree structures that are used frequently for ECG classification. The Random Forest Tree is a type of ensemble classifier that uses many decision trees [74]. In this approach, multiple decision trees are trained with subsets of training data. This approach uses a type of majority voting in which the output class label is assigned according to the number of votes from all the individual trees. This approach is also frequently used for ECG classification studies [74,81,135,163,165].

6.6. Bayesian

Bayesian classifiers are the systems that are based on Bayes' decision theory. This theory is a fundamental statistical approach [210]. The idea behind these classifiers is that if the class is known, the values of the other features can be predicted. If the class is not known, then Bayes' rule can be used to predict the class label according to the given feature values. In Bayesian classifiers, probabilistic models of the features are built to predict the class label of a new sample. Bayesian classifiers, which are one of the widely used methods for pattern recognition problems, are utilized in most of the recent studies [48,54,55,73,163,165,185,189,209,211]. The types of Bayesian classifiers utilized for ECG classification are the Bayesian network [165,189], naïve Bayes [73,81,163,189], and Bayes maximum likelihood classifier [55].

6.7. Others

Apart from the abovementioned classification methods, there are also various classifiers that have been utilized for ECG classification, such as fuzzy logic classifier [32,168], genetic fuzzy classifier [168], template matching technique [53,182], Gaussian mixture model based classifier [70,73,100], local fractal dimension-based nearest neighbor classifier [212], a new classification tree algorithm [138], linear regression [37], logistic regression [34,62,81,135], hybrid Bees algorithm-radial basis function [85], threshold-based classifier [6], modified artificial bee colony algorithm [5], ensemble models (Bagging and AdaBoost) [81], Bootstrap aggregating ensemble method (to combine 100 DT learners) [4], hidden Markov model-based detection approach [62], and random under-sampling boosting [141].

In addition, fuzzy clustering [136,186,187], expectation maximization [165,174,175,181], k-means [97,165], and self-organizing maps [34] are employed as unsupervised learning methods.

7. Application fields

In the literature, there are various application fields for ECG analysis and classification tasks. According to the recent studies reviewed in this paper, these fields can be grouped as disease classification, heartbeat type detection, biometric identification, and emotion recognition. All of these common fields that the studies mostly focused on and other uncommon fields are explained in the next subsections.

7.1. Disease classification

Since interpretation of ECG signals is critical for correct diagnosis of the heart diseases, much effort has been made to analyze and classify ECG signals that belong to various heart problems. The aim of these efforts is the early detection of heart disease in general. Early detection can rescue the patient's life or prevent permanent damage to human organs [201]. The heart problem that most of the studies have focused on is arrhythmia. Apart from arrhythmia, there are also some studies on other disease types.

Abnormality of the ECG shape is called cardiac arrhythmia. During cardiac arrhythmia, the heart can beat too fast, too slow, or with an irregular rhythm. Arrhythmia prevents the heart from pumping enough blood to the body, and some of the arrhythmias can be even life threatening. At critical levels, cardiac arrhythmias are divided into two categories [20,48]: life-threatening and non-life-threatening. The first category includes ventricular fibrillation and tachycardia and could stimulate cardiac arrest and sudden death, and thus, it requires immediate treatment [4,47]. In the case of ventricular fibrillation, chaotic irregular deflections of varying amplitudes are observed in ECG recordings. There are no identifiable P waves, QRS complexes, or T waves. The heart rate can be from 150 to 500 per minute, and the amplitude decreases with the duration. Tachycardia mainly refers to a heart rate that is greater than 100 per minute for an adult. Tachycardias are commonly categorized as regular or irregular, and narrow complex or wide complex. As an example, for sinus tachycardia, the heart rate is approximately 150 bpm, and the P waves are usually hidden within each preceding T wave.

The second category includes arrhythmias that are not imminently life-threatening, and treatment is still needed to prevent further problems [4,20,48]. Due to these characteristics, this category is one of the most often addressed fields by researchers [4,5,7,13,16,32,35,36,54,58,64,65,77,85–87,89,95,96,106,107,120,121,133,136,140,148,149,151,158,168,186,190,194,201,206,207,209,212,213].

Table 3 presents information about the settings used in those cardiac arrhythmia detection studies that were in the top-10 highest performances in terms of accuracy. According to Table 3, PNN and SVM are the most successful classification algorithms for cardiac arrhythmia detection. PCA, LDA, FCM, divergence analysis, ICA, and Fisher score are dimension reduction methods that are used in cardiac arrhythmia detection studies with the highest performances. It should be noted that only 2 out of 10 studies in Table 3 do not apply dimension reduction methods.

Table 3
Performances of the cardiac arrhythmia detection algorithms.

Ref.	Dimension reduction	Classifier	Accuracy (%)
[133]	PCA, LDA	PNN	99,71
[35]	FCM	PNN	99,58
[190]	PCA	PNN	99,52
[5]	Divergence analysis	Modified Artificial Bee Colony	99,30
[86]	ICA	PNN	99,28
[148]	N/A	Complex valued ANN	99,20
[16]	PCA, ICA	SVM	98,91
[120]	PCA	SVM	98,82
[140]	PCA, Fisher score	SVM	98,60
[121]	N/A	SVM	98,46

In addition, there are some more specific types of ECG arrhythmias. An example that has been addressed by researchers in this field is atrial fibrillation [49,51,73,74,163]. In the case of atrial fibrillation, the heart rhythm is irregularly irregular. There are no P waves or isoelectric baseline. Fibrillatory waves could be present and can be either fine or coarse. They could also mimic P waves and thus lead to possible misdiagnosis.

The tasks that are related to other various disease types are sleep apnea detection [62,63,91,141,164,184], severity classification for Parkinson's disease [137], ischemia detection [138], detection of heart rate turbulence [31], sleep bruxism [50], detection of myocardial infarction [34,57], detection of myocardial scar [60], detection of hypertrophic cardiomyopathy identification [135], detection of inferior myocardial infarction [6] and classification of coronary artery disease [75].

7.2. Heartbeat type detection

The purpose of this task is to separate different ECG beats from each other. This task is a part of ECG data analysis. There are various efforts that have concentrated on the separation of different types of ECG beats from one another. These efforts differ according to the used ECG beat types and applied detection approaches. There are many studies in the literature about heartbeat type detection [21–23,27,38,52,55,76,90,97,128,139,159,160,162,179,183,198,214–216].

7.3. Biometric identification

The term biometric refers to human specific characteristics or metrics. Biometric identification, which is associated with the term biometric, means identification of an individual inside a group of people using this characteristic information automatically. The purpose of biometric identification is usually to increase security for any reason. There are various types of biometric information that can be extracted from humans, such as face, fingerprint, and retinal data. There are many recent studies related to ECG-based biometric identification in the literature [12,13,25,26,28–30,53,79,93,113,130,175,182].

7.4. Emotion recognition

Emotion recognition is the one of the fundamental techniques of affective computing, which is the key technology for human-machine interaction [155]. Emotion can be recognized from facial expression, speech, physiological signals, and so on. Some examples of emotions are joy, anger, sadness, and pleasure. In this paper, ECG-based emotion recognition is only addressed. There is a limited number of recent studies related to ECG-based emotion recognition in the literature [13,155,217].

7.5. Others

The tasks that cannot be categorized into the four specific topics above are driver drowsiness classification [44,193,195], fetal heart rate detection [143], sleep/wake states classification [161], and physical activity recognition [98].

8. Databases

Various databases are publicly available to evaluate the methods proposed in studies that target the analysis of ECG signals. The following databases [218] are widely used for different purposes in ECG signal analysis:

a) **The Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) Arrhythmia database** is widely used for ECG signal analysis and is described in detail in Section 8.1.
b) **Physionet PTB Diagnostic ECG database** includes 549 records from 290 persons with 52 healthy and 148 sick persons. Each subject is represented by one to five records. Each record includes 15 simultaneously measured signals. The sampling rate is 1000 samples/second with a 16-bit resolution over a range of ±16.384 mV. The subjects were 209 men and 81 women, 17–87 years of age.
c) **The QT database** contains ECG recordings selected primarily from existing ECG databases, including 15 recordings from the MIT-BIH Arrhythmia Database, 6 recordings from the MIT-BIH ST Change Database, 13 recordings from the MIT-BIH Supraventricular Arrhythmia Database, 4 recordings from the MIT-BIH Long Term Database, 10 recordings from the MIT-BIH Normal Sinus Rhythm Arrhythmia Database, 33 recordings from the European Society of Cardiology ST-T Database, and 24 recordings from the sudden death patients gathered at Boston's Beth Israel Deaconess Medical Center. The QT Database covers a total of 105 recordings of two channel ECGs, which were chosen to prevent important baseline fluctuations or other artifacts. All the ECG signals were sampled at 250 samples/second.
d) **The Apnea-ECG database** contains 70 recordings with the time interval of ECG recordings ranging between 401 and 578 min. The sampling rate is 100 Hz. Each recording contains a continuous digitized ECG signal, a set of apnea annotations, and a set of machine-generated QRS.
e) **Non-Invasive Fetal ECG database** comprises 55 multichannel non-invasive fetal electrocardiogram recordings, collected from only one subject at 21–40 weeks of pregnancy. The records have changeable durations and were collected weekly. These records can be used for testing signal separation algorithms.
f) **Creighton University (CU) Ventricular Tachyarrhythmia database** contains 35 eight-minute (slightly less than 8.5 min) single-channel ECG recordings of subjects who suffered from episodes of sustained ventricular tachycardia, ventricular flutter, and ventricular fibrillation. The sampling rate is 250 Hz with a 12-bit resolution over a 10-V range.
g) **The American Heart Association (AHA) database** contains 80 two-channel ECG recordings. The sampling rate is 250 Hz per channel with a 12-bit resolution over a 10-mV range. The short version comprises five minutes of unannotated ECG prior to a thirty-minute annotated section in each recording, and the long version contains 2.5 h of unannotated ECG preceding each annotated segment. This database was developed for the evaluation of ventricular arrhythmia detectors.
h) **Fantasia database** contains records of 40 subjects. Half of them are young people between the ages of 21 and 34, and the remaining half are elderly people between the ages of 68 and 85. There is a single record for each person with a two-hour interval. The sampling rate is 250 Hz
i) **The BIDMC Congestive Heart Failure database** is composed of 20 h of ECG recordings from 15 subjects. The recordings have a sampling rate of 250 samples/second with a 12-bit resolution over a range of ±10 millivolts. The subjects were 11 men, 22–71 years of age, and 4 women, 54–63 years of age.
j) **The European ST-T database** is composed of 90 two-hour annotated ECG recordings from 79 persons. Each record has two signals; the sampling rate for each signal is 250 Hz with a 12-bit resolution over a nominal 20-millivolt input range. The subjects were 70 men, 30–84 years of age, and 8 women, 55–71 years of age. The ST segment and T-wave changes were identified in both leads, and their onsets, extrema, and ends were annotated by two cardiologists.
k) **The Long-Term ST database** covers 86 lengthy ECG recordings of 80 persons. Each recording ranges between 21- and 24-h time intervals and is composed of two or three ECG signals. The sampling rate is 250 Hz with a 12-bit resolution over a range of ±10 millivolts.
l) **The St. Petersburg Institute of Cardiological Technics (INCART) database** is composed of 75 annotated recordings collected from 32 holter contacts. Each record is 30 min and includes 12 standard leads. The sampling frequency of each record is 257 Hz. The subjects were 17 men and 15 women, 18–80 years of age.

Table 4 lists some of the most common databases and detailed information: the number of records, number of subjects, duration of each recording, sampling frequency, sample resolution and number of leads for each database; the recent studies that employed these databases are listed in Table 5. The interested reader can determine detailed information on the databases mentioned in this paper at https://www.physionet.org/physiobank/database/#ecg.

8.1. MIT-BIH

The MIT-BIH Arrhythmia Database includes 48 parts that contain two-channel ECG recordings. Those parts were recorded between 1975 and 1979 at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center) and obtained from 47 persons. Each part has a duration of half an hour. The persons were 25 men and 22 women. The men were 32–89 years of age, and the women were 23–89 years of age (two records are collected from the same male subject among all the records). The sampling rate is 360 samples per second, and the resolution for digitization is 11-bit over a 10-mV range.

a) **MIT-BIH Normal Sinus Rhythm database** contains 18 long-term ECG recordings of persons who have no significant arrhythmias. The persons are 5 men, 26–45 years of age, and 13 women, 20–50 years of age. The recordings were gathered at the Laboratory of Boston's Beth Israel Hospital, and the sampling rate is 128 Hz
b) **MIT-BIH Noise Stress Test database** is composed of 12 half-hour ECG recordings and 3 half-hour noisy ECG recordings. The ECG recordings were produced by adding adjusted amounts of noise to uncontaminated ECG signals from the MIT-BIH Arrhythmia Database.
c) **MIT-BIH Atrial Fibrillation database** consists of 25 long-term ECG signals of persons who are suffering from atrial fibrillation disease. The sampling rate is 250 Hz, and the resolution for digitization is 12 bit over an interval of ±10 mV
d) **MIT-BIH T-Wave Alternans Challenge database** covers 100 ECG records. The sampling rate is 500 Hz, and the resolution for digitization is 16 bit over an interval of ±32 mV. The patients who are suffering from myocardial infarctions, transient ischemia, ventricular tachyarrhythmias, and other diseases relevant to sudden cardiac death have given their ECG signals. This database also includes healthy controls and synthetic cases, with adjusted amounts of T-wave alternans. Each record has a duration of two minutes.
e) **MIT-BIH Supraventricular Arrhythmia database** is composed of 78 half-hour ECG recordings selected to add the cases of supraventricular arrhythmias to the MIT-BIH Arrhythmia Database. The ECG signals have a sampling rate of 128 Hz, and the resolution for digitization is 10 bit.
f) **MIT-BIH Malignant Ventricular Arrhythmia database** contains 22 ECG recordings of persons who are suffering from episodes of ventricular tachycardia, ventricular flutter, and ventricular fibrillation. The sampling rate is 250 Hz, and the resolution for digitization is 12 bit.
g) **MIT-BIH Long Term database** is composed of 7 long-term ECG recordings. Each record has a duration of 14–22 h. The sampling

Table 4
Databases [218].

Databases	Records	Subjects	Duration (min.)	Fs:Sampling frequency (Hz)	Digitization resolution (bit/sample)	Channels (leads)
MIT-BIH Arrhythmia	48	47	30	360	11	2
MIT-BIH Normal Sinus Rhythm	18	18	24 h	128	N/A	2
MIT-BIH Noise Stress Test	12 ECG + 3 noise	12	30	360	N/A	2
MIT-BIH Atrial Fibrillation	25	25	10 h	250	12	2
MIT-BIH T-Wave Alternans Challenge	100	N/A	2	500	16	Multi (12,2,3)
MIT-BIH Supraventricular Arrhythmia	78	N/A	30	128	10	2
MIT-BIH Malignant Ventricular Arrhythmia	22	16	30	250	12	2
MIT-BIH Long Term	7	7	14–22 h	128	2lead:12 1lead:10	2lead:6 1lead:3
MIT-BIH-ST Change	28	28	13–67	360	N/A	1–2
Physionet PTB	549	290	N/A	1000	16	12 – 3
QT	105	N/A	15	250	N/A	2
Apnea-ECG	70	N/A	401–578	100	16	N/A
Non-Invasive Fetal ECG	55	1	N/A	1000	16	multi
CU Ventricular Tachyarrhythmia	35	N/A	8	250	12	1
AHA short/long	10/67	N/A	30/150	250	12	2/99
Fantasia	40	40	120	250	N/A	N/A
BIDMC Congestive Heart Failure	15	15	20 h	250	12	N/A
European ST-T	90	79	120	250	12	2
Long Term ST	86	80	21–24 h	250	12	2–3
IN—CART	75	32	30	257	N/A	12
PhysioNet/Computing in Cardiology Challenge 2011			>10 s	500	16	12

Table 5
Recent studies that employ the common databases.

Databases	Studies
MIT-BIH Arrhythmia	[4,5,7,13,16,21,23,24,27,31,36,39,41,48,52,54,55,58,59,64–67,70–74,76,77, 80,82–90,93–96,101,103,105–107,111,117,120,121,129,132–134,136,139,140, 142,145,148,149,151,152,156,158,165,167,168,183,186,190,194,196,198,201, 204,206,207,209,212–215,219–223]
MIT-BIH Normal Sinus Rhythm	[22,24–26,28,37,66,92,93,105,130,159,160,165,182]
MIT-BIH Noise Stress Test	[66,72,82,90,223]
MIT-BIH Atrial Fibrillation	[74,159,160]
MIT-BIH T-Wave Alternans Challenge	[31,45]
MIT-BIH Supraventricular Arrhythmia	[129,165,174,179]
MIT-BIH Malignant Ventricular Arrhythmia	[13,32,46,47,150]
MIT-BIH Long Term	[25,97,129]
MIT-BIH-ST Change	[129]
Physionet PTB	[6,24,25,28,30,34,40,57,60,80,92,113,141,153,154,224]
QT	[31,40,53,71,93,117,154,211]
Apnea-ECG	[62,63,91,105,141,208]
Non-Invasive Fetal ECG	[143]
CU Ventricular Tachyarrhythmia	[13,46,47,150,159,160,181,185]
AHA	[14,46,152,225]
Fantasia	[25,28,75,102,105]
BIDMC Congestive Heart Failure	[37,159,160,165,185,189]
European ST-T	[31,70,93,128,129]
Long Term ST	[129]
IN—CART	[75,129,179]
PhysioNet/Computing in Cardiology Challenge 2011	[72,80]

rate is 128 Hz, and the resolution for digitization is 12 bit for 2-lead and 3-lead ECG recordings.

h) **MIT-BIH-ST Change database** consists of 28 ECG recordings. Each record has a duration that is between 13 and 67 min. These records are collected during workouts, and they include instantaneous ST depression. In addition to them, the last five records include the ST elevation. The sampling rate is 360 Hz

In terms of arrhythmia classification, the MIT-BIH database is unique since it presents the five arrhythmia groups suggested by the Association for the Advancement of Medical Instrumentation (AAMI) standards, as described in Table 6 [9]. Heartbeat types that exist in this database are grouped into 5 different classes: Normal (N), Supraventricular ectopic beat (SVEB), Ventricular ectopic beat (VEB), Fusion beat (F) and Unknown beat (Q). The 5 superclasses, 15 classes and their symbols are listed in the same table.

There are many studies in the field of arrhythmia classification, which are mentioned in [9]. Some of them utilize the AAMI standards, but a variety of studies miss these standards, and most of these studies use an intra-patient paradigm. In this scheme, the dataset is separated into training and testing subsets based only on the beat label, where an ECG recording, which belongs to the same patient, can partly appear in both subsets. In [20], the authors showed that the usage of heartbeats from the same patient for both data subsets makes the evaluation process unfair. This heartbeat (patient) division scheme is named in the literature as the intra-patient paradigm, which is also known as the "class-oriented" scheme [142]. Using this paradigm, the classifiers usually produce overly optimistic results [48]. On the other hand, in clinical practice, an inter-patient paradigm that is also known as the "subject-oriented" scheme [142] is more appropriate because the classification performance declines due to the inter-individual variation. In this scheme, the classifier would exhibit better gen-

Table 6
Heartbeat types presented in the MIT-BIH database according to ANSI/AAMI EC57:1998 standard classes.

AAMI heartbeat classes	N Any heartbeat not classified as SVEB,VEB, F or Q	SVEB (S) Supraventricular ectopic beat	VEB (V) Ventricular ectopic beat	F Fusion beat	Q Unknown beat
MIT-BIH heartbeat types	Normal beat (NOR)	Atrial premature beat (AP)	Premature ventricular contraction (PVC)	Fusion of ventricular and normal beat (fVN)	Paced beat (P)
	Left bundle branch block beat (LBBB)	Aberrated atrial premature beat (aAP)	Ventricular escape beat (E)		Fusion of paced and normal beat (fPN)
	Right bundle branch block beat (RBBB)	Nodal (junctional) premature beat (NP)			Unclassifiable beat (U)
	Atrial escape beat (AE)	Supraventricular premature beat (SP)			
	Nodal (junctional) escape beat (NE)				

Table 7
Heartbeat distribution for each class according to the heartbeat division schema proposed in [20].

Set	N	SVEB	VEB	F	Q	Total
DS1	45886	944	3788	415	8	51021
DS2	44259	1837	3221	388	7	49712
DS1 + DS2	90125	2781	7009	803	15	100733

Recordings in DS1: 101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230.
Recordings in DS2: 100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234.

eralization ability [48]. The number of heartbeats for each class in the MIT-BIH database according to the heartbeat division schema proposed in [20] is given in Table 7.

8.2. Others

Some researchers prepared their own databases [33,61,79,81,98,112,135,155,163,185,226]. Mendez et al. used polysomnographies collected at the sleep laboratory of the Philipps Universitat [164]. Custom databases that include a different number of subjects were also used in some studies [29,31,49–51,77,138,193,195,198].

Dima et al. preferred the Database of Cardiology Department of the University Hospital Southampton NHS Trust [60]. Other databases used in the literature are the following: OSAS [184], PA database [98], Sleep Heart Health Study Polysomnography database [90], MIT Media Lab database [166], HiMotion database [30], AFPDB [130], SVDB [130], DalSy database [143], Abdominal and Direct Fetal Electrocardiogram database [143] and Southampton General Hospital Cardiology Department's database [153], medical imaging technology database [47], UofTDB [12], Allergy database [105], St. Vincent's University Hospital/University College Dublin (SVUH/UCB) Sleep Apnea Database [63,91,141], TELE database [223], and CinC CAP sleep database[44].

9. Success measures

In the literature, there are various success measures that are used to evaluate ECG analysis and classification tasks. Because these tasks are a part of the pattern recognition research field, the metrics are also a subset of the success measures that are widely used in general pattern recognition tasks. For pattern recognition tasks, a confusion matrix is derived from the classification results, and most of the success measures are variants of the information that the matrix stores. To explain these metrics, an example confusion matrix for the two-class case is shown in Table 8.

The entries in the confusion matrix have the following meaning. *TP* is the number of correct predictions for positive samples, *TN* is the number of correct predictions for negative samples, *FN* is the number of incorrect predictions for positive samples, and *FP* is the number of incorrect predictions for negative samples.

Table 8
An example confusion matrix for the two-class case.

	Positive (Predicted)	Negative (Predicted)
Positive (Actual)	TP	FN
Negative (Actual)	FP	TN

According to the recent studies reviewed in this paper, these measures can be listed as the accuracy, precision, recall (or sensitivity), F-measure, specificity, Matthews correlation coefficient, and area under curve (receiver operating characteristic). All of these metrics are explained in the next subsections.

9.1. Accuracy

The accuracy can be defined as the ratio of correct classification to the number of total classified samples. Most of the ECG-related studies prefer accuracy as the success measure [5,6,16,21–24,27,28,30,32,34–36,38,48,50,51,53,55,57,60,62,70,72,75–77,81,83–85,90,91,95,97,106,107,120,121,130,132,134,136,138,139,141,142,148–150,155,158–162,164,165,167,168,174,179,181–183,185,193–195,198,201,206–208,213,214,216]. According to Table 8, the accuracy can be formulized as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

9.2. Precision (or positive predictivity)

The precision, also known as the positive predictivity, is a metric that measures how many of the positively predicted samples are relevant. It is simply the proportion of the actual positives inside the total number of positively predicted samples. Some of ECG-related studies prefer the positive predictivity (or precision) as the success measure [31,39,41,47,74,77,80,88,105,117,120,121,135,158,179,189,196,215]. According to Table 8, the precision can be formulized as follows:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

9.3. Recall (or sensitivity)

The recall, which is also known as the sensitivity for various tasks, is a metric that measures how many of the actually positive samples are predicted as positive. It is simply the proportion of positively predicted samples to the total number of actually positive samples. Some of the ECG-related studies prefer recall (or sensitivity) as the success measure [6,16,21,27,29,31,37,39,41,47,48,52,57–62,64,65,73–75,77,80,81,86–88,96,103,105,111,117,120,121,133,135,141,143,151, 153,158,163,179,185,189,190,196,208,209,211,212,215]. According to Table 8, the recall can be formulized as follows:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

9.4. F-measure

F-measure is the harmonic mean between the precision and recall. It is used as the success measure for ECG classification studies infrequently [135,189]. According to Table 8, the F-measure can be defined as follows:

$$F - measure = 2 \,.\, \frac{precision \,.\, recall}{precision + recall} \tag{4}$$

9.5. Specificity

The specificity is a metric that measures how many of the actually negative samples are predicted as negative. It is simply the proportion of negatively predicted samples to the total number of actually negative samples. Specificity is one of the mostly preferred success measures for ECG classification tasks [6,16,37,41,47,52,59–62,65,73–75,77,86,87,103,111,133,135,141,158,163,190,204,209,215]. According to Table 8, the specificity can be formulized as follows:

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

9.6. Matthews correlation coefficient (MCC)

The MCC is used to measure the correlation between the actual classes and predicted classes. It returns a value between +1 and −1. An MCC value of +1 represents a perfect prediction, while 0 indicates no better than random prediction, and −1 shows a total disagreement between the predicted classes and actual classes. MCC is used as the success measure for ECG classification studies rarely [163]. According to Table 8, it can be formulized as follows:

$$MCC = \frac{TP.TN - FP.FN}{\sqrt{(TP + FP)(TP + FN)(TP + FP)(TN + FN)}} \tag{6}$$

9.7. Area under curve (AUC) (or receiver operating characteristic (ROC))

Receiver operating characteristic curve is a plot of the true positive rate against the false positive rate at various settings. AUC is the area under this curve, and it is infrequently used in some ECG classification studies [47,49,81,113,128].

10. Discussion

The preprocessing step is crucial in the analysis of ECG signals for different purposes. Therefore, almost all the filtering techniques are mentioned in this paper. Different combinations of these techniques can be tried to increase the performances. Studies about the filtering can be concentrated on the adaptive filters. Frequency bands, cut-off and center frequencies of the filters can be changed by well defining the types of noise in the ECG signals.

Although researchers have proposed various types of features for ECG analysis, stating the best feature extraction method directly is not possible at all. Many aspects, such as the classification algorithm, processing time expectations, and problem domain (disease classification, biometrics), are all important factors when deciding on the feature extraction method. Therefore, one should decide which features to use by considering all of those aspects.

Considering the factors such as processing time and classification accuracy, the high dimensionality of the feature space is a critical problem in ECG analysis. To overcome this problem, researchers utilize either feature selection or transformation methods. Feature selection methods reduce the dimension by selecting a more discriminative subset among an initial feature set, whereas feature transformation achieves this goal by transforming the original space into a lower-dimensional subspace. While some methods offer the optimal solution, some might give suboptimal results. Since there is a tradeoff between the optimality of the result and the entire processing time of the employed method, one should choose the method that fits best the expectations for the processing time and accuracy of the analysis.

Classifiers commonly used for ECG analysis are mainly grouped into categories such as ANN, LDA, kNN, SVM, DT, and Bayesian classifiers. ANN and SVM are more common than LDA, kNN, DT, and Bayesian classifiers. Fuzzy clustering ANN, recurrent ANN, BPNN, PNN, RBFNN are the most often applied ANN algorithms for ECG analysis. It should be noted that PNN is known to be one of the most effective classification algorithms among these ANN algorithms. The usage of the non-linear SVM classifier appears to be more frequent than linear SVM in the ECG analysis studies mentioned in this review article. However, the most often used non-linear kernel version for the SVM classifier is the Gaussian radial basis function. Therefore, the PNN classifier and SVM classifier with the Gaussian radial basis kernel function can be recommended as first choices for new studies.

Application fields for ECG analysis and classification tasks can be mainly categorized as disease classification, heartbeat type detection, biometric identification, and emotion recognition. Because the early diagnosis of heart diseases can be critical for treatment, disease classification is the most frequent focus of researchers. This finding is not surprising because the reason that ECG analysis and classification are popular is the effort for early diagnosis of diseases. Cardiac arrhythmia classification appears to be the most popular type among the disease types. Heartbeat type detection, which is another popular application field, aims at separating different ECG beats from one another. Biometric identification and emotion recognition are more recent application fields of ECG analysis. The problems related to the biometric identification and emotion recognition application fields can be solved by using different techniques, unlike disease classification and heartbeat type detection. For example, image classification is also widely applied for solving problems related to the biometric identification and emotion recognition application fields.

The most important advantage of ECG databases is that not only the number of databases but also the number of signal conditions (either healthy or patients) is very high, and thus, a researcher can easily attain an appropriate result for his study. However, ECG signals in these databases, especially acquired from patients, could include one of the main types of noise. Although power line interference can be effortlessly removed from an ECG signal, the other two types of noise, muscle noise and baseline wander, cannot be removed easily. Therefore, one should be very careful in the selection of appropriate filter types and frequencies since some databases do not include detailed information about the corresponding measurement environment.

Success measures for ECG analysis and classification can be listed as the accuracy, precision, recall (or sensitivity), F-measure, specificity, Matthews correlation coefficient, and area under curve (receiver operating characteristic). The most often used measure among all these measures is the accuracy. However, most researchers prefer presenting the results with more than one success measure due to the imbalanced nature of ECG data. As an example, while a high percentage of ECG signals inside cardiac arrhythmia data can be normal, a low percentage of signals contain arrhythmia characteristics. For this purpose, the accuracy scores can be supported by some other measures, such as the precision, recall (or sensitivity), and specificity.

11. Conclusions

Many researchers around the world address various problems related to the analysis of ECG signals. Therefore, they need particular information on the different stages of ECG signal analysis. Although there already exist many review articles in the literature on ECG analysis, they are limited to only a few aspects. Unlike the previous work, in this paper, a comprehensive study has been conducted, and the subject has been handled using various aspects, including preprocessing, feature extraction, selection and transformation, classification, application fields, databases and success measures. In this way, interested readers can obtain the latest developments on various aspects of ECG analysis from a single resource.

Recent studies on the preprocessing step of ECG signal analysis are summarized in this paper. This step is discussed in four subsections, which are filtering, resampling and digitization, normalization and the other preprocessing methods.

In addition to the preprocessing step, the feature extraction, feature selection and feature transformation steps are also very important for different tasks, such as classification or identification. Those three steps are comprehensively reviewed with the related subcategories.

In the Classifier section, six widely used classifiers, ANN, LDA, *k*NN, SVM, DT and Bayesian, are reviewed in detail. Rarely used classifiers are also given in the Others subsection. Future work would cover classifiers published in the literature in view of their accordance with the databases. In addition, analysis of their effects under varying preprocessing procedures is of outstanding importance for the literature in this area.

Additionally, the application fields of ECG signal analysis are reviewed in this paper. These fields are grouped into five main categories, and detailed information about these categories are presented.

Most of the databases on ECG signals are introduced in this paper. Some of those databases are frequently used databases, and brief information about them is provided. There are also many custom databases, and therefore, these and rarely used databases are also referenced. The MIT-BIH Arrhythmia is well-known and the most often used database. This database and some of its derivatives are given in detail. It is clear that one of the main difficulties in ECG research is the limited number of publicly available databases. Therefore, we suggest that researchers publish their databases and provide the related information. We believe that sharing such databases with the research community would be a great chance for the appropriate analysis of ECG signals.

Success measures are very crucial for the performances of classifiers as well. Seven well-known success measures are also introduced together with their formulations.

In summary, this survey aimed to consolidate the fundamental information on all the aspects of ECG analysis and to present this information for the benefit of the research community to enable researchers to obtain the answers to the possible questions on any stage of ECG analysis via a single resource.

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