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REVIEW

A review of intelligent systems for heart sound signal analysis

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ABSTRACT

Intelligent computer-aided diagnosis (CAD) systems can enhance the diagnostic capabilities of physicians and reduce the time required for accurate diagnosis. CAD systems could provide physicians with a suggestion about the diagnostic of heart diseases. The objective of this paper is to review the recent published preprocessing, feature extraction and classification techniques and their state of the art of phonocardiogram (PCG) signal analysis. Published literature reviewed in this paper shows the potential of machine learning techniques as a design tool in PCG CAD systems and reveals that the CAD systems for PCG signal analysis are still an open problem. Related studies are compared to their datasets, feature extraction techniques and the classifiers they used. Current achievements and limitations in developing CAD systems for PCG signal analysis using machine learning techniques are presented and discussed. In the light of this review, a number of future research directions for PCG signal analysis are provided.

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1. Introduction

Cardiovascular disorders (CVDs) or heart diseases are broad terms that can refer to a human heart condition. CVDs are the leading cause for the increase in mortality globally. More people die annually from CVDs than from any other cause. An estimated 7.4 million people died from CVDs in 2016, representing 31% of all global deaths [1].

According to the latest World Health Organization data published in May 2016, coronary heart disease deaths in Egypt reached 107,232 or 23.14% of total deaths. Early detection of the heart diseases is very important and the motivation for future studies [2,3].

Intelligent computer-aided diagnosis (CAD) systems for heart diseases have been developing rapidly in the last two decades [4]. The main idea of CAD systems is to assist physicians in heart disease diagnosis by using dedicated computer systems to provide "second opinions". Studies of CAD systems show that CAD systems can help to improve the diagnostic accuracy of heart disease diagnosis.

Many different techniques used for developing a CAD scheme have been summarised in several review purpose. To create a CAD system for heart sound signals analysis, the integration of various signals preprocessing operations such as signals denoising and signals segmentation, feature extraction and classification is essential. Recently, various types of heart sound signal CAD systems have been developed by a number of researchers using phonocardiogram (PCG) signals based on several types of machine learning techniques. The challenge remains to provide CAD systems that work with high efficiency, regardless of the datasets used. The main contribution of this study is to review the most recent preprocessing, feature extraction and classification algorithms for PCG signal analysis and their state of the art. Also, we summarised the advantages and disadvantages of the reviewed algorithms in tables.

The organisation of the paper is as follows. Section 2 presents a brief introduction phonocardiography and heart diseases and Section 3 reviewing on generic methodologies of PCG diagnosis systems with a comparative study on the recent segmentation, feature extraction and classification techniques for heart diseases. Finally, our conclusion is presented.

2. Phonocardiography and heart diseases

PCG signals are high and complex non-stationary signals and it is the result of the mechanical activity of the body and is valuable in the diagnosis of CVDs [4,5]. PCG signals are still the primary tool for screening and diagnosing many pathological conditions of the human heart. Using auscultation technique for

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heart sound analysis is still insufficient. The reason of insufficiency reported by Avendaňo-Valencia et al. [6] is due to the human ear limitation and subjective of the analyst and the discriminatory skills that can take many years to acquire.

The heart sounds recorded by an electronic stethoscope are converted to digital signals known as PCG signals [7]. Recording of heart sounds in the form of PCG signals has been developed to visually inspect heart sounds for the purpose of clinical diagnosis [8]. The valvular cardiac defect can be detected cheaply and efficiently using auscultations with advanced techniques of signal processing. The process of auscultations has two stages: acquisition and analysing heart sounds [9]. Also, a computerised system could provide physicians with a suggestion about the diagnostic suggestion about the heart diseases.

Phonocardiography overcomes some of the drawbacks of basic auscultations in providing information about the detection of heart diseases. This is because the waveform of healthy PCG is well known for the clinicians so any variation in the PCG waveform can be considered as a disorder in the heart. However, according to Martínez-Alajarín et al. [10], the contribution of the PCG signals is still very difficult to use due to many variables that have an influence on the generation and transmission of heart sounds. The drawbacks of the PCG include [11]:

- Failure to present frequency components information of PCG signals.
- Inability to differentiate between separate frequencies of various sounds.
- The presence of artefacts and noises that can visually mask weak heart sounds.
- The problems of identifying a specific heart sound boundaries.

The PCG recording may consist of four heart sound components (S1, S2, S3 and S4). The first sound and second heart sound (S1 and S2) can be heard from the normal heart. They are produced by the closure and opening of the normal valves. The interval between the ends of S1 to start of same cycle's S2 is called systole. The interval between the ends of S2 to beginning of the next cycle's S1 is called diastole. For the abnormal heart, a third sound and a fourth sound (S3 and S4) may also exist in addition to S1 and S2. S3 occurs just after the S2 and S4 occur just before the S1 [3]. The four heart sounds (S1, S2, S3 and S4) are shown in Figure 1 and Table 1 shows the four components of the heart sound and their properties [12]. Figure 2 shows the diastole and systole of the heart.

The unusual sound that heard during the heartbeat cycle is called murmurs. A murmur is one of the more common abnormal phenomena of the heart activities. The substantial difference between heart sounds and murmurs is that murmurs are noisy and have a longer duration. Heart murmurs can be classified as a systolic murmur occurring in the systolic interval, and diastolic murmur or continuous murmurs occurring in the diastolic interval [15].

The most common type of coronary artery disease is heart valve disease. These valves are actual flaps that are located on each end of the two ventricles. They act as one-way inlets of blood on one side of a ventricle and one-way outlets of blood on the other side of a ventricle. The most common heart diseases are heart valve disease that can affect the flow of blood through the heart. There are two main types of valve problem:

- Valve stenosis means that the opening of the valve is narrowed and the valve does not open fully. So, there is some restriction in blood flow through the

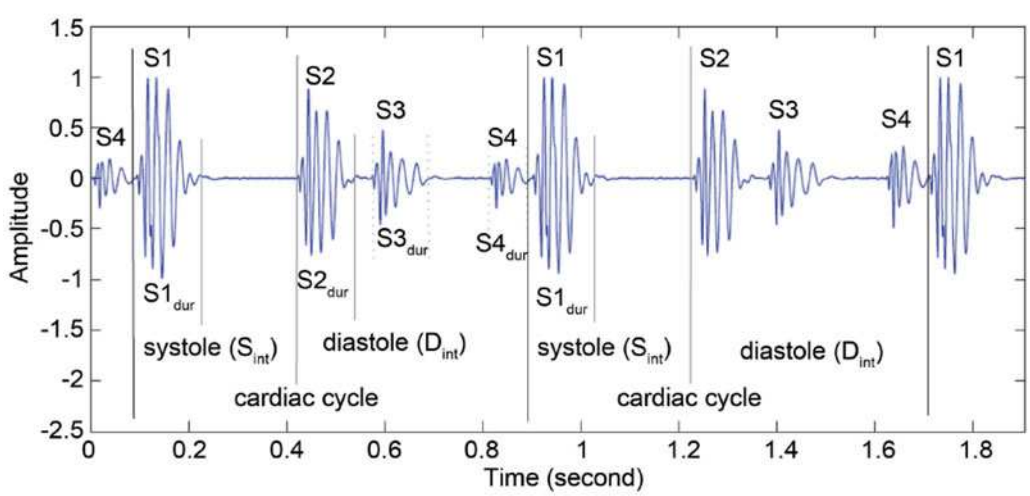

Figure 1. Normal heart sound signal [13].

Table 1. Heart sound components and its properties.

Sound	S1	S2	S3	S4
Frequency	30–100 Hz	Above 100 Hz	20–25 Hz	Below 30 Hz
Time	50–100 ms	25–50 ms	120–150 ms	90 ms before S1
Occurrence	Closure of mitral and tricuspid valve	Closure of aortic and pulmonary valve	Caused by the rapid ventricular filling in early diastole	Caused by ventricular filling due to atrial contraction

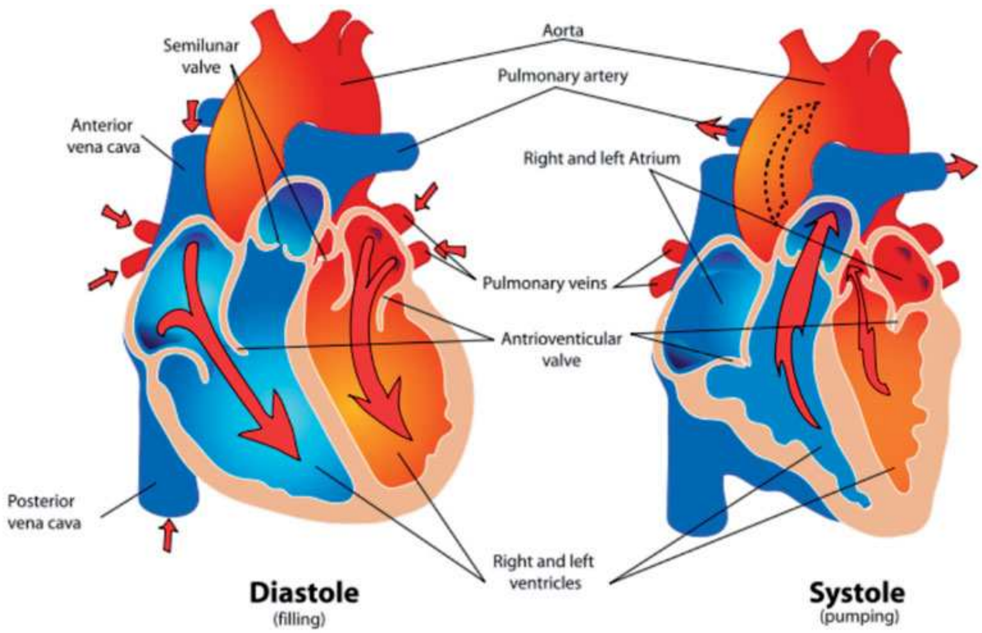

Figure 2. Diastole and systole of heart [14].

Table 2. Heart valve diseases and its symptoms.

Diseases	S1	S2	Murmurs
AS	Normal	Single or paradoxically split	Mid- to late systolic may be soft or absent if severe.
MS	Loud	Normal	Diastolic rumble and it increased with brief exercise.
AR	Soft	Normal	Blowing diastolic and increased with handgrip or squatting.
MR	Soft	Normal or split	Holosystolic and louder.
Mitral valve prolapsed (MVP)	Normal	Normal	Mid- to late systolic and increased with standing.

valve, e.g. mitral stenosis (MS) and aortic stenosis (AS).

- Valve regurgitation (sometimes called valve incompetence or a leaky valve) means that the valve does not close properly and there is a backflow of blood through the leaky valve, e.g. aortic regurgitation (AR) and mitral regurgitation (MR).

So, we can conclude that heart sounds and murmurs can give a primary diagnosis method for heart valve diseases according to its duration and frequency. For this purpose, CAD systems are increasingly being used as an aid by clinicians for detection and interpretation of diseases. CAD systems mark regions of the PCG signal that may reveal specific abnormalities and are used to alert clinicians to these regions during the PCG interpretation and also it provides an assessment of a disease using the PCG information alone or in combination with other relevant diagnostic data and is used by clinicians as a decision support in developing their diagnoses. Table 2 will summarise some of valvular heart diseases and symptoms associated with the diseases [16–18].

3. Generic CAD systems for PCG analysis

The importance of developing automated tools can be of immense importance to help in diagnosis, prognosis, and presurgical and postsurgical procedures, depending on whether the subject is a healthy one or is a pathological subject, suffering from some heart disorders. The extraordinary level of detail that can be

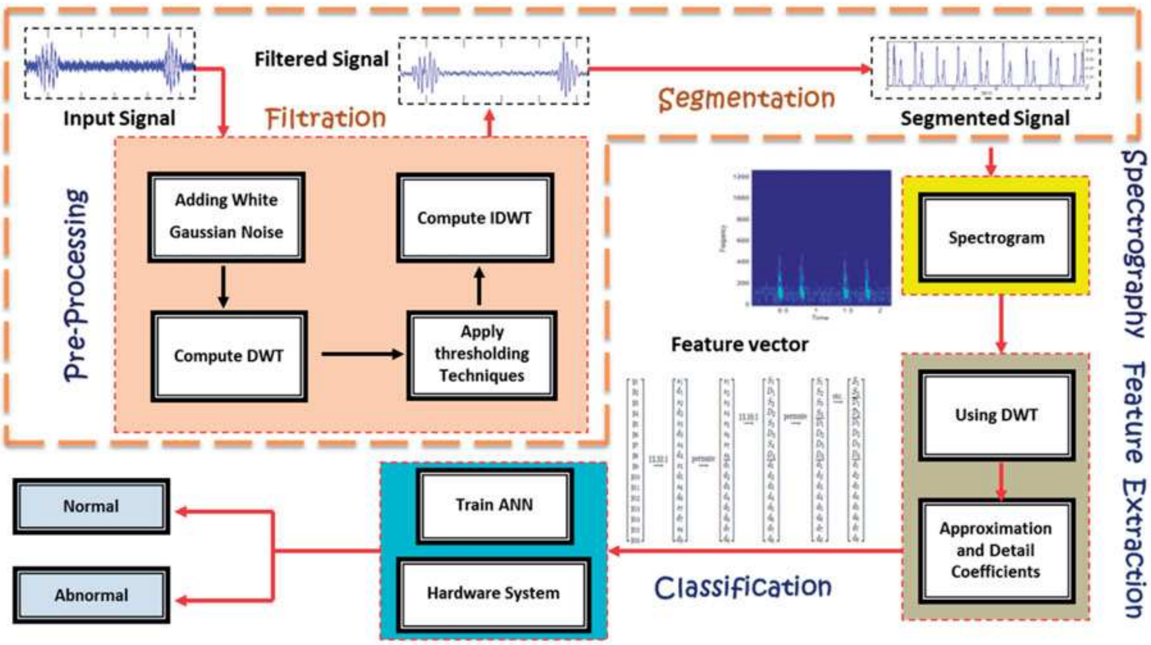

Figure 3. Typical methodology of a CAD scheme.

obtained with PCG signal can be efficiently utilised by performing some powerful signal processing techniques, especially suitable for automated analysis. This is because, with the huge information repository associated with PCGs, it becomes almost impossible to manually interpret each signal, necessitating the development of automated tools.

Figure 3 shows the details of the PCG diagnosis system. The first stage of PCG signal analysis for diagnosis is to provide it as an input to the diagnostic system. The second stage of PCG diagnosis system is signal preprocessing which includes PCG denoising signal from noise and artefacts and PCG signal segmentation to extract the most predominant components of PCG signal. The third stage of the proposed PCG diagnosis system is to extract features from this input signal. Then, the obtained features independently are used for classification as normal and abnormal PCG signal. The classification of the PCG signal into normal and abnormal can be done using different classification techniques. No more processing is required once the PCG signal is determined as normal. But when the PCG signal is determined as abnormal by the classifier, it is further processed for extracting abnormality portions from it.

In the following three subsections, we have reviewed various preprocessing, feature extraction and classification techniques and their performance of CAD heart disease detection through the PCG signal. We identified the strengths and the weakness of the reviewed algorithms from the literature.

3.1 Preprocessing

Recording biomedical signals in general, like PCG signals, is subject to noise and artefacts which are introduced through a variety of external influences. These noises may affect the outcome of the recording procedure, so it is necessarily to develop methods that appropriately eliminate the noise without altering original PCG signals. Signal denoising is the first stage of a signal preprocessing operation whose objective is to process a signal in order to manipulate the information contained in the signal. In other words, a filter is a device that maps an input signal to an output signal facilitating the extraction (or elimination) of information (or noise) contained in the input signal [19]. The recording of PCG usually has a sampling frequency higher than 8000 Hz. In the event that the recording environment is not well controlled, noise is coupled to the PCG. To avoid unpredictable effects brought by noise, the denoised signal is obtained as follows:

- Filtering: The reserved PCG signals were high-pass-filtered to remove unwanted low-frequency component.
- White denoising: It is a random signal that contains equal amounts of every possible frequency, and PCG signals were filtered to remove white noise using wavelet packet.
- Normalisation: PCG signals were normalised so that the expected amplitude of the signal is not affected.

Table 3. Overview of preprocessing techniques (denoising–segmentation) for medical signals.

Author	Denoising techniques	Segmentation technique	Purpose
Hedayioglu et al. [21]	Wavelet transform (WT)	Peak-picking (thresholding the normalised average Shannon energy and discarding extra peaks via analysis of the mean and variance of peak intervals)	Identify and segment the four main components of a cardiac cycle by identifying the position and the duration of S1 and S2.
Pedrosa et al. [22]	Continuous wavelet transform (CWT) (Morlet mother wavelet)	Autocorrelation function	Find the periodic components of the PCG signal.
Debbal el al. [23]	Low-pass FIR filter	Normalised average Shannon energy	Detection of heart and heart murmurs. The segmentation algorithm, which separates the heart signal
Kumar et al. [24]	WT	Wavelet decomposition (with adaptive thresholding)	Discriminate S1/S2 sounds from murmurs.
Quiceno et al. [25]	Coifman 4 with 8th level of decomposition	DII lead of the ECG recording for locating the occurrence S1. Recurrence time statistics	Locating the occurrence of S1 using ECG signal. Detect changes in the signal dynamics, corresponding to S1 and S2.
Gupta et al. [26]	Low-pass Chebyshev type I filter (cut-off frequency at 750 Hz)	Homomorphic filtering and K-means clustering	Homomorphic filtering converts a non-linear combination of signals into a linear combination by applying the logarithmic transformation. K-means clustering: non-hierarchical partitioning method, which helps to indicate single cardiac cycle in the PCG signal.
Kouras et al. [27]	WT (Db10)	Normalised Shannon entropy for wavelet detailed coefficients	Distinguish between the main component (S1–S2) of the PCG signal and the murmur by thresholding the entropy values
Wang et al. [28]	WT	Adaptive algorithm for sublevel tracking (based on wavelet transform)	Separation of S1 and S2 from murmurs and noises.
Moukadem et al. [29]	High-pass filter (cut-off frequency at 30 Hz)	S-transform	Segments the PCG signal into four parts: S1, systole, S2 and diastole
Dokür and Ölmez [30]	Discrete wavelet transform (DWT)	Timing between peaks Peak–peak magnitude	Segmentation S1 and S2.
Liu et al. [31]	10th order Butterworth filter		Autonomous detection and classification of congenital heart diseases using auscultation vest.
Kumar et al. [32]		Complexity signatures.	Segment murmurs from other heart sound components.
Guillermo et al. [33]	Anti-aliasing filter (4 KHz low-pass filter)		Intelligent classification of real heart sound diseases.
Liang et al. [34]	Chebyshev type I low-pass filter (with cut-off frequency at 882 Hz)	Average Shannon energy	Separates PCG signals into S1, systole, S2 and diastole.
Kang et al. [35]	Band pass filter (cut-off frequency at 40–500 Hz)	Average Shannon energy	Identifying S1 and S2 candidates from the envelope signal.
Nieblas et al. [36]		Matching pursuit algorithm	Detects the onsets and offsets of the cardiac cycle events present in heart sound signal.
Deng and Ji-Qing [37]	Band-pass, zero-phase, Butterworth filter order 6 (25–900 Hz)		Heart sound classification without segmentation.
Boutana et al. [38]		Intrinsic mode functions empirical mode decomposition	Segmentation algorithm to obtain the main components (S1 and S2) and pathological murmur separately.
Salleh et al. [39]	Kalman filter		Denoising statistical heart sound

The second stage of preprocessing of PCG signals is signal segmentation in which PCG signals partition into cardiac cycles and further into S1, systole, S2 and diastole [20]. Through this study, we have made a survey of the preprocessing techniques using the PCG signals. In this section, we have made a comparison between a number of published preprocessing techniques (denoising–segmentation) as shown in Table 3.

From Table 3, it is observed that several algorithms and techniques have been developed for preprocessing of PCG signals (denoising–segmentation) summarised in Figure 4. The most common technique for PCG signals denoising is passing signals through suitable filters (low-pass or high-pass), and also it is noticed that wavelet transform, especially discrete wavelet transform (DWT), is the most recent technique used for PCG signals denoising because of

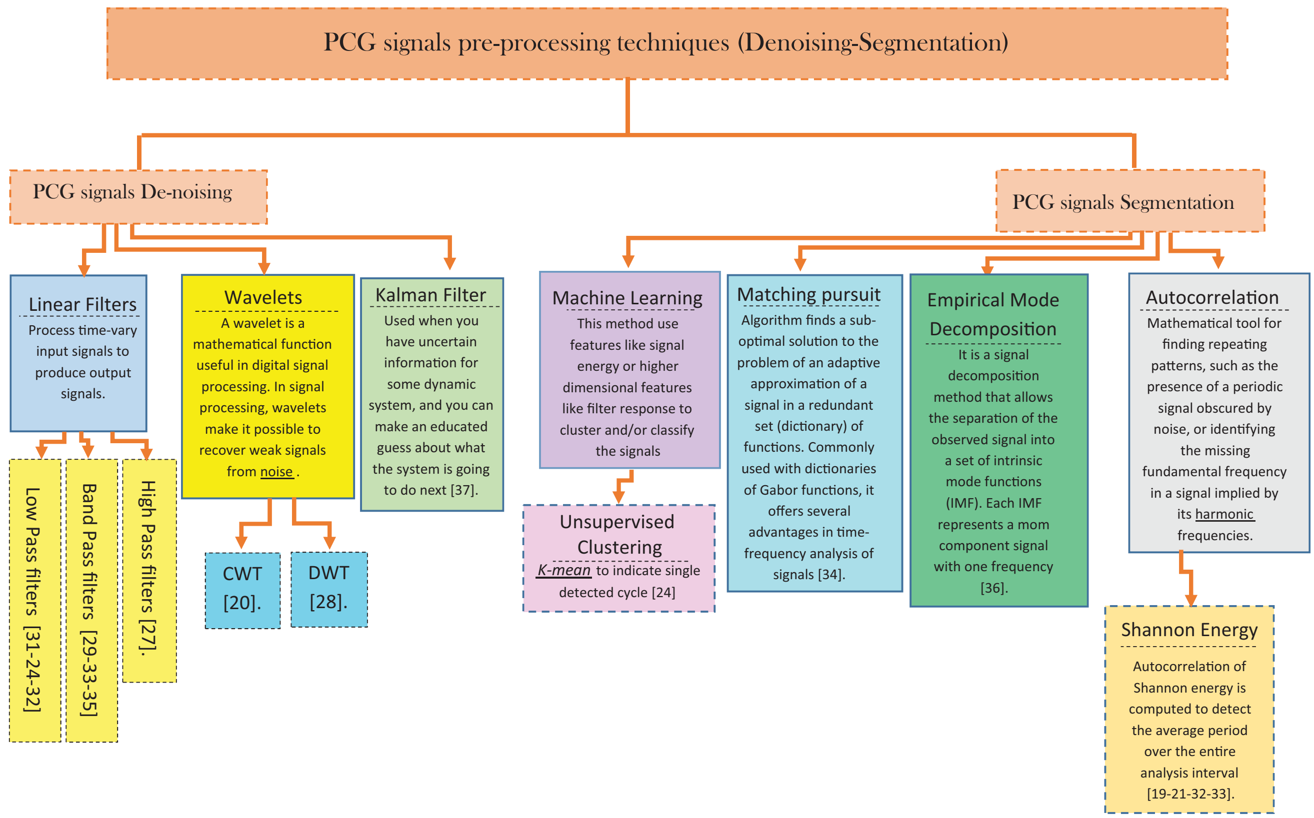

Figure 4. Overview of the most commonly used preprocessing techniques in CAD systems for PCG signal analysis.

its structure which is a series of high-pass and low-pass filter. For segmentation stage, normalised average Shannon energy is the commonly used technique for identifying the most predominant events from PCG signals.

3.2 Feature extraction and classification techniques for PCG signals

Feature extraction is the important step in detection and classification of heart diseases. It is a challenging task to extract a set of good features from PCG signals for classification stage. Many techniques are used for feature extraction, e.g. linear frequency band cepstral (LFBC), discrete cosine transform (DCT), Fourier transform, fast Fourier transform, short-time Fourier transform (STFT), the mel-frequency cepstrum coefficients (MFCC), Choi–Williams distributions (CWD), linear predictive coding (LPC) and DWT [40].

The most recent and more efficient CAD systems for heart disease diagnosis perform DWT decomposition of the PCG signal to obtain the wavelet coefficients at different levels. A set of highly significant features of PCG signals have been extracted and used as input to classify them into normal and abnormal classes. The integration between features generated by two or more algorithms led to develop CAD systems which is capable of classifying PCG signals with clinically acceptable accuracy, using less number of features that can be extracted with less computational cost. This developed CAD systems can be used as an automated, simple, fast, cost-efficient and effective secondary diagnostic tool that provides additional confidence to the clinician's initial diagnosis of human heart diseases.

Machine learning employs computer algorithms to perform specific operations. We might, for instance, be interested in learning to complete a task, or to make accurate predictions, or to behave intelligently. The primary goal of machine learning research is to develop general purpose algorithms of practical value. Such algorithms should be efficient.

Classification is one of the machine learning usage used for classifying the input patterns into specific classes. Selection of suitable classifiers requires consideration of many parameters such as (a) classification accuracy, (b) algorithm performance and (c) computational resource. Many classification methods are used in the classification of PCG signals like artificial neural network (ANN), least square support vector machine (LS-SVM), K-nearest neighbour (KNN) and Euclidean distance [41,42].

In this study, we present most recent published classification techniques. Table 4 shows a survey of

Table 4. Overview of feature extraction and classification techniques for medical signals.

Author	Dataset	Feature extraction	Classification technique	Performance
Reed et al. [43]	5 different normal and abnormal PCGs	Coifman 4th order wavelet (7th order level of decomposition)	ANN	Accuracy 100%
Gupta et al. [26]	41 PCG from Singapore General Hospital	Daubechies 2nd order wavelet	MLBP-NN GAL	The classification accuracy using GAL Dataset 1 97.01% Dataset 2 98.50% Dataset 3 95.55% The classification accuracy using MLP-BP Dataset 1 97.01% Dataset 2 97.01% Dataset 3 95.55%
Dokür and Ölmez [30]	14 different PCG signals	DWT	Kohonen's ISOM Incremental ANN	ISOM accuracy 95% ANN accuracy 70%
Jaramillo-Garzón et al. [44]	16 normal PCG signals and 6 signals with murmurs	STFT and CWD	KNN classifier	The classification accuracy using CWD Accuracy 97.85% Sensitivity 98.50% Specificity 95.55% The classification accuracy using STFT Accuracy 96.78% Sensitivity 96.79% Specificity 96.77%
Ari and Saha [45]	104 PCG signals provided by the Maulana Azad Medical Institute	WT	ANN	Accuracy 99.279%
Das et al. [46]	215 PCG signals: 56 normal, 54 abnormal aortic, 39 normal and 66 abnormal mitral.	WT	ANN	Accuracy 97.4% Sensitivity 100% Specificity 96%
Bunluechokchai and Ussawawongaraya [47]	Normal and MR signals	CWT	Local intermittency factor	Accuracy 99.9%
Wen-Chung and Chih-Chao [48]	44 PCG signals from Texas laboratory	STFT 2-D DCT	SVM + adaptive feature selection	Accuracy 94.79%
Phanphaisarn et al. [49]	80 PCG signals	LPC	ANN	Accuracy 100%
Liu et al. [31]	270 PCG signals: 104 normal and 166 abnormal	WT	SVM	Accuracy Normal PCG 99.04% Atrial defect 100% Ventricular defect 97.03%
Safara et al. [50]	59 PCG signals: 16 normal and 43 abnormal	Wavelet packet transform	SVM	Accuracy 97.56% Normal HS Sensitivity 91.34% Specificity 98.40% MR defects Sensitivity 96.98% Specificity 98.79% AR defects Sensitivity 91.84% Specificity 95.76%

(*continued*)

Table 4. Continued

Author	Dataset	Feature extraction	Classification technique	Performance
				Septal defects Sensitivity 92.25% Specificity 97.15%
Amiri and Armano [51]	110 normal and abnormal PCG signals	Complex Morlet wavelet transform	Regression tree	Accuracy 98.18% Sensitivity 96.13% Specificity 100%
Roy and Armano [52]		DWT	KNN	Accuracy 100%
Farzam and Jalil [53]	Michigan University online PCG dataset	MFCC	SVM	Accuracy 100%
Guillermo et al. [33]	17 different pathological PCG signals	Complex Morlet wavelet transform	Feed-forward ANN	Accuracy using a radial wavelet neural network with EKF learning algorithm is 96.74%. Accuracy using multilayer perceptron with Levenberg–Marquardt learning algorithm is 76.08%
Redlarski et al. [54]		LPC	SVM + modified cuckoo search algorithm	Accuracy 95.43%
Shivnarayan et al. [55]		Tunable Q-wavelet transform	SVM	Normal HS Accuracy 99.35% Sensitivity 98.37% Specificity 99.50% Valvular defects Accuracy 97.84% Sensitivity 96.84% Specificity 99.44% Other defects Accuracy 98.49% Sensitivity 100% Specificity 98.21% Septal defects Accuracy 100% Sensitivity 100% Specificity 100%
KOÇYIĞIT [56]	14 different PCG signals	DWT	SVM, linear discriminant analysis and naïve Bayes classifier	Best results using the naïve Bayes classifier Sensitivity 98.53% Specificity 99.89% G-means 99.21% Accuracy 99.79%
Harfash [57]		MFCC	Eigenvectors	Accuracy 86%
Imani and Hassan [58]	98 PCG signals: 40 normal PCG signals and 58 abnormal PCG signals	Curve fitting + wavelet filter banks	Maximum likelihood classifier with Gaussian distribution + SVM with polynomial kernel	Accuracy 81.49% Sensitivity 74.48% Specificity 88.50%

Table 5. Advantages and disadvantages of the most used classifiers of human PCG signal [59].

Approach	Advantages	Disadvantages
ANN	• ANN is a non-linear classifier which make it flexiable in modelling real complex problems and can perform tasks that linear classifiers cannot perform it. • It can be self-learned without needing to be relearned. • ANN is a data-driven self-adaptive method in that they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model.	• ANNs need to be trained to operate. • It requires more time for processing. • It minimises over fitting requires a great deal of computational effort
SVM	• It minimises the number of misclassified objects in any possible set of samples. • SVM offers an option to train generalisable, non-linear classifiers in high-dimensional spaces using a small training set.	• Its algorithms require computing and storing in memory the complete kernel matrix of the input samples. • Its solution can depend on the kernel that has been used, and there is no method to know a prior which will be the best kernel for a task.
SOM	• SOM are simple and easy to understand and good for visualisation.	• It is difficult to evaluate correctly distances and similarities between input vectors. Moreover, if the output dimension and learning algorithm are chosen improperly, similar input vectors may not always close to each other. • The weight vectors must be based on data that can successfully group and distinguish inputs. • Randomness will be added due to lack of data or unnecessary data in the weight vectors. • Its algorithms are often difficult to obtain a perfect mapping.
Hybrid techniques	• They combine the relative strengths of different classifiers in a single system and applied them in such a way that the overall accuracy was the maximised.	• They are sophisticated and high computational costs.

the feature extraction and classification techniques for PCG signals that published during 2004–2016.

Table 4 demonstrates the importance and the efficiency of the CAD systems in heart disease diagnosis with high accuracy level. The list of researches listed in Table 4 has used wavelet transform specially DWT to extract features from PCG signals. Also, the majority of this studies used ANN and SVM classifiers which are naturally complex for classification stage. Table 5 gives the advantages and disadvantages of the most commonly used classifiers. It illustrates that classification of human PCG signals is possible via supervised techniques such as ANN, SVM and unsupervised techniques such as self-organizing maps (SOM) and KNN.

In particular, this paper reviews recent papers between 2004 and 2016. Regarding the comparative results of related work, developing heart sound analysis systems using machine learning techniques still needs to be researched. The following issues could be useful for future research:

- CAD systems for PCG signal analysis have demonstrated good performance in the experimental setting and have a high level of acceptance among patients. However, at present, such systems cannot be used to provide the best diagnostic results or replace the clinicians' skill or histopathology. Nonetheless, these systems are now used for educating general practitioners, giving advanced training to expert clinicians and providing second opinions during screening procedures (i.e. these systems, at the current stage of their development, used "clinical diagnosis support system").
- Databases: The chosen one plays a vital role in reaching high performance for CAD systems.
- Existence of low-energy levels and noise can decrease the efficiency of the classification accuracy.
- Feature selection: As there are numbers of feature selection approaches, the reviewed studies which consider feature selection only choose one specific method, and it is not known which method performs the best especially under what classification techniques for intrusion detection.
- The architecture of multiple classifiers: Designing more sophisticated classifiers via combining ensemble and hybrid classifiers can be examined. Since the idea of combining multiple classifiers is to collaborate each other instead of competition, it may be worth combining ensemble and hybrid classifiers for intrusion detection.

4. Conclusion

With the advance of computational intelligence and machine learning techniques, computer-aided diagnostic systems for heart disease diagnosis attract more and more attention. Processing of medical signals becomes one of the major research issues. In this study, we reviewed current studies of the different preprocessing, feature extraction and classification algorithms for PCG signal analysis. In particular, this paper reviews recent researches for CAD systems based on PCG signals for heart disease diagnosis during 2004–2016. These techniques also suffer from some drawbacks like using small datasets, existence of low energy levels and noise. These causes limit the classifiers' accuracy in detecting and diagnosing heart diseases. The large database can also be used in different machine learning techniques in order to achieve high accuracy; also depth in the process of preprocessing processes can also overcome on noise exists in the heart sound signal.

Disclosure statement

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of this article.

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