IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received November 7, 2018, accepted December 5, 2018, date of publication December 24, 2018,
date of current version January 23, 2019.

Digital Object Identifier 10.1109/ACCESS.2018.2889437

Algorithms for Automatic Analysis and Classification of Heart Sounds–A Systematic Review

AMIT KRISHNA DWIVEDI, (Graduate Student Member, IEEE), SYED ANAS IMTIAZ, (Member, IEEE), AND ESTHER RODRIGUEZ-VILLEGAS, (Senior Member, IEEE)

Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, U.K.

Corresponding authors: Amit Krishna Dwivedi (a.dwivedi16@imperial.ac.uk) and Esther Rodriguez-Villegas (e.rodriguez@imperial.ac.uk)

This work was supported by the European Research Council under Grant 724334. The work of A. K. Dwivedi was supported by Imperial College London, U.K., through the President's PhD Scholarship.

ABSTRACT Cardiovascular diseases currently pose the highest threat to human health around the world. Proper investigation of the abnormalities in heart sounds is known to provide vital clinical information that can assist in the diagnosis and management of cardiac conditions. However, despite significant advances in the development of algorithms for automated classification and analysis of heart sounds, the validity of different approaches has not been systematically reviewed. This paper provides an in-depth systematic review and critical analysis of all the existing approaches for automatic identification and classification of the heart sounds. All statements on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2009 Checklist were followed and addressed thoroughly to maintain the quality of the accounted systematic review. Out of 1347 research articles available in the academic databases from 1963 to 2018, 117 peer-reviewed articles were found to fall under the search and selection criteria of this paper. Amongst them: 53 articles are focused on segmentation, 72 of the studies are related to the feature extraction approaches and 88 to classification, and 56 reported on the databases and heart sounds acquisition. From this review, it is clear that, although a lot of research has been done in the field of automated analysis, there is still some work to be done to develop robust methods for identification and classification of various events in the cardiac cycle so that this could be effectively used to improve the diagnosis and management of cardiovascular diseases in combination with the wearable mobile technologies.

INDEX TERMS Segmentation, feature extraction, classification, heart sounds databases, wearable cardiac monitoring, heart sounds analysis.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are the leading cause of mortality worldwide resulting in over 17.7 million deaths each year [1]. This number is predicted to increase to approximately 23 million per year by 2030 [2]. Apart from the personal consequences, the high prevalence and cost of cardiovascular diseases constitute a serious social and financial burden. As an illustration, 85 million Americans suffer from cardiovascular diseases resulting in an approximate healthcare cost of $320 billion annually, with a projected increase to nearly $1 trillion by 2030 [3]. While the estimated number of cardiac patients and health care costs are too high, an important thing to consider is that most cardiovascular diseases are preventable and curable. However, this requires early-stage diagnosis and proper disease management [4]. Consequently, there is an urgent need to improve technologies to intensively monitor and analyze physiological parameters related to cardiac function in a timely and cost-effective manner. With recent evolution of mobile technologies, there is a growing, justified, interest on finding ways to continuously track the cardiovascular system for long periods of time, as a potentially more effective way to both diagnose and manage cardiac conditions.

In literature, both invasive and non-invasive approaches for monitoring the cardiovascular system using different sensing schemes have been investigated. However, some of these approaches are not suitable for long-term continuous real time monitoring of cardiac signals in unsupervised

environments, which would, however, be the optimum way of monitoring/managing some cardiac conditions. An example is atrial fibrillation, in which events do happen scattered in time and hence might not be caught in short monitoring sessions [5].

Recent advancements in computing together with the ever-shrinking size of electronic devices have enabled the design of wearable devices loaded with sensors that can perform the task of long-term continuous monitoring and have the potential of facilitating timely medical interventions for treatment and care. Wearables have the advantage of usability. Thus, wearables can allow self-health monitoring and save the time required for clinical appointments. This is why wearables have attracted a lot of attention from scientists in this field. Though, potentially, available cardiac wearables can assist in real time monitoring, it is challenging to obtain a high degree of accuracy, especially under varying environmental conditions. Furthermore, in some cases, algorithms for signal interpretation have been validated with a limited database and hence their clinical reliability and diagnostic accuracy cannot be extrapolated for real clinical applications.

The sensing modality, and hence the measured physiological signal, used by different kind of wearables varies and which one to choose depends on a number of tradeoffs that need to be made considering the particular clinical application, usability aspects and accuracy, amongst others. In the case of wearables for cardiac applications, one of the physiological signals that can potentially provide a lot of information is the sounds generated by the heart. Heart sounds auscultation is a simple, convenient, cheap and non-invasive approach that has been used for over a century by physicians. More recently human-only stethoscope based interpretation is being complemented by computer-aided heart sounds. This has a potential advantage that the interpretation of heart sounds is not as subjectively dependent on factors such as ear sensitivity, skills, and the experience of the individual physicians [6], [7]. Furthermore, a wearable automated system capable of processing cardiac sounds could potentially be used for the early cost-effective screening of cardiovascular diseases, as well as to manage the progression of the condition. However, in order for this to practically happen, algorithms are required that can shift the signal interpretation load from the clinician to the technology, since otherwise the amount of information generated would be unmanageable in practice. This is a reason why automated analysis and interpretation of heart sounds is a prolific area of research, with an also rapidly increasing interest. Though computerized analysis of heart sounds has been the focus of increasing number of studies recently, a consistent approach to analyze various heart sounds signals has not been established and a comprehensive critical review of available approaches together with performance comparison has not been carried out. Previous reviews [8]–[12] present a well-organized discussion of the origins of heart sounds, sensing systems, and recent developments in heart sounds analysis. However, the validity of the different approaches and performance comparison of algorithms for segmentation, feature extraction and classification of heart sounds in different applications have never been systematically reviewed.

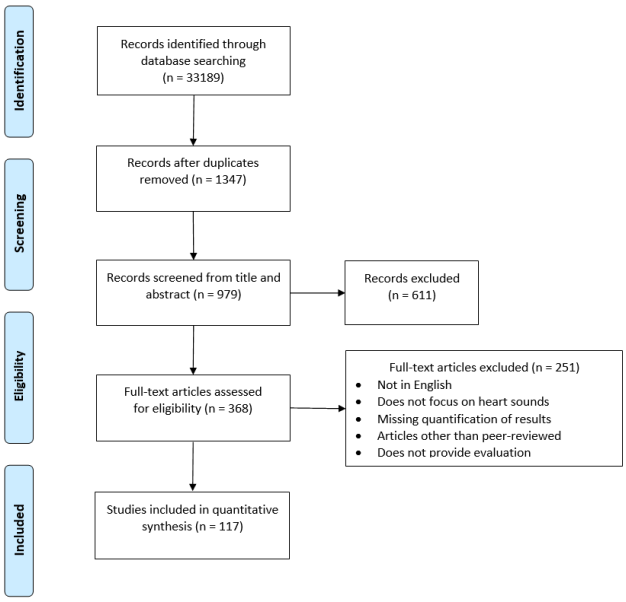

FIGURE 1. PRISMA 2009 flow diagram for this systematic review.

This paper goes beyond previously published reviews by:

1) Evaluating different methods reported for automated heart sounds analysis, specifically for detection and classification of cardiac abnormalities, and analyzing the different performance metrics reported.
2) Synthesizing the heart sounds' detection and classification approaches accuracy evidence from existing research works.
3) Comprehensively reviewing all features relevant to pathological sounds detection as well as heart sounds databases.

The rest of the paper is organized as follows: Section II describes the methods used in this systematic review. A description of the pathophysiology of normal and abnormal heart sounds is presented in Section III. Approaches for segmentation, feature extraction and classification are reviewed in Section IV. The evidence collected from different research works is synthesized in Section V and findings are discussed in Section VI. Finally, the study limitations and concluding remarks are covered in Sections VII and VIII, respectively.

II. MATERIALS AND METHODS

This systematic review adopts the guidelines published by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) consortium reported in the PRISMA 2009 Checklist [13]. All preferred reporting items on the PRISMA statement were addressed thoroughly and has been provided as an evidence in Appendix file. Furthermore, Fig. 1 establishes the PRISMA flow diagram for this systematic review. The main objective of this study is to present a

detailed discussion of the state-of-the-art algorithms for heart sounds analysis and classification, and to highlight existing limitations.

A. LITERATURE SEARCH

Based on the primary search strategy, a systematic search of the literature was carried out in the following databases: IEEE Xplore, Scopus, PubMed, Web of Sciences (Web of Knowledge), ScienceDirect, Google Scholar, EMBASE, and ACM Digital Library. Publications were extracted from these databases using key search terms and their possible combination using logical operators 'and/or'. Key search terms included 'heart sounds' or 'heart sounds analysis algorithms' or 'heart sounds classification' or 'identification of heart sounds' or 'phonocardiography' or 'continuous monitoring of cardiovascular diseases' and/or 'wearable cardiac monitoring devices'. A non-automatic search of references listed in the relevant publications was also performed to discover additional studies. Articles with algorithms for heart sounds detection, classification, and analysis were the focus. Articles with uncertainty regarding the eligibility were fully evaluated before taking a decision for their inclusion in the study.

B. EXCLUSION CRITERIA FOR THE SYSTEMATIC REVIEW

Specific eligibility criteria were followed to shortlist the research articles to be included in this systematic review. Studies found within the searched databases were screened after the initial search. Initial removal of duplicates and suitability check of articles were performed after examining the title and abstract first, and then through the full text. Only articles in which the methodology for data acquisition, analysis, and processing of heart sounds were reported with a clear demonstration of the approaches, met the eligibility criteria. All papers found were included in the review apart from the following: (1) papers which did not include quantification of results; (2) papers others than peer-reviewed articles; and (3) articles published in languages other than English.

C. STUDY DESIGN

The review is organized as follows: Various databases used for the validation of algorithms for heart sounds analysis are reviewed and discussed. This is followed by a review of approaches for heart sounds segmentation, feature extraction, and classification. Articles on segmentation and classification of heart sounds are the main focus of this systematic review. Apart from this, pathophysiology of normal and abnormal heart sounds is summarized in the context of automated continuous monitoring systems.

D. STUDY SELECTION

The initial search output contained 33,189 research articles published from 1947 to 2018. Out of these, 1347 articles were included after initial screening and removal of duplicates. Further, 979 articles were omitted based on abstract and title screening. 368 articles were finally shortlisted for review and out of these 117 articles met the inclusion criteria. A total of 56 reports on databases and heart sounds acquisition, were also included. Additional articles were used in this study to inform the background of data acquisition systems, feature extraction approaches and other relevant information related to this systematic review.

E. STUDY LIMITATIONS

Performance parameters of existing algorithms cannot be directly compared mainly because of the diversity of the test datasets used for evaluation. In addition, no standard validation methods were used in the articles, consequently leading to non-uniform performance assessments. Further, in some cases, statistical validation was not reported, or partial results were provided, limiting the usefulness of the assessment metrics.

F. DATA EXTRACTION AND SYNTHESIS OF RESULTS

Data from eligible articles were extracted and summarized in the tables for discussion. Methods and approaches were classified into different categories to present a significant comparison among the class. The data extracted was related to the type of approach and level of analysis for heart sounds segmentation, feature extraction, and classification. For accuracy measurement under different conditions, performance parameters such as segmentation rate (SR), accuracy (Acc), sensitivity (S_e), specificity (S_p), positive predictive value (PPV), number of features, and classification accuracy (CA) were extracted. Additional information included the demographics of the study group in the relevant database (such as the age and type of subjects); the signal investigated; the number of heart sounds recorded; the duration; the sampling frequency; and the type of device used for recording signals. Overall accuracy measures were also obtained from selected studies that reported significant information for evaluation. Finally, the synthesis of results is reported.

III. PATHOPHYSIOLOGY OF NORMAL AND ABNORMAL HEART SOUNDS

The electrical activity of the cardiovascular system causes atrial and ventricular contractions that assist in blood circulation between the chambers of the heart and around the body. Mechanical interactions between the blood flow and the different valves that operate to regulate the circulation of blood, contribute to rhythmic heart sounds and murmurs. Heart sounds are audible on the chest wall and can be captured using acoustic sensors from different auscultation areas associated with the valve locations [14], [15]. Heart sounds can also be graphically represented as a phonocardiogram, in which pathological signs are used as diagnostic features. However, the correct interpretation of phonocardiograms is challenging because of the overlapping of normal and abnormal heart sounds in the cardiac cycle. This section briefly summarizes different types of heart sounds that may be observed in a cardiac cycle. Characteristics of adventitious heart sounds are also tabulated in Table 1.

TABLE 1. Pathophysiology of normal and abnormal heart sounds.

Heart Sounds		Frequency Range	Qualitative sounds characteristics	Duration/location in the cardiac cycle	Cause	Description
First heart sound (S_1) or *lub* sound		10-200 Hz (lower pitch than S_2)	Dull and prolonged	0.12-0.15 seconds (longer than S_2)	Closure of the atrioventricular valves	Composed of M_1 and T_1 components
Second heart Sound (S_2) or *dub* sound		20-250 Hz (higher pitch than S_1)	Sharp and short	0.08-0.12 seconds (shorter than S_1)	Closure of the semilunar valves (at the end of systole)	Composed of A_2 and P_2 components
Third heart sound (S_3)		25-70 Hz (very low frequency, lower pitch than S_1 and S_2)	Soft and thudding quality	≈0.04 s, early-diastole (140-220 ms after S_2)	Early diastolic filling of the ventricle by blood rushing in from the atria	Due to the excess blood volume in the ventricle (left ventricle failure), benign in children and in pregnancy
Fourth heart sound (S_4)		15-70 Hz (lower than S_3, low pitch)	Weak and rumbling, less loud than S_1 or S_2	Late-diastolic/pre-systolic, slightly before S_1	Diastolic dysfunction because of the stiff ventricle	Due to atrial contraction, manifests coronary heart disease
Gallop	Ventricular (S_3 gallop rhythm)	15-50 Hz (very low frequency, low pitch, short and faint)	Galloping rhythm, lilt, trot or canter quality	≈ 0.15 s after S_2, early-diastole	During S_3 due to rapid deceleration of blood flow into the ventricle	Gallop rhythms indicate serious myocardial dysfunction
	Atrial (S_4 gallop rhythm)			≈ 0.08 – 0.20 s just before S_1	During S_4, due to decreased ventricular distensibility	S_4-S_1 may be confused with a split S_1
	Summing (both S_3 and S_4 gallops)		Quadruple rhythm, loud sound	During diastole period	Both S_3 and S_4 are superimposed	Occurs with the improvement of heart failure
Murmurs	IM	120-250 Hz (mid-range frequency, high pitch)	Whooshing, roaring, turbulent fluid noise	Mostly in early-systole, short duration	Due to the turbulent flow of the blood which may occur inside or outside the heart	Frequently heard in children and during exercise, position dependent
	SM	Up to 600 Hz (frequency range usually lower than DM, high pitch)	Rasping and blowing, usually crescendo-decrescendo	Early-, mid-, late- or holo-systolic	Mechanical systolic and ventricular ejection	Includes PS, AS, ASD, HOCM, MI, TI, MVP, PDA and VSD
	DM	Up to 600 Hz (high or low pitch)	Puffing and rumbling quality, usually decrescendo	Early-, mid- or late-diastolic	Ventricular relaxation and filling	Difficult to hear, Includes PI, AI, MS, TS
Opening snaps		100-800 Hz (high pitch)	Snapping sound	During diastole period	Inspissating of valve leaflets	The sudden opening of the stiff mitral valve
Rubs			Scratching, harsh, creaking sound	Loudest in systole and can be heard in the beginning and end of diastole	Friction between layers, abrasion of pericardial surfaces	Depends on the body position and breathing
Clicks			Short and loud	Very early systole, mid-systolic click, may be immediately after S_1	Due to the opening of a rigid and calcifies aortic or pulmonary valve	Includes AEC, SEC, mechanical valve click, or prosthetic valve click

*Information regarding frequency range and timings from [14], [19], [24]–[27]
Abbreviation: IM: innocent murmurs, SM: systolic murmurs, DM: diastolic murmurs, PS: pulmonary stenosis, AS: aortic stenosis, ASD: atrial septal defect, HOCM: hypertrophic obstructive cardiomyopathy, MI: mitral insufficiency, TI: tricuspid insufficiency, MVP: mitral valve prolapse, PDA: patent ductus arteriosus, VSD: ventricular septal defect, PI: pulmonary insufficiency, AI: aortic insufficiency; TS: tricuspid stenosis, MS: mitral stenosis; AEC: aortic ejection click, SEC: systolic ejection click.

A. FUNDAMENTAL HEART SOUNDS –S_1 AND S_2

Mechanical actions of heart valves produce heart sounds including fundamental heart sounds (FHSs), S_1 followed by S_2 [16]–[18]. The first heart sound (S_1) is heard at the onset of the systolic phase. This sound results from the sequential closure of the atrioventricular (AV) mitral and tricuspid valves [19]. S_1 has a frequency range between 10 and 200 Hz. Its amplitude has a great correlation with cardiac output [20]. Normally, S_1 is heard as a single sound with internal components M_1 and T_1, separated by a very small gap of nearly 20-30 milliseconds (ms) [21]. However, during some cardiac abnormalities (such as right bundle branch block) splitting of S_1 can be observed.

The second heart sound (S_2) occurs at the beginning of the diastolic phase, and is caused by the closure of the aortic and pulmonic valves. S_2 is a higher-pitch sound than S_1, with a frequency range between 20 and 250 Hz, and is also shorter in duration. S_2 is heard as a single sound with internal components A_2 and P_2. However, during cardiac abnormalities, S_2 may be observed as two split beats of A_2 and P_2, because of a noticeable time gap existing between the closure of A_2 and P_2. This gap may vary between 30 to 80 ms during inhalation and may reduce to 15 ms during exhalation [22], [23].

B. ABNORMAL HEART SOUNDS

During normal cardiac operation, a clear S_1-S_2 pattern with a systolic period (S_1 to S_2) and diastolic period (S_2 to S_1) is observed. However, in the case of abnormalities being present, apart from S_1 and S_2, other sounds, such as a third heart sound (S_3), fourth heart sound (S_4), gallops, clicks, opening snaps (OS), and murmurs might occur.

Early diastolic filling of the ventricle, caused by blood rushing in from the atria, produces S_3 shortly after S_2. This is due to vibrations caused by blood going backwards and forwards between the walls of the ventricles. S_3 is noted as a benign sound in the case of young people, athletes, and during pregnancy. In other cases, however, it is considered an important indicator of reduced systolic function. Diastolic dysfunction because of a stiff ventricle gives rise to an audible S_4 happening shortly before S_1 that contributes to the late diastolic filling. The occurrence of S_4 is considered as a significant indicator of cardiac abnormalities.

Clicks and snaps are also important evidence of abnormalities related to the operation of the valves. Systolic clicks are brief and high-pitch sounds, usually noticed during the opening of the semilunar valves. These occur shortly after S_1. Opening snaps may be observed shortly after S_2, with the

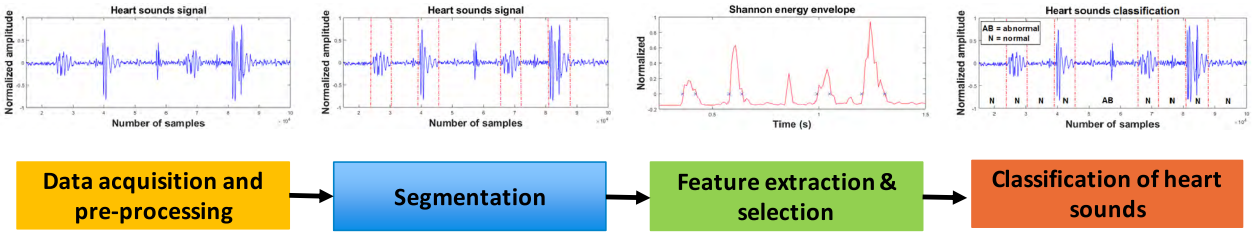

FIGURE 2. Different steps involved in the automated heart sounds analysis and classification.

opening of the mitral and tricuspid valves. These abnormal sounds are indicators of mitral valve prolapse (MVP), mitral regurgitation (MR), and other pathological conditions. Gallops are sounds that resemble galloping rhythms. These signpost serious myocardial dysfunction because of noncompliance of one or both ventricles. Gallop sounds may be observed during S_3 or S_4 or both [19], [28].

Turbulence due to accelerations and de-accelerations of blood in chambers of the heart, stiffening/narrowing or incompetence of the heart valves because of regurgitation, produce mechanical vibrations that propagate to the surface and give rise to audible whooshing sounds called murmurs. Most murmurs are intra-cardiac events observed in the frequency range between 20-600 Hz. The frequency spectrum of murmurs, artifacts, fundamental heart sounds and other heart sounds present in the cardiac cycle, overlap significantly. However, murmurs are more chaotic in nature. Murmurs can be broadly classified based on their characteristics: timings (systolic murmurs, diastolic murmurs, or maybe both); shape (crescendo, decrescendo or crescendo-decrescendo) and location in the cardiac cycle (early, mid or late or continuous) [29]. They may be also classified as stenosis (such as aortic stenosis (AS)) or regurgitation (such as mitral regurgitation (MR)) murmurs. Murmurs may be innocent or else may indicate clinical signs of cardiac diseases.

IV. REVIEW OF ALGORITHMS FOR HEART SOUNDS ANALYSIS

Many algorithms have been reported for automated classification of heart sounds with approaches that range from traditional thresholding methods to recent statistical machine learning and neural network based ones. The main aim of automatic heart sounds analysis is to achieve a precise classification of the pathological events present in the cardiac cycle. The different steps involved (as shown in Fig. 2) in the automated heart sounds analysis are reviewed in the following sections.

A. DATABASES FOR HEART SOUNDS ANALYSIS

Non-availability of standardized, good-quality, thoroughly validated, and documented datasets hinder the development of algorithms for heart sounds analysis. Currently, the most extensive database of heart sounds recordings is PhysioNet [10], [14], [30], [31]. Other databases used for the validation of algorithms in the reviewed papers included the PASCAL database [32], the Open Michigan Heart Sound & Murmur Library (OMHSML) [33], the Cardiac Auscultation of Heart Murmurs database (eGeneralMedical) [34], the heart sounds library by Thinklabs [35], the heart sounds Podcast Series by Robert J. Hall Heart Sounds Laboratory, Texas Heart Institute, Texas [36], Bioscience normal and abnormal heart sounds database (BHSD) [37], and the Cardiac Auscultatory Recording Database (CARD) [38]. In addition, a book by D. Mason comprises a CD with a limited number of heart sounds and murmurs [19]. Similarly, heart sounds signals from an audio-visual presentation by Tavel *et al* was also used as a database in some of the reviewed papers [39].

Other than these available databases, researchers have also collected their own data. Most of these recordings were obtained during clinical trials in hospitals by auscultation using a digital stethoscope/microphone. A list of existing databases and their characteristics is provided in Table 2. Most of the existing databases are restricted by the number of recordings, duration and sampling frequency. Also, other potentially important information such as gender, age and auscultation positions are not always specified, despite these being important for proper algorithm validation. In addition, in many cases, the signals had been pre-processed leading to the loss of both, pathological characteristics, as well as real-world artifacts which are nonetheless important to take into account when designing the algorithms/acquisition systems. Also, the length of the individual recordings available is not sufficient to validate algorithms intended for continuous heart sounds analysis, and are not in agreement with the Task Force recommendations [40] that suggest short-term 5-min recordings to evaluate parameters such as heart rate variability (HRV).

B. HEART SOUNDS SEGMENTATION

The purpose of heart sounds signals segmentation is to localize sounds peaks including the fundamental heart sounds (S_1 and S_2). The peaks of S_1 and S_2 are required for determining the systolic and diastolic phases and to help in the subsequent estimation of cardiac cycles. This facilitates identification and extraction of acoustic signals of interest in each cardiac cycle. Broadly, reported segmentation methods can be classified into: envelope based methods [47], [57], [58], [68], [79], [84]–[89], ECG and/or carotid

TABLE 2. Databases used for validation of algorithms for heart sounds analysis.

Reference	Source	Type of sound/ # Subjects	# recordings	Age (Mean ±SD) years	Gender (M/F)	Sensor	Sensor position	Format	Total participants	Sampling rate	Frequency band	Duration (Seconds)	Comments
(a) Public heart sounds databases													
[14], [30], [31]	PhysioNet database (Computing in Cardiology Challenge 2016) ♥	Normal and pathological sounds	4,430 records (including training and test sets)	Variable	Variable	Variable	Different positions	Variable	1297 (1072 included for training and test dataset)	Variable	Variable	5-120 s each	Open access database, comprises nine databases, performance of dataset reported in [10], [41]
[42], [43]	MITHSDB (collectively from [42], [43]) ♥	Normal (38)	117 records	-	-	Welch Allyn Meditron stethoscope (Skaneateles, USA)	9 different positions and orientations	-	121	44.1 Hz	20 -20 k Hz	9-37 s each (33±5 s)	Simultaneously recorded with ECG, MITHS database included in [14]
		IM (34)	118 records										
		MVP (37)	134 records										
		AD (5)	17 records										
		MPC (7)	23 records										
[25], [44]	TUTHSDB (collectively from [25], [44]) ♥	Normal (28) and pathological (16)	174 records	-	-	‡	Aortic, pulmonic, apex and tricuspid positions	-	44	4 kHz	-	15 s each position	TUTHS database included in [14]
[45], [46]	AADHSDB (collectively from [45], [46]) ♥	Normal (121)	544 records	-	93M/58F	‡	4th ICS at the left sternal border on the chest	-	151	4 kHz	20 - 1000 Hz	8 s each	AADHS database included in [14]
		CAD (30)	151 records										
[47], [48]	UHAHSDB (database in PhysioNet [30]) ♥	Normal (25)	39 records	18 to 40 years	-	Prototype electronic stethoscopes	-	WAV format	55	8 kHz	-	6-49 s each	UHAHS database included in [14]
		Pathological sounds (30)	40 records	44 to 90 years	20M/10F								
[49]	AUTHHSDB (database in PhysioNet [30]) ♥	Normal (11)	11 records	29.3±10.7	4M/7F	Custom-made electronic stethoscope	Auscultation for valve murmurs & apex area	WAV format	45	44.1 Hz	4 kHz	10-122 s each (50 ± 26 s)	AUTHHS database included in [14]
		MR (17)	17 records	75.3±10.2	6M/10F								
		AS (17)	17 records	76.1±7.2	6M/10F								
[50] – [53]	DUTHSDB (database in PhysioNet [30]) ♥	Normal (174)	338 records	4 to 35 years (25 ± 3 years)	172M/2F	Microphone sensor (MLT201) or piezoelectric	Various sites	WAV format	509	8 kHz – 22050 Hz	Variable	209 ± 78 s each	DUTHS database included in [14]
		CAD (335)	335 records	10 to 88 years (60 ± 12 years)	108M/227F	‡	Mitral site at the chest			8 kHz		17 ± 12 s each	
[54]	SUAHSDB (database in PhysioNet [30]) ♥	Normal (79) and pathological (33)	114 records	16 to 88 years (56 ± 16 years)	43M/69F	An electronic stethoscope	Apex	-	112	8 kHz, 44.1 kHz and 384 kHz	20-1000 Hz	30-60 s (33 ± 5 s) each	SUAHS database included in [14]
[14]	SSHHSDB (database in PhysioNet [30]) ♥	Normal (12) and pathological (23)	35 records	-	-	-	2nd intercostal	-	35	8 kHz	-	15-69 s (36 ± 12 s) each	SSHHS database included in [14]
[14]	SUFHSDB (database in PhysioNet [30]) ♥	Fetal (116)	119 records	-	-	An electronic stethoscope (GS Technology Co. Ltd, South Korea)	-	8 kHz and 44.1 kHz	225	8 kHz and 44.1 kHz	20-1000 Hz	Average 90 s each	SUFHS database included in [14]
		Maternal (109)	92 records	29 ± 6 years	109F						-		
[19]	Daniel Manson 2000 ♥	Normal and pathological sounds	Over 180 records	-	-	-	-	WMA format	-	-	-	Variable	Book with CD recordings, reported in [55]
[32]	The PASCAL database (CHSC 2011) ♦	Dataset A: Normal, murmur, EHS & artefact	176 records	-	-	†	-	WAV/ aif format	-	44.1 kHz	-	1-30 s each	Segmented data with S_1 and S_2 location, reported in [56], low-pass filtering at 195 Hz
		Dataset B: Normal, murmur and extrasystole	656 records			‡				4 kHz			
[33]	OMHSML (The University of Michigan database) ♦	Normal and pathological sounds	23 records	-	-	Stethoscope	Apex, aortic and pulmonic area	MP3	-	44.1 kHz	-	Total of 1496.8 s	Reported in [57], [58]

TABLE 2. ***(Continued.)*** **Databases used for validation of algorithms for heart sounds analysis.**

[34]	CAHMDB (eGeneral Medical Inc. database) ♦	Pathological and non-pathological	64 records	-	-	-	-	WAV format	-	11/8 kHz	-	Total of 338 s (1-10 s each)	Requires permission, reported in [14], [59]–[61]
[35]	Heart sound library by Thinklabs ♦	Normal and pathological	41 records	-	-	Thinklabs stethoscope	-	-	-	-	-	Variable	Available online, reported in [58]
[36]	Texas Heart Institute database ♦	Pathological (50) (information from [62])	50 records	-	-	Stethoscope	-	MP3	-	44.1 kHz	-	Variable	Database reported in [62], more information in [63]
[37]	BHSD ♦	Normal and pathological	25 records	-	-	-	-	WAV format	-	-	-	Total of 49.94 s	Online available, reported in [64]
[38]	CARD database ♦	Normal and pathological	Variable	-	-	Hewlett Packard 21050A microphone	-	MP3 format	-	-	-	20 s each	Login required to access database, ECG records available, reported in [64], [65]
(b)	Heart sounds recorded by researchers for validation of algorithms												
[25]	Naseri and Homaeinezhad 2013 ♦	Pathological (AS, AR, MS, MR) (50)	50 records	48 years (average)	25M/25F	‡	Aortic, pulmonic, apex and tricuspid positions	-	50	4 kHz	700 Hz	Total of 52 minutes	TUTHS database included in [14]
[29]	Ari *et al* 2008 ♦	Normal and nine different pathological sounds	71 records	No age group associated	-	‡ and ⁑	-	WAV format	71	8, 11, 22 & 44.1 kHz	Below 150 Hz	-	ECG signals for validation
[42]	Syed 2003 ♥	Normal (30) and MVP (21)	102 records	-	-	-	Apex and left lower sternal border	-	51	44.0 Hz	-	-	Simultaneously recorded EKG signals, included in [14]
[43]	Sayed *et al* 2007 ♥	Normal murmurs (15), MR (11) and normal (13)	39 records	-	-	⁑	Left apex and left parasternal	-	39	44.1 Hz	4096 Hz	30-40 s each	Simultaneously recorded ECG signals, included in [14]
[44]	Naseri *et al* 2013 ♥	Normal and pathological (AS, AR, MS, MR)	63 normal and 63 pathological	-	-	‡	Aortic, pulmonic, apex and tricuspid positions	-	-	4 kHz	-	2 minutes each	TUTHS database included in [14]
[45]	Schmidt *et al* 2010 ♥	Normal (13) and pathological (100)	73 records	-	-	‡ (handheld stethoscope)	4th ICS at the left sternal border on the chest	-	40 (training data) and 73 (test data)	4 kHz	-	8 s each	Without ECG signals, database included in [14]
[46]	Schmidt *et al* 2015 ♥	Non-CAD (70) and CAD (63)	231 (Non-CAD) and 204 (CAD)	60.1±9.9 (Non-CAD) & 66.1±10.7 (CAD)	35M/35F (Non-CAD) & 47M/16F (CAD)	‡	4th ICS at the left sternal border on the chest	-	133	4 kHz	20-1000 Hz	8 s each	Unsupervised, database included in [14]
[47]	Moukadem *et al* 2013 ♦	Normal	40 records	18-40 years	-	Prototype electronic stethoscopes	-	WAV format	-	8 kHz	-	6-12 s each	UHAHS database included in [14]
		pathological sounds	40 records	44 to 90 years									
[49]	Papadaniil and Hadjileontiadis 2014 ♦	Normal (14)	11 (698 cycles)	29.3±10.7	4M/7F	Electronic stethoscope	Auscultation for valve murmurs & apex area	WAV format	52	44.1 Hz	4 kHz	10-122 s each	AUTHS database included in [14]
		MR (19)	16 (827 cycles)	75.3±10.2	6M/10F								
		AS (14)	16 (1077 cycles)	76.1±7.2	6M/10F								
[52]	Tang *et al* 2012 ♥	Normal (3) and pathological (23)	26 records	-	-	Vibration (piezoelectric) sensor	Mitral site	-	26	2 kHz	Below 600 Hz	-	Simultaneously recorded with ECG, DUTHS database included in [14]
[53]	Li *et al* 2011 ♦	Normal and pathological	27 cardiac cycle	-	-	-	Mitral site	-	-	2 kHz	-	≈ 9 s each	DUTHS database included in [14]
		Normal (45)	3390 s of									600 s	
		ASD (14)										620 s	

TABLE 2. ***(Continued.)*** **Databases used for validation of algorithms for heart sounds analysis.**

[57]	Sun *et al* 2014 ♥	F4 (7) PDA (10) VSD (33) Mixed CHD (12) RHD	CHD, 3940 s of RHD and 600 s of normal HSs	-	-	‡	Tricuspid site	-	121	44.1 kHz	20 – 20k Hz	270 s 550 s 1290 s 660 s 3940 s	Michigan HSs database [33] also considered for validation
[64]	Varghees and Ramachandran 2017 (AUHSD) ♦	Normal heart sounds	25 records	-	-	Microphone	-	-	-	2 kHz	800 Hz	-	Databases from other sources also used for validation
[66]	Amit *et al* 2009 ♥	HSs with alternating breath resistance	10 records	29±12 y	8M	-	-	-	12	-	20-250 Hz	40 s each	Single-lead ECG
		Pharmacological stress data	-	60±14 y	11M				11			30-45 minutes each	Dobutamine stress echocardiography
[67]	Gupta *et al* 2007 ♦	Normal and murmurs	340 HSs segments	-	-	-	-	-	41	8 kHz	4 kHz	-	No ECG information used
[68]	Javed *et al* 2006 ♥	Pathological sounds	40 records	16 to 79 years	-	‡	-	.e4k and WAV format	40	8 kHz	-	8 s each	Supervised recordings
[69]	Turkoglu *et al* 2003 ♦	Normal (95) and pathological (120)	215 records	15 to 80 y (average 48.77 y)	132M/83F	Acuson Sequoia 512 Model Doppler Ultrasound system	Chest	-	215	20 kHz	0.5-10 kHz	5 s each	Doppler HSs signals
[70]	Safara *et al* 2013 ♥	Normal (16) and pathological (43)	59 records, 804 heart cycles	-	-	Welch Allyn Meditron and ECG analyzer, Meditron	-	-	-	4 kHz	-	15 s each	ECG is recorded simultaneously
[71]	Banerjee and Mondal 2015 ♥	Pathological (60)	-	-	45M/16F	⁂	-	WAV format	86	8 kHz	2 kHz	-	Recordings in sitting and relaxed conditions
		Non-pathological (60)			15M/10F								
[72]	Iwata *et al* 1980 ♥	N (60), FM (40), MI (32), AI (38), ASD (9), & VSD (8)	187 samples, 881 cardiac cycle	-	-	4-channel PCG (Fukuda Densi EMR60SD)	Cardiac apex area	Magnetic tape	69	2 kHz	880 Hz	-	ECG and PCG are recorded simultaneously
[73]	Zheng *et al* 2015 ♥	Normal (88)	88 records	18-60 y (mean 35.64±7.5)	44M/40F	Self-developed cardiac reserve monitor	Apex	-	152	11025 Hz	-	One minute each	Color Doppler Ultrasound medical machine (Vivid-7, GE company, USA) also used
		CHD patients (64)	64 records	38-70 y (mean 61.56±9.7)	36M/28F								
[74]	Zhang *et al* 2014 ♦	N (225) and abnormal (180) (MS (60), VSD (60) & AS (60))	405 (225 (N) and 180 (AN))	-	-	Phonocardiogram sensor	Precordium	-	405	11025 Hz	2205 Hz	-	Pathologies confirmed by experts
[75]	Guillermo *et al* 2015 ♦	Pathological and non-pathological	92 cardiac cycles (38 (PI) and 54 (TI))	-	-	Microphone	-	-	-	8 kHz	30-600 Hz	15 s each	Self-developed cardiac monitoring platform
[76]	Elgendi *et al* 2014 ♦	Pathological and normal	-	3 months to 19 years	12M/15F	‡	Cardiac apex and 2nd LICS	WAV format	27	4 kHz	-	Over 20 seconds each	Sounds from subjects undergoing cardiac catheterization
[77]	Hassani *et al* 2014 ♦	N (5), VSD (36), ASD (12) & ASD and VSD (6), TOF (10), PS (10) & 21 others	100 records (14,000 cardiac cycles)	1-26 y	-	-	-	-	100	44.1 kHz	Below 800 Hz	-	Heart sounds from children
[78]	Choi and Jiang 2010 ♦	N (6) and pathological (34) (AF, AI, AS, MR, MS and Split)	196 (N) and 293 (AN) records	30±14 y (N), 47±19 y (AN)	-	Electronic stethoscope	Four auscultation sites	-	40	8 kHz	700 Hz	12 s each	Self-developed stethoscope to record signals

TABLE 2. *(Continued.)* **Databases used for validation of algorithms for heart sounds analysis.**

[79]	Zhang *et al* 2017 (The Pascal CHSC 2011) ♦	N (45), M (48), EHS (27) and artefact (56) N (336), M (105), extrasystole (66)	176 records 507 records	-	-	† ‡	-	WAV format	-	44.1 kHz 4 kHz	2 kHz	-	Database from [32]
[80]	Springer *et al* 2016 ♥	Normal (38), MVP (37), IM (36), AD (5), MPC (7)	S_1: 12181 and S_2: 11627	-	-	⁂	Parasternal, apical, aortic, and pulmonic	-	123	44.1 kHz	1 kHz	Total of 10172 s	Verified using ECG
[81]	Turkoglu *et al* 2003 ♦	Normal and pathological (AV and MV)	215 records	15-80 y (average 48.77 y)	132M/83F	Acuson Sequoia 512 Model Doppler Ultrasound system	-	-	92 for training and 123 for testing	20 kHz	500 Hz	5 s each	Doppler HSs signals
[82]	Uğuz 2012 ♦	Normal (40), PS (40) and MS (40)	-	4-65 y	55M/65F	‡	-	e4k/ WAV format	120	8 kHz	-	-	-
[83]	Kang *et al* 2017 ♦	Innocent murmurs (87) and pathological murmurs (170)	257 records (1212 cycles)	-	-	‡	RUSB, LUSB, LMSB, LLSB and apex	-	-	8 kHz	40-500 Hz	3-8 s each	Heart sounds from pediatric patients

Note: Data collected in controlled conditions is indicated with symbols '♥', while '♦' symbol is used where no information related to recording conditions is available. iStethoscope is indicated with symbol '†', electronic stethoscope 3M Littmann is indicated with symbol '‡' and Meditron (NY, USA) stethoscope with symbol '⁂'.

Abbreviation: N: normal heart sounds, M: murmurs, EHS: extra heart sounds, CAD: coronary artery disease, CHD: congenital heart disease, EAS: early aortic stenosis, LAS: late aortic stenosis, FM: functional murmurs, MI: mitral insufficiency, AI: aortic insufficiency, ASD: atrial septal defect, VSD: ventricular septal defect, PCHSC: Pascal classifying heart sound challenge, IM: innocent murmurs, MPC: miscellaneous pathological condition, AD: aortic disease, LICS: left intercostal space, ICS: intercostal space, MVP: mitral valve prolapse, AS: aortic stenosis, AR: aortic regurgitation, MR: mitral regurgitation, MS: mitral stenosis, RUSB: right upper sternal border, LUSB: left upper sternal border, LMSB: left middle sternal border, LLSB: left lower sternal border, AUHSD: Amrita university heart sounds database, TOF: tetralogy of Fallot, AF: atrial fibrillation, MITHSDB: the Massachusetts Institute of Technology heart sounds database, AADHSDB: the Aalborg University heart sound database, AUTHHSDB: the Aristotle University of Thessaloniki heart sounds database, UHAHSDB: the University of Haute Alsace heart sounds database, TUTHSDB: The K N Toosi University of Technology heart sounds database, DUTHSDB: the Dalian University of Technology heart sound database, SUAHSDB: the Shiraz University adult heart sounds database, SSHHSDB: the Skejby Sygehus Hospital heart sounds database, SUFHSDB: the Shiraz University fetal heart sounds database.

pulse reference based methods [72], [90]–[99], probabilistic models [45], [52], [65], [67], [77], [80], [100]–[105], feature based methods [25], [29], [49], [61], [75], [106]–[108], time-frequency analysis based methods [55], [59], [62], [109], [110], and learning based methods [50], [111]–[113].

1) ENVELOPE-BASED METHODS

The envelope of heart sounds is used to identify S_1 and S_2 in the cardiac cycle using different approaches. Typical methods used for the envelope extraction are: normalized average Shannon energy, homomorphic filtering, Hilbert transform, moving window Hilbert transform, and short-time modified Hilbert transform.

Most of the envelope based segmentation algorithms perform heart sounds segmentation with an assumption that the systolic period is shorter than the diastolic period. However, this may not be true in the case of infants and other cardiac patients having abnormal heart sounds [114]. In addition, envelope-based methods generally fail when additional peaks (such as those caused by artifacts) appear superimposed to the fundamental heart sounds [91], [115]. Furthermore, medium amplitude peaks including murmurs are attenuated in the envelope analysis while large and low peaks may appear as a single envelope [108]. Thus, these methods fail to locate peaks of very low amplitude present in the cardiac cycle [61]. Also, in some cases, manual selection of threshold to localize fundamental heart sounds may result in loss of some of the peaks of interest.

2) ECG AND/OR CAROTID PULSE REFERENCE BASED METHODS

A number of the reported segmentation approaches require an auxiliary signal (ECG signal and/or carotid pulse) as a reference to identify the locations of fundamental heart sounds in the cardiac cycle [72], [90]–[99], [116].

The general disadvantage of these methods is that a secondary signal is required, which is more complex both, from the point of view of a sensing and also synchronization. Also, these methods are affected by the mismatch in timing between the electrical and mechanical (E-M) activities of the cardiovascular system, which in turn depends on the pathological conditions of patients [115]. Also, methods that require the identification of R-peaks and T-peaks are more computationally hungry and demanding in processing power. In addition, accuracy also varies with low amplitude and abrupt changes in the QRS morphologies, which can make the identification of the R-peaks and T-peaks complex on its own.

3) PROBABILISTIC MODELS FOR SEGMENTATION

As envelope-based methods have shown a modest success, many probabilistic models for segmentation were reported

in recent studies to try to overcome their shortcomings. The aim of probabilistic models is to characterize the fundamental heart sounds based on some discriminative features, such as temporal correlation, waveform function, time-frequency energy, and other information. Among all available probabilistic models, HMMs were mostly used for the segmentation of heart sounds in recent articles.

Though probabilistic models were efficient in improving the performance of the segmentation methods, the overall performance of these methods still needs to be validated using a larger datasets. This is because, amongst other things, the characteristics of the fundamental heart sounds which were used to develop the various models, varies largely from infants to old people and from healthy to cardiac patients.

4) FEATURE-BASED METHODS

Feature-based methods are based on extracting certain features such as energy fraction, sample entropy, total variation filtering, Shannon entropy, instantaneous phase boundary, boundary location identification, likelihood computation, etc., to identify peaks present in the cardiac cycles. The main drawback of these methods is that the extracted features may vary with the signals they are tested on and hence they need to be verified using standardized databases.

In recent approaches, researchers segmented cardiac signals directly into cardiac cycles and skipped the steps used to identify individual locations of S_1 and S_2 peaks [56], [79], but this requires prior knowledge of the cardiac cycles. These methods have similar drawbacks to the envelope analysis.

The works reported using the different segmentation methods have been classified in the following and summarized in Table 3. In general, accurate segmentation is one of the most challenging tasks in heart sounds analysis, especially, when the signals are corrupted by real-world artifacts. Also, most of the available algorithms are designed to segment fundamental heart sounds. However, other abnormal peaks and irregularities with low amplitudes also need to be investigated. In addition, existing segmentation algorithms mostly depend on absolute measures like time or frequency distributions which exhibit large disparity within subjects and hence result in poor segmentation accuracy. The limitations in segmentation methods consequently impact the overall accuracy of the PCG signals classification.

C. FEATURE EXTRACTION

Representations of the cardiac signals in different domains reveal various physiological and pathological characteristics and allow efficient feature extraction. To capture concurrent variations and structural components in both time and frequency, time-frequency representation of the transient signals has been reported as a preferred mean over the time-domain and frequency-domain representations. Qualitative and quantitative measurements of the signals were obtained using different transforms for heart sounds analysis; for instance, time-frequency representation using S-transform [47], Fourier transform, Short-Time Fourier Transform (STFT) [120], Wigner-Ville Distribution (WVD) [121], [122], Choi-Williams Distribution (CWD) [66], [123], wavelet transform [124], [125], and Short-Time Modified Hilbert Transform (STMHT) [57]. Though the Short-Time Fourier transform (STFT) was found to be popular, obtaining a proper resolution for feature extraction using STFT is challenging because of the fixed window available for the analysis [56], [126], [127]. Wavelet analysis emerged as an alternative by substituting the frequency shifting operation of the STFT by a time or frequency scaling operation [127]. Wavelet transform was widely reported in literature because of its suitability for representing signals where the length of the temporal window can be engineered for multi-resolution analysis with wide frequency range across the length [128]. Discrete Wavelet Transform (DWT) [91], Continuous Wavelet Transform (CWT) [129]–[131], and Mel-Scaled Wavelet Transform [107], [132]–[134], have all been used for heart sounds analysis.

Feature extraction and selection play an important role in pattern recognition and classification of heart sounds signals. Reviewed articles extracted features based on the cardiovascular disease being diagnosed and optimized them to reduce the complexity and computational burden of the system. Features with high-order statistics, non-linear fractal complexity, entropy information and chaos theory helped in capturing relevant information from non-stationary PCG signals, required for proper classification. Other features included Shannon energy envelope of the frequency spectrum, wavelet coefficients, perceptual features such as Mel-Frequency Cepstral Coefficients (MFCCs), bispectrum, Variance Fractal Dimension (VFD), and fractal features such as largest Lyapunov Exponents or Hurst Exponent.

Time-domain features are easy to extract and quantify. These features mainly include timing characteristics such as locations of S_1 and S_2, systolic and diastolic intervals, and amplitude information (such as the mean absolute value of the S_1 and S_2 and other peaks in the cardiac cycle). Some physiological and pathological information that is missed in the time-domain analysis can be visualized in the frequency domain analysis. Frequency-domain based feature extraction methods used mainly included band-pass filter banks and zero-crossing analysis [11], [59], [72], [123], [135]–[137]. Other discriminant features included the mean power of distinct cardiac sounds segments (S_1, S_2, systole and diastolic) in different frequency bands and MFCCs [107], [132]–[134]. Details of feature extraction methods and type of features extracted are presented in Table 4.

D. CLASSIFICATION OF HEART SOUNDS

The final step of a heart sound analysis algorithm is to take the extracted features and feed them to an appropriate classifier to interpret them. Reported approaches for classification include Support Vector Machine (SVM) [56], [58], [70], [71], [73], [74], [78], [79], [85], [105], [107], [111], [114], [124], [138]–[148], Hidden Markov

TABLE 3. Summary of heart sounds segmentation methods and their performance comparison.

Year	References	Segmentation Methods	Signal Type	# Subjects	Records (# and duration in seconds)	Cardiac Cycles (or periods)	Noise tolerance	S_1	S_2	S_3	S_4	Murmurs	Performance			Comments
													S_e (%)	*PPV* (%)	Accuracy (%)	
Envelope analysis																
2018	[117]	Shannon envelope and threshold adjustment	Normal (1) and pathological (4)	5	5 records	-	-	•	•	•	•	-	98.1	-	-	Only detection of sounds S_1 to S_4 was reported, validated with a limited number of recordings.
2017	[64]	Shannon entropy envelope and instantaneous phase	Normal and pathological	Databases from [32], [14], [34], [37], [33], [38] and HSs, Littmann HSs, WHSMD and AUHSD (Total 278 records)			SNR 10 dB	•	•	•	•	•	N: 94.38, M: 97.58	N: 97.25, M: 96.46	N: 91.92, M: 94.21	Information was extracted after splitting signals as low frequency and high frequency signal contents
2017	[83]	Shannon energy envelope	Normal	-	257 records	627 cycles	-	•	•	-	-	•	N: 99.2, PM: 89.3	N: 99.2, PM: 96.4	-	Recordings form children, murmurs were segmented, assumption
			Innocent murmurs			376 cycles										
			Pathological murmurs			209 cycles										
2017	[79]	Scaled spectrogram and PLSR	Normal, murmurs and extrasystole sounds	Datasets A & B (176 & 507) records, database from [32]			-	-	-	-	-	•	-	-	-	PLSR for identifying most relevant features, only heart cycles were identified
2015	[58]	CSCW envelope	Pathological	11 (AF)	-	152 periods	-	•	•	-	-	-	-	-	-	AF, AR, MR, PS, VSD and normal sounds were identified (Classification accuracy was reported)
				15 (AR)		169 periods										
				22 (MR)		231 periods										
				20 (N)		268 periods										
				6 (PS)		138 periods										
2014	[85]	Moving windowed HT	Normal and VSD HSs	16 healthy and 37 VSD patients	242 (N) and 226 (VSD)	-	-	•	•	-	-	•	98.8	-	-	VIM for heart sounds envelope analysis, *CA*: 98.4, higher sensitivity than threshold based methods
2014	[57]	STMHT	Normal	45	600 s	-	-	•	•	-	-	-	-	-	S_1: 98.53, S_2: 98.31, Cycle: 97.37	Unsupervised, using Hilbert transform and the Viola integral waveform method
			CHD	76	3390 s											
			RHD	-	3940 s											
			Database [33]	23	1496.8 s											
2013	[47]	Shannon envelope using S-transform	Normal (40)	-	80 records (6-12 s)	-	-	•	•	-	-	-	96	95 (using SSE)	-	Localization tolerance is absent, unsupervised
			Pathological (40)										97			
2010	[86]	CSCW (based on variance on PCG timing scales)	Normal and pathological	-	9 records (≤ 5 s each)	-	-	•	•	-	-	•	-	-	99.11	Results validated using a very small dataset, Viola integral method applied
2009	[87]	Short time spectral energy & autoregression characteristics	Normal (20)	120	Total of 1200 s	823 cycles	-	•	•	-	-	-	-	-	93.6	Pediatric heart sounds segmentation,
			Abnormal (40)													
2008	[88]	CSCW (also reported in [6])	Normal and abnormal	-	-	500 cycles	-	•	•	-	-	-	-	-	N: 100 and AN: 88.2 (MODSG2)	CSCW achieved higher accuracy compared to Shannon envelope and Hilbert envelope
2006	[68]	Normalized average Shannon energy	Pathological and non-pathological	40	8 s each	120 systolic periods	-	•	•	-	-	•	-	-	-	Patients aged between 16-79 years were considered, Segmentation results were not found
1997	[89]	Normalized average Shannon energy	Pathological (14) & physiological (23)	-	37 records	515 periods	-	•	•	-	-	-	-	-	93.00	No individual S_1 and S_2 identification reported
ECG pulse reference based methods																
2017	[90]	Probability analysis for feature extraction	Normal and abnormal	PhysioNet database [14]			-	•	•	-	-	-	76.96	-	-	ECG based segmentation using R-R interval estimation, *CA*: 84.11%
2011	[92]	Joint ECG and PCG signals	Normal	120	120 records (Each 10 s)	1976 cycles	-	•	•	-	-	-	-	-	S_1: 97.00, S_2: 94.00	Results are reported for paediatric HSs segmentation
			Pathological (80)													
2011	[93]	Using MMP	Normal (35)	70	Each 10 s	-	-	•	•	-	-	•	-	-	-	ECG recorded simultaneously, *CA*: 92.5% (using MMP classifier)
			Pathological murmurs (35)													
2009	[94]		Normal (50)	148		360 beats							100	92.0		

TABLE 3. ***(Continued.)*** **Summary of heart sounds segmentation methods and their performance comparison.**

		Fractal features for segmentation	Murmurs (98)		164 records ≤ 8 s		–	•	•	–	–	•			–	Intra-beat segmentation (ECG records)
2006	[95]	Feature selection with ECG signal	Valvular heart patient	36	15 s for each subject	445 cycles	–	–	–	–	–	•	–	–	–	207 features extracted, *CA*: 86 (For MI, AS and PM)
2005	[96]	R- and T-waves of ECG as reference	Data from known cardiac defects	300	40-45 s each	–	SNR > 40 dB	•	•	–	–	•	–	–	S_1: 100, S_2: 97.00	ECG gating applied, STFT, sounds form children
2001	[97]	Matching pursuit method	Normal and abnormal	15 (each for N & AN BMV)	–	–	–	•	–	–	–	–	–	–	–	ECG signals are also recorded at 500 Hz, *CA*: 93.00%, no segmentation results founds
1992	[98]	Microcontroller based HSs gating	Pathological	19	–	–	–	•	•	–	–	–	–	–	–	Gating device for medical imaging
1987	[99]	ECG and carotid pulse based	Normal and pathological	5 healthy and 20 CVD patients	94 signals (10 s)	–	–	•	•	–	–	–	–	–	–	Systolic and diastolic segmentation
1980	[72]	Segmentation using spectral tracking	Pathological and non-pathological	60 (N), 40 (FM), 32 (MI), 38 (AI), 9 (ASD) & 8 (VSD)	–	187 samples with 881 cardiac cycle	–	•	•	–	–	–	–	–	–	Zero-crossing positions are used for identification
Probabilistic models																
2017	[102]	Modified Springer's method [80]	Normal and pathological	PhysioNet database [14]			–	•	•	–	–	–	S_e: 91.38 (best)	–	–	Segmentation using CQA
2017	[103]	Springer's HSMM and Viterbi decoding	Normal and pathological	PhysioNet database [14]			–	•	•	–	–	–	–	–	–	Manual segmentation of HS signals
2017	[104]	Duration-dependent HSMM	Pathological and non-pathological	PhysioNet database [14]			–	•	•	–	–	–	–	–	79.30 (all dataset)	Segmentation algorithm by Springer *et al* [80]
2016	[80]	Logistic Regression-HSMM	Normal and pathological	123	10172 s (total)	S_1: 12181 S_2: 11627	–	•	•	–	–	–	95.34 ±0.88	95.92±0.83	92.52±1.33	HSMM performed better than HMM, error rate 0.23 with Shannon energy
2014	[77]	HF for segmentation	Normal and pathological	100 (N and AN)	100 records	14,000 cardiac cycles	–	•	•	–	–	–	S_1: 80.3 S_2: 77.5	S_1: 80.2 S_2: 77.6	–	Time-domain intensity envelopes, results not suitable for clinical applications
2012	[52]	Dynamic clustering	Normal and abnormal	3 healthy and 23 patients	26 records	565 cycles	–	•	•	–	–	–	–	–	S_1: 94.86, S_2: 95.92	Localization tolerance is absent, No split between training sets
2012	[65]	Hilbert-Huang Transform	Normal and pathological	800 records form CARDJHU [38]		15 records with S_3 and S_4	–	–	–	•	•	–	S_3: 90.40, S_4: 94.50	S_3: 90.4, S_4: 85.5	–	S_1 and S_2 were not identified
2012	[105]	HMM based segmentation	N and abnormal	80 (N) & 80 (Abnormal)	–	–	–	•	•	–	–	•	–	–	–	HMM based segmentation, *CA*: 85.6%
2010	[45]	Duration-dependent HMM	Normal and pathological	73	113 records (each 8 s)	–	–	•	•	–	–	–	98.8	98.6	–	HMM achieved 59.9% of *Se* and 54.8% of *PPV* for the same algorithm
2007	[67]	HF and *k*-means clustering	Normal and murmurs sounds	41	–	340 HSs segments	–	•	•	–	–	•	–	–	N: 99.09, SM: 85.47 & DM: 86.47	Not suitable for high intensity murmurs [29], unsupervised
2005	[100]	HE and self-organizing PM	Normal and abnormal	17	44 PCG records (30-60 s)	–	–	•	•	–	–	–	S_1: 98.6 S_2: 98.3	S_1: 96.9, S_2: 96.5	–	Extracted features from events are segmented using HMM
2005	[101]	HMM	Clean and dirty	9	46 files (~2286 s)	–	–	•	•	–	–	–	–	–	98	Shannon energy features are extracted for segmentation
Feature-based Methods																
2017	[106]	Identification of S_1 and S_2 using DNN	Normal and abnormal	28	–	460 each S_1 and S_2 HSs	–	•	•	–	–	–	–	–	–	Acoustic features using MFCC, *CA*: 91.12%, 17M/11F were considered
2015	[75]	Detection of heart sound murmurs	Pathological and non-pathological	–	38 (PI) and 54 (TI)	92 cardiac cycles	–	•	•	–	–	•	–	–	–	Classification of murmurs only
2015	[107]	Energy fraction and entropy based features	Normal (40) / CVD patients (67)	107	80 (N) and 167 (SHM)	–	–	•	•	–	–	•	93.48	–	–	Unsupervised, S_p: 98.55% and *CA*: 97.17%
2014	[49]	EEMD & kurtosis features	N (11) and pathological (32)	43	43 records	2602	–	•	•	–	–	–	–	–	83.05±15.14	HSS-EEMD/K achieved prediction power of 94.56±6.58%

TABLE 3. *(Continued.)* **Summary of heart sounds segmentation methods and their performance comparison.**

2014	[61]	HSAD method	Normal and pathological PCG	Online available [34] (each less than 10 s)		701	Up to 5 dB	•	•	•	•	•	99.43	93.56	93.95	Tested with limited database, no stated segmentation tolerance
2013	[25]	Frequency-energy based metric	Different valve disease	50	Total of 52 min	–	–	•	•	•	•	•	99.00	98.60	–	S_3, S_4 and murmurs were also investigated
2008	[29]	Clinical features for locating FHSs and murmurs	Normal 9 different pathologies	71	71 records	357 cycles	Up to 25 dB Up to 10 dB	•	•	–	–	•	–	–	97.47 (overall)	Robustness analysis and no split between training sets, systolic and diastolic murmurs
2005	[108]	Complexity-based segmentation	Online database [34]	–	–	–	–	•	•	–	–	•	–	–	–	No ECG gating used, not suitable for continuous murmurs.
Time-frequency/wavelet analysis based methods																
2018	[118]	Wavelet analysis and Shannon energy calculation	Normal sounds and abnormal sounds	230 subjects	230 records	–	–	–	•	–	–	•	–	–	–	Statistical results for the segmentation were not found.
2013	[62]	Tunable-Q wavelet transform	Pathological signals	Database from [36]			–	•	•	•	•	•	–	–	*SR*: 92.15 (overall)	Envelope based on CSCW
2011	[59]	Time-domain analysis of pathological PCG signals	Normal EAS LAS PS MR	Database from [34] (6 records for each class)			–	•	•	•	–	•	–	–	–	Unsupervised, TFD analysis using RME
2011	[109]	ASSA approach	Normal and pathological	12	20 s each	8 segments	–	–	–	–	–	•	–	–	–	Welch Allyn Tycos stethoscope, only correlation estimation
2008	[110]	Wavelet transform for segmentation	14 pathological HSs signals	Data from two patients, online and CD book	Each record of 20 cycles	140 cycles	–	•	•	–	–	–	–	–	–	Statistical results for the segmentation were not reported.
2007	[55]	Segmentation and feature extraction using wavelets	Normal and pathological (AR)	Database from [19]			–	•	•	–	–	–	–	–	–	Statistical results for segmentation were not reported.
Learning based methods																
2014	[111]	A system for heart sounds classification	Normal and pathological	Database from [119]	6 records for each class	72 Signals	–	•	•	•	•	•	–	–	S_1: 94.63, S_2: 97.25, S_3: 96.63, S_4: 96.66	Pathological and non-pathological signals are considered, No reported methods for segmentation
2010	[50]	Fuzzy detection method	Normal (3) Pathological (23)	26	26 records	565 cycles	0 dB and -5 dB	•	•	–	•	•	–	–	Best is 94.0% for 0 dB SNR	Noise reduction technique applied
2008	[112]	Fuzzy clustering approach	Database from [34], Normal (5) and SM (15)	–	20 records	–	-20 dB to 60 dB	–	–	–	–	•	73.0	–	SM: 80.00	S_p: 100.00% was reported
2002	[113]	Time-delay neural network	Normal and pathological	30	Each 20 s	–	–	•	–	–	–	–	98.4	97.8	–	ECG (training) with time domain analysis

Abbreviation: PLSR: partial least squares regression, RHD: rheumatic heart disease, MMP: multivariate matching pursuit, CQA: cycle quality assessment, SR: segmentation rate, HMM: Hidden Markov model, MFCC: mel-frequency cepstral coefficient, PM: probabilistic model, HE: homomorphic envelogram, HF: homomorphic filtering, DHMM: duration-dependent hidden Markov model, WD: wavelet decomposition, CSCW: cardiac sound characteristic waveforms, STMHT: short-time modified Hilbert transform, SHM: systolic heart murmurs, ASSA: adaptive singular spectral analysis, RME: Rényi marginal entropy, BMV: bioprosthetic mitral valves, CARDJHU: cardiac auscultatory recording database of Johns Hopkins University, CA: classification accuracy, WHSMD: Washington heart sounds and murmurs database, VIM: Viola integral method, DNN: deep neural network.

Models (HMMs) [118], [132], [133], [149], [150], k-Nearest Neighbors (k-NN) [94], [123], [151]–[153], Neural Networks [21], [47], [55], [67]–[69], [81]–[83], [91], [93], [95], [102], [104], [106], [110], [154]–[172], rule-based classifier or decision trees [173], [174], BayesNet classifier [175], machine learning based approaches [90], [144], [160], Gaussian-Bayes model [176], Naïve Bayes [177], Gaussian Mixture Model (GMM) [178], random forest [177], and discriminant analysis [66].

1) SUPPORT VECTOR MACHINE (SVM)

Support vector machines are non-probabilistic binary linear data-based machine learning models suitable for classification of heart sounds using different kernel functions. Implementation of a support vector network for non-separable training data was firstly reported by Cortes and Vapnik [179]. This has been extended for supervised machine learning problems including classification of heart sounds signals.

In general, most of the studies reported were focused towards improving the classification performance either by modifying the existing approach of SVM based classification or by adding new features to the classifier. Heart valve diseases were mostly classified using an SVM classifier in recent articles. Other than this, SVM classifiers were found suitable in identifying innocent murmurs when compared to artificial neural network [83]. SVM classifier are suitable for high dimensionality classification problems even if sample

TABLE 4. Feature extraction and selection approaches.

Year	References	Analysis/Transform	Feature extraction methods	Number of features	Feature details/Characteristics	Feature selection
2018	[118]	Wavelet transform and spectral analysis	Short-term windowing technique	8 features	Time-domain and frequency-domain features	Adaptive feature selection
2018	[182]	Wavelet analysis	Curve fitting and MFCC	34 features	Wavelet and entropy features	-
2017	[56]	TF analysis	Tensor decomposition method on scaled spectrograms	-	Features from scaled spectrogram	Tensor decomposition
2017	[183]	FFT and wavelet analysis	-	2 types of features	Spectral amplitude and wavelet entropy	-
2017	[79]	TF analysis	Feature extraction from scaled spectrogram	-	Scaled spectrogram features	PLSR
2017	[90]	Frequency and statistical properties of envelope	Statistical properties of averaged shapes for a different frequency band	53 features (total 228 features)	Symmetry of line segments surrounding S_1 and S_2, skewness, kurtosis and centers of gravity, mean, SD and ratios	Probability assessment
2017	[102]	WPD and CWT	Feature extraction using CQA	90-dimensional features vector	4 set of features from the time, TF and perceptual domain	Fisher's discriminant analysis
2017	[103]	Wavelet analysis	-	131 features	Time, frequency, wavelet and statistical features	CFS algorithm
2017	[104]	Wavelet analysis	Time/frequency characteristics using 'Gaus4' mother wavelet	220 (CWT), 400 (MFCC), inter-beat (20), 35 (Complexity)	MFCC and complexity measurement (spectral entropy, SD, skewness, and kurtosis)	PCA (50 features selected)
2017	[106]	TFD analysis using acoustic features	*k*-mean algorithm (Euclidean distance)	39 MFCCs (velocity and acceleration) features & 264 acoustic features (Fbank)	HSAD, MFCC and *k*-means	-
2017	[138]	Time, frequency and sparse coding algorithm	Sparse coding for unsupervised feature extraction	20 TD features & sparse coding features	Sparse coefficients, N-points FFT	-
2017	[155]	TF analysis	-	-	MFSC	No
2016	[144]	Wavelet analysis	WT	20 features and some additional wavelets based features	Duration of each cardiac state, mean amplitude and their ratios	-
2016	[114]	DWD	Diffusion maps for unified feature representation	-	Autocorrelation features	-
2016	[80]	DWT	WD	-	HE, Hilbert, wavelet and PSD envelopes	Wavelet feature optimization
2016	[158]	T, F, TFD analysis	-	40 features	LPC, entropy, MFCC, PSD and wavelet based features	WFSS (18 features)
2016	[157]	FD analysis	Power spectrum analysis	16 features using PSA	-	-
2016	[156]	FFT	Clustering method	3,500 features	Spectral features	40 features selected using filter method
2015	[58]	Wavelet analysis	STMHT based FFM	10-dimensional FFM	FFM	PCA
2015	[75]	Wavelet analysis	Feature extraction algorithm	36 features from diastole and systole of every cardiac cycle	Dimensional features from segmented cardiac cycles	-
2015	[107]	WPD	EFSE evaluated from reconstructed selective frequency components of HSs	5 features	EFSE, Sampling frequency dependent features	-
2015	[139]	TQWT	SAMDF based feature set derived with TQWT	-	Wavelet-based features	-
2015	[73]	Wavelet packets	MF-DFA, MESE and EMD	5 features	D/S, amplitude (S1/S2), Multifractal spectrum parameters, f_{PSDmax}, adaptive sub-band energy fraction	-
2015	[46]	EMD for IMF	PSM, IF & amplitude, and power in frequency bands, sample & spectral entropy, simplicity and statistical moments	5029 features within nine classes	Spectral features, signal complexity features	PCA
2014	[85]	Moving windowed Hilbert Transform)	Envelope of HSs using VIM	4 features	Envelope extraction, diagnostic features in TD and FD	-
2014	[49]	EEMD and Kurtosis features	EMD	-	EEMD and Kurtosis features	-
2014	[74]	Ensemble Empirical Mode Decomposition (EEMD)	EMD/EEMD and IMF correlation dimensions	13 IMF components	IMFs and correlation dimensions of the IMF components were used as feature sets	-
2014	[111]	TF analysis	Linear Predictive Coding coefficients for feature extraction	12 different classes	Spectral analysis for features	MCS algorithm
2013	[47]	*S*-transform	SVD of S-matrix	70 features	TFD features	-
2013	[25]	TF and frequency analysis	Short-time frequency amplifier technique	2 frequency and amplitude features	Frequency and amplitude based features	-
2013	[70]	MLBS of wavelet features	WPD	448 nodes for feature extraction	Frequency and TD features	Exclusion criteria for feature reduction
2012	[105]	TF analysis	Murmur likelihood as temporal features	39-dimensional features (best results)	MFCC and HMM states likelihood features	-
2012	[175]	Wavelet analysis	Wavelet packet transformation using Daubiches8	128 entropies	Wavelet entropy-based features	PCA (32 features)

TABLE 4. *(Continued.)* **Feature extraction and selection approaches.**

2012	[184]	Wavelet analysis	Time-domain, wavelet features and entropy	32 features	Linear and nonlinear time-domain, wavelet and entropy features	PCA, GDA and GA for feature selection
2012	[82]	DFT	DFT and Burg autoregressive spectrum analysis	300 DFT and 33 Burg-AR features	Frequency domain features	PCA (8 DFT and 6 Burg-AR features)
2012	[162]	DWT	DWT for feature extraction	6 wavelet entropies	TFD features	Shannon energy
2012	[149]	DFT	–	–	FD features	PCA
2012	[185]	CWT	SVD and QR decomposition	83 features based on CWT, SVD, QRD	Shannon entropy and the Gini index using WT	SFFS
2011	[109]	TF analysis using FFT	Adaptive singular spectral analysis	–	Correlation & kurtosis features	–
2011	[91]	DWT	–	32 features	TF based features	PCA
2011	[93]	Wavelet analysis	MP and MMP based feature extraction	–	TF based features	–
2010	[45]	TF domain analysis using STFT	HE for features extraction	4 feature set of single and multi-feature	Frequency & HE features	–
2010	[78]	Wavelet analysis	–	2 diagnostic features	Frequency domain features (f_{max} and f_{width} for NAR-PSD)	–
2010	[152]	Feature extraction from TF representation	Linear decomposition and tiling partition of TF plane	851 features	TF based features	Linear grid, Quadtree, PCA, PLS, 2D-PCA
2010	[124]	TF analysis	Wavelet-based features	–	Clinical features (normal split sound duration, frequency content)	–
2010	[151]	Spectrogram, WVD, SPWVD, CWD, ETD, HTD and scalogram	TF representation	–	MFCC, energy, frequency, BW, Eigen vectors, and spectral centroid	–
2009	[66]	TF analysis	Hierarchical clustering	3500 features approx.	Feature-space of cluster distances, correlation and Euclidean distance	Clustering for feature reduction
2009	[146]	TF domain analysis using wavelet	WD	100 scalar features	4 (SD and HR), 8 (S_1 and S_2 each), 24 (systolic), 48 (diastolic) & 8 (energy) scalar features	–
2009	[94]	STFT, Gabor Transform, WVD, Wavelet transform	–	149 features	T varying & TF, perceptual and fractal features (Eigenspace, MFCC, LLE, Hurst Exponent, Correlation Dimension)	PCA
2009	[186]	Wavelet analysis	Rectangular window and power content in the window	50-dimensional feature vectors	Power of the detailed coefficients in each segment with and without filtering	Divergence analysis
2009	[145]	Wavelet analysis	–	12 features	12 wavelet entropies	–
2009	[163]	Wavelet analysis	db4 decomposition filter within five resolution levels	–	Diagnostic features	–
2008	[29]	TD analysis	–	–	Clinical features (duration of split-sounds, systole, and diastole, frequency)	–
2008	[153]	Wavelet analysis and STFT	STFT and WD	91 features	Wavelet entropy	–
2008	[147]	WPD	–	2 features	Wavelet packet energy (mean and SD)	–
2008	[110]	Wavelet analysis	Wavelet transform for feature extraction	50 features for each record	Wavelet features	Divergence analysis
2008	[133]	TD and STFT	–	3 classes of features	TD, STFT and MFCC features	–
2007	[67]	Wavelet analysis	Daubechies-2 wavelet coefficient decomposition	32 wavelet features	Wavelet features	HF and k-means clustering
2007	[55]	Wavelet analysis	–	64 features	Wavelet features	–
2007	[150]	Wavelet analysis and STFT	WD, STFT, wavelet entropy	–	Daubechies-10 WD, STFT & wavelet entropy	–
2007	[148]	Wavelet analysis and STFT	WD, STFT and wavelet entropy	91 features	–	–
2006	[68]	Spectral analysis	SPWVD	–	FFT (spectrogram)	–
2006	[95]	FFT, DWT, Wavelet analysis	RQA	207 features	Time, TFD, nonlinear and chos based features and HOS, state space, fractal dimension, bispectrum, wavelet entropy, fractals, Gaussian mixture model, Eigenvalues	Pudil's SFFS method
2004	[21]	Wavelet decomposition	–	256 elements feature vector	TF features	–
2003	[69]	WPD and NN	TFD adaptive feature extraction, WPNN	256-Wavelet packet entropy per DHSs signal	Wavelet packet entropy	–
2003	[81]	TF analysis using wavelets	WD and wavelet entropy	12 wavelet entropy values	–	Adaptive feature extraction
2003	[169]	TF analysis using wavelets	–	336 feature vectors for the training set and 336 feature vectors for the test set	Wavelet-based features	Divergence analysis (16 features)
2002	[170]	TF analysis using FFT	FFT and the Levinson-Durbin auto-regression	–	Spectral estimation	Auto-regression
2001	[97]	TF analysis	Matching pursuit	2 features	Dominant frequency-based features	–
1995	[171]	TF using wavelet	–	2 features	Average correlations and Euclidean distance	–
1987	[99]	TD and FD analysis	Energy spectrum analysis	4 EDC	Energy curve, spectrum & distribution coefficients	–
1980	[72]	Frequency domain spectral tracking	Analysis using linear-prediction method	–	Spectral level tracking by evaluating spectral density function	–

TABLE 4. ***(Continued.)*** **Feature extraction and selection approaches.**

Abbreviation: TF: time-frequency, TD: time-domain, FD: frequency domain, TFD: time-frequency domain, PLSR: partial least squares regression, CFS: correlation-based feature selection, LPC: linear predictive coefficient, WFSS: wrapper feature selection scheme, SVD: singular value decomposition, EFSE: energy fraction and sample entropy, SAMDF: sum of average magnitude difference function, MF-DFA: multifractal detrended fluctuation analysis, MESE: maximum entropy spectra estimation, DWD: discrete wavelet decomposition, CWT: continuous wavelet transform, TQWT: tunable-Q wavelet transform, PSM: parametric spectral modelling, MCS: modified Cuckoo search, MLBS: multi-level bias selection, QRD: QR-decomposition, SFFS: sequential forward floating selection, MP: matching pursuit, MMP: multi-variate matching pursuit, HE: homomorphic envelogram, WVD: Wigner-Ville distribution, SPWVD: smoothed pseudo WVD, ETD: exponential T-distribution, HTD: hyperbolic T-distribution, RQA: recurrence quantification analysis, WPD: wavelet packet decomposition, SD: standard deviation, HT: Hilbert transform, EDC: energy distribution coefficients, LLE: largest Lyapunov exponent, FFM: frequency feature matrix, EEMD: ensemble Empirical mode decomposition, IMF: intrinsic mode functions, DHS: Doppler heart sounds, MFSC: mel-frequency spectral coefficients, WD: wavelet decomposition, WPNN: wavelet packet neural network, NAR-PSD: normalized auto-regressive power spectral density, CWD: Choi–Williams distribution.

sizes are small [180], [181]. Also, the performance of the SVM classifier does not correlate directly to the dimensionality of the input vectors [124]. Further, the SVM classifiers provide flexibility to use an optimum kernel function from the available kernel functions (linear, Gaussian, polynomial, radial basis, exponential radial basis, sigmoid, spline, Fourier, Gaussian radial basis, Morlet wavelet kernel, Mexican hat wavelet and bspline) based on the cardiac abnormality under investigation. The parameters of the kernel function can be tuned further to improve the training efficiency and to achieve the best performance. However, this demands an additional optimizer in the system [111]. Other than this, SVMs are cumbersome for multi-class problems as it requires an individual model for different classes.

2) NEURAL NETWORKS

Neural networks are also widely used potential machine-learning based methods with remarkable ability to detect the trends based on the sample data. Due to their self-organization properties, real-time operation, and adaptive learning, neural networks find applications in cardiac abnormities detection.

Though, neural networks achieved promising results in terms of classification accuracy and are frequently used as a computational tool for pattern classification of heart sounds, large training datasets are required to train neural networks. Also, it requires more computational power and time to accomplish the classification task compared to an SVM classifier. Other than this, it has been found that Back-Propagation Artificial Neural Networks (BP-ANN) are unable to produce a global solution to a classification problem as the initial weights are randomly selected [73].

3) HIDDEN MARKOV MODELS (HMM)

HMMs are probabilistic statistical, double-layered stochastic finite state machine with hidden Markov process. From the articles reviewed, it was found that HMM models were mostly used for segmentation. However, only a limited number of studies employed them to classify normal and abnormal heart sounds.

In general, HMM classifiers often have a large set of parameters and the classification accuracy was found to be directly dependent on the HMM parameters selected in the model [118]. Additional drawbacks of HMM in heart sounds classification include slow interpretation, parameter optimization, memory requirements and computational time.

4) K-NEAREST NEIGHBOR (K-NN)

Feature distances (Euclidean, Manhattan, Minkowski, Mahalanobis, etc.) were estimated to compute the nearest neighbors when the most relevant patterns were close to each other in the feature space [173], [176]. The k-nearest neighbor algorithm was successfully applied to classify normal and abnormal heart sounds and for murmur detection [94], [151], [187], [188]. Classification performance was found to be dependent on the k parameter used in the algorithm and various features were suggested to improve the classification performance.

In general, a k-NN classifier offers advantages in terms of training time, simplicity and ease of implementation compared to others. However, it demands large memory space and offers slow estimation [189]. Further, the k-NN classifier also offers robustness to noisy training data [47].

Attempts to classify heart sounds with modified classifiers or rule-based classifiers were also found. Decision trees based on certain rules and decision nodes were considered as rule-based classifiers [173]. Other efforts to classify heart sounds using a combination of different classifiers were also reported [83]. Works reported using all of these approaches are presented in Table 5.

V. SYNTHESIS OF RESULTS

Data synthesis to evaluate the accuracy of the algorithms was performed on articles that reported an analysis of fundamental and other pathological heart sounds, including segmentation and classification. Performance of data acquisition methods was not assessed, as a proper index was not reported in the articles studied. Similarly, feature extraction approaches were reviewed thoroughly; however, were not included in the data synthesis. The study was formulated to consider articles with first heart sounds (S_1) detection (FHSD), second heart sounds (S_2) detection (SHSD), pathological heart sounds detection (PHSD) including S_3 and S_4, murmurs, classification between S_1 and other heart sounds (FHSC), classification between S_2 and other heart sounds (SHSC) and classification of pathological heart sounds (PHSC) including murmurs, S_3 and S_4 and other abnormal heart sounds. Some articles with particular identification and classification of very specific type of murmurs and heart sounds were also reviewed; however, were

TABLE 5. Summary of heart sounds classifiers and their performance comparison.

Year	References	Method	Transform	Subject type	Records (# or duration in seconds)	Sampling rate	Type of features/size of feature vector	Classifiers	Performance (%)	Type of cardiac abnormality investigated
SVM based classifier										
2017	[56]	Scaled spectrogram and tensor decomposition	TFD	Datasets A & B from [32]		44.1 kHz	Tensor decomposed features	SVM, SS-PLSR, SVM-DM, SS-TD	Normalized precision: 76.0, 74.0 and 90.0 using SS-TD with Datasets A, B and C, respectively	Normal, murmurs, extra heart sounds, extrasystole and artefacts
				Dataset C [14]		4 kHz				
2017	[79]	HSs classification based on scaled spectrogram and PLSR	TFD	Datasets A & B (176 & 507) records available from [32]		44.1 & 4 kHz	Scaled spectrogram based TF features	SVM	S_e: 100 (best with artefacts), S_p: 64.0 (artefacts)	Normal, murmurs, extra heart sounds, extrasystole and artefacts
2017	[138]	Sparse coding features with TD features using SVM	T, F and TF domain	PhysioNet database [14]		Varied	Sparse coefficient matrix and time-domain features, 20 features	SVM	S_p: 88.45, S_e: 90.07, MAcc: 0.892 (modified results)	S_1, systolic, S_2 and diastolic sounds
2016	[114]	Without segmentation, classification using autocorrelation feature and diffusion maps	TFD	Datasets A & B (176 & 507) records available from [32]		44.1 & 4 kHz	TF based autocorrelation features	SVM-DM, SVM-A, and SVM-AD	S_e: 100.0, S_p: 64.0 (using SVM-AD classifier for artefacts)	Normal, murmurs, extra heart sounds, extrasystole and artefacts
2015	[73]	Cardiac reserve and HSs characteristics analysis	WT	88 (N) and 64 (CHF)	88 (N) and 64 (CHF), 1 minute each	11025 Hz	Wavelet features based 5 features	LS-SVM and compared with BP-ANN and HMM	S_p: 93.75, S_e: 96.59, Acc: 95.39 (using LS-SVM)	Chronic heart failure, subjects without murmurs
2015	[58]	STMHT-based FFM for classification	WT	14 (AF)	188 periods	44.1 kHz	Dimensional FFM, 10 features	SVM	S_p 90.6, S_e 96.9, Acc 91.7	AF, AR, MR, PS, VSD and normal sounds were classified
				17 (AR)	181 periods				S_p 98.9, S_e 98.5, Acc 98.8	
				25 (MR)	257 periods				S_p 98.5, S_e 98.1, Acc 98.4	
				25 (N)	325 periods				S_p 100, S_e 99.6, Acc 99.8	
				7 (PS)	150 periods				S_p 98.6, S_e 99.9, Acc 98.7	
2015	[71]	Structural complexity based feature extraction	TFD	60 (N) and 60 (pathological)	-	8 kHz	Sample entropy	SVM	Clean data: S_p: 100, S_e: 93.33, Acc: 96.67 & 91.66 (with 10 dB SNR)	Classification between normal and abnormal heart sounds
2015	[107]	Energy fraction and sample entropy	WT	40 healthy and 67 CVD patients	80 (N) and 167 (SHM)	2205 Hz	Energy and entropy	SVM with LKF, PKF, GRKF and SKF, 5 features	S_p: 98.55, S_e: 93.48, Acc: 97.17 (using GRKF)	Normal, aortic/pulmonary stenosis and tricuspid/mitral insufficiency
2015	[139]	Least-square support vector machine (LS-SVM)	WT	163 HSs signals (N, septal, valvular and other defects)	4628 cycles (626 N and 4002 pathological)	44.1 kHz	SAMDF derived with TQWT, 21 features	SVM with different kernel functions	S_p: 99.29, S_e: 98.80, Acc: 98.92 (using Q = 6 and MWKF)	Septal, valvular and other mechanical defects
2015	[140]	GTSVM for murmur classification	WT	14 (45-93 y) PM, 16 (1-16 y) PM, 26 (2-14 y) IM, 30 (4-15 y) NM	10s duration each	44.1 kHz	TF features	GTSVM classifier	S_p: 89.30, S_e: 86.30, CR: 88.10	Innocent and pathological murmurs
2015	[141]	Intelligent PCG system	TFD	30 (N) and 26 (IM) and 30 (AS)	-	-	Frequency features	SVM	S_p: 89.3, S_e: 86.4	Aortic stenosis severity assessment
2015	[142]	HOC of wavelet packet coefficients for HSs classification	WPD	16 (N), 19 (MR), 14 (AS) & 10 (AR)	59 records, 820 cycles, each 15s	4 kHz	Wavelet based 46 features	SVM	Acc: 99.39 (using CT_LDB method)	Normal, MR, AS, and AR heart sounds
2014	[85]	Features from envelope of HSs using VIM	WT	VSD, normal HSs, AR, AF, AS and MS	242 (N) and 226 (VSD)	44.1 kHz	Time and frequency domain features, 4 features	SVM	S_p: 98.1, S_e: 98.8, Acc: 98.4 using boundary curves & S_p: 98.4, S_e: 98.6, Acc: 98.5 using ellipse model (for VSD detection)	VSD, AR, AF, AS, MS and normal heart sounds
2014	[74]	HSs classification and recognition based on EEMD	WT	225 (N) and 180 (60 (MS), 60 (VSD) & 60 (AS))	405 HSs, testing with 75 (N) and 20 (MS), 20 (VSD) & 20 (AS)	11025 Hz	EEMD and IMF correlation dimensions, 13 features	Binary tree SVM (BT-SVM)	Acc: 98.67 (normal) and 91.67 (abnormal)	MS, VSD, AS and normal heart sounds

TABLE 5. ***(Continued.)*** **Summary of heart sounds classifiers and their performance comparison.**

2014	[111]	HSs classification using SVM-MCS	TFD	3M Poland microphone samples from [119], 72 records		–	12 features using LPCC	SVM and MCS algorithm	Acc: 95.43 (average using SVM-MCS)	Ejection click, split of S_1 & S_2, FHSs, S_3, S_4, pan-systolic, late systolic, early systolic murmurs, opening snap and diastolic rumble
2014	[143]	Feature extraction based on OMS-WPD	WT	50 (healthy) and 68 (pathological)	Each 5s duration	22050 Hz	Features using OMS-WPD	SVM	S_p: 94.00, S_e: 85.29, CR: 88.98 (using db8)	Normal, presystolic gallop, early diastolic, enhanced S_2, aortic systolic ejection and mid-systolic rattling sounds
2013	[70]	MLBS of wavelet features	WT	59 (Normal and pathological)	16 (N), 19 (MR), 14 (AS), 10 (AR)	4 kHz	Wavelet based features	SVM with MLBS	S_p: 100.0, S_e: 98.0, Acc: 97.56	Normal, AS, MR and AR sounds
2012	[105]	Classification using murmur likelihood and HMM state likelihood	TFD	Normal and pathological	80 (N) and 80 (abnormal) HSs signals	8 kHz	MFCC and HMM states likelihood, dimensional, 39 features	SVM classifier	Acc: 80.6 (6-HMM state and 3-Gaussian mixtures) and 85.6 (SVM classifier)	Various murmurs and normal heart sounds
2010	[124]	LMS based LS-SVM	TFD	64 (Normal and pathological)	64 recordings (512 cycles)	8 kHz	Wavelet features	LS-SVM	Acc: 92.889 (average of Sets 1-16)	Normal and five different pathological sounds
2010	[78]	NAR-PSD and multi-SVM	WT	6 healthy and 34 pathological	196 (N) and 293 (AN)	8 kHz	f_{max} and f_{width} as features from NAR-PSD	Multi-SVM	S_p: 99.9, S_e: 99.5, Acc: 99.6 (best case)	Normal, AF, AS, MR, MS, aortic insufficiency and split sounds
2010	[144]	Machine learning based identification	WT	PhysioNet database [14]	4,430 recordings	Varied	Wavelet based 20 features	Bagging trees, boosted trees, logistic classifier and SVM	Validation Acc: 94, 93, 85 and 91, respectively S_e: 79.58 and S_p: 74.59, overall: 77.08	Heart sounds were classified as normal or pathological sounds
2010	[190]	CWT and SVM based detection of the paradoxical splitting of S_2	CWT	13 (LBBB and paradoxical splitting), 18 (AS and paradoxical splitting), and 11 (N)	Total 42 samples used from 250 records	–	Time-frequency maps, total 5 features	SVM	S_e: 94.44, S_P: 87.5, and Acc: 90.97	Detection of the paradoxical splitting of S_2
2009	[145]	Genetic-SVM (GSVM)	DWT	132 M/83 F (Age: 15-80 y)	215 samples (5s each) (Doppler heart sounds signals)	20 kHz	Wavelet entropies based 12 features	SVM tested with 8 different kernel functions	Acc: 96 (N) and 94.52 (AN) using GSVM Model-4 (ERBF) (best results)	Heart valve diseases
2009	[146]	Identification of valvular diseases using SVM	WT	Healthy, AS, AR, MS and MR, (age: 18-22 y)	38 (N), 41 (AS), 43 (MR), 38 (AR), 38 (MS)	–	TFD and wavelet features, total 100 features	SVM (Gaussian radial basis function)	S_p: 94.74, S_e: 87.50, Acc: 91.43 (b/w N and AN) using GRBF	Normal, AS, AR, MS and MR heart sounds signals
2008	[147]	Wavelet packet energy features using WPD and SVM	WT	30 (N) and 52 (VHD) (for testing)	–	8 kHz	Wavelet packet energy based features	SVM	S_p: 96.67, S_e: 100.0	Aortic and mitral valvular heart disorders
2007	[148]	LS-SVM and BP-ANN	WT and STFT	Normal and abnormal (DHSs signals) for 5 seconds each, 132M/83F	215 samples (54 (NAHV), 56 (ANAHV), 66 (ANMHV), 39 (NMHV)	20 kHz	WD, STFT and entropy based 91 features	LS-SVM and BP-ANN	S_p: 94.0, S_e: 95.9 (for BP-ANN) & S_p: 90.0, S_e: 94.5 (for LS-SVM)	Cardiac abnormalities related to aortic and mitral valves (AR, AS, MS and MR) and normal heart sounds
Neural Network based classifier										
2018	[154]	Gram polynomials and PNN	FFT	Normal and pathological sounds from PhysioNet database [14], 3126 records		2 kHz	Gram polynomial and FFT, 64 features	PNN	S_p: 91.0, S_e: 93.0, Acc: 94.0	No clinical abnormality studied
2018	[83]	ANN and SVM classifier	STFT	87 innocent murmurs and 170 pathological murmurs	257 records	8 kHz	Temporal and spectral features, 14 features	ANN and SVM	S_p: 91.0-99.0, S_e: 84.0-93.0	Identification of innocent murmurs in children
2017	[102]	Feature extraction using CQA	TD and TFD	Normal and pathological sounds from PhysioNet database [14], 1277 records (308 patients)		2 kHz	TD, TFD and perceptual features, 90 features	FFNN, dimensional features	S_p: 87.14, 87.21 & 88.51 and S_e: 75.44, 91.38, 88.83, for data set1, set2 and set3, respectively using CQA	Classification as normal and abnormal heart sounds
2017	[104]	Drop-Connected neural network	TFD	Normal and abnormal HSs from PhysioNet database [14]		–	MFCC, inter-beat and complexity features, 675 features	Two-hidden layer NN trained by EBP	Acc: 85.2 (on test data)	Normal, MVP, aortic disease, CAD, MR, AS and other miscellaneous pathological heart sounds

TABLE 5. ***(Continued.)*** **Summary of heart sounds classifiers and their performance comparison.**

2017	[106]	Identification of S_1 and S_2 using DNN	TFD	28 subjects (17M/11F)	460 each S_1 and S_2 peaks in HSs	48 kHz	MFCC and acoustic features, 303 features	DNN (KNN, LR, SVM and GMM for comparison)	Acc: 85.0 (using 39 dimensions with K-means) and 91.12 of accuracy overall	First and second heart sound identification
2017	[155]	MFSC based deep CNN classifier	TFD	Normal and abnormal HSs from PhysioNet database [14]		-	MFSC features	Deep CNN	S_p: 87.66, S_e: 80.63, Overall: 84.15 (CinC 2016)	Normal and abnormal heart sounds classification
2016	[156]	2-means clustering and ANN	FFT	Database from [14], [31]	304 records	-	Time-frequency spectral features, 40 features	ANN	S_e: 84.4, S_p: 86.9, Acc: 86.5	Classification as normal and abnormal heart sounds
2016	[157]	Power spectrum analysis	FFT	Normal and abnormal HSs from PhysioNet database [14]		-	16 Frequency features	NN	S_p: 78.80, S_e: 74.70, Acc: 76.7	Normal and abnormal heart sounds classification
2016	[158]	Ensemble of NN without segmentation	T, F and TFD	Normal and abnormal HSs from PhysioNet database [14]		-	T, F and TF based 18 features	FFNN	S_p: 94.23, S_e: 88.76, Overall Acc: 91.5	Classification for anomaly and quality detection
2016	[159]	Ensemble of feature and deep learning based classifier	TD and FD	PhysioNet database [14], 2575 (N) & 665 (pathological) records		1 kHz (resampled)	124 time-frequency features	AdaBoost and CNN	S_p: 77.81, S_e: 94.24, Overall: 86.02	Classification as normal and abnormal heart sounds
2016	[160]	Deep structured features for classification	WT	PhysioNet database [14], 764 subjects	3153 records	-	Wavelet based 20 features	CNN	S_p: 77.6, S_e: 84.8, Score: 81.2	Normal and abnormal heart sounds classification
2014	[161]	Spectral analysis with a time growing window	WT	Normal and SEC from 40 children (age 3-9 years)	614 normal and abnormal cardiac cycles	44.1 kHz	Spectral analysis with a time growing window	TGNN, TDNN and MLP	S_e: 98.1, Acc: 97.0 (TGNN), S_e: 76.4, Acc: 85.1 (TDNN), S_e: 85.7, Acc: 92.7 (MLP),	Systolic ejection clicks in children
2012	[82]	PCA and ANN for diagnosis of heart valve disease	TFD, DFT and Burg AR	40 (N), 40 (PS) and 40 (MS)	-	8 kHz	Time-frequency based 14 features	DFT/Burg AR-PCA-ANN	S_p: 97.44, S_e: 90.48, Acc: 95.0	Heart valve diseases
2012	[162]	ANFIS for identifying heart valve disease	DWT	40 (N), 40 (PS) and 40 (MS)	-	8 kHz	Wavelet entropies based 6 features	ANFIS (ANN)	S_p: 95.24, S_e: 100.0, Acc: 98.33	Normal, pulmonary, and mitral stenosis heart valve diseases
2011	[91]	HSs analysis without segmentation using DWT, PCA and NN	WT	Various murmurs	57 HSs signals	4 kHz	Time-frequency based 32 features	PCA and NN	Acc: 92.0 (noise free), 90.0 (≈10 dB SNR)	Normal, S_3, S_4, ejection sound, AR, AS, MR, MS, PS, split S_2, systolic click and opening snap
2011	[93]	MMP based on three-layer FF-MLP network	TFD	70 patients (N and pathological murmurs)	70 records (35 normal)	44.1 kHz	Time-frequency features	FF-MLP	Acc: 92.5 & 77.5 using MMP and MP, respectively	VSD, ASD, PS, MR, and innocent murmurs
2008	[110]	SOM network and ISOM analysis	WT	Data from two patients, online and CD book	14 records, each record with 20 cycles of HS	2 kHz	Wavelet features, 50 features for each	NN	Acc: 95.0% (using ISOM) and 70% (using Kohonen network)	VSD, MR, LSM, early systolic, opening snap, diastolic rumble, AR, AS, MS, Ebsteins anomaly, summation gallop, venus hum, normal FCG and aortic insufficiency
2009	[163]	WT and NN for classification	DWT	-	102 (N), 96 (AI), 92 (AS) & 82 (PS) cycles	11.025 kHz	Wavelet features	ANN (MLP-BP)	Acc: 94.42	Aortic insufficiency, AS, PS and normal sounds
2008	[164]	Arash-Band frequency features with ANN	WT	90 children (36 N and 54 pathological)	40 training & 50 test signals (each 10s)	44.1 kHz	Arash frequency bands based 5 features	ANN	CA: 94.00	Congenital heart diseases in children
2007	[67]	Homomorphic segmented HSs	WT	Mix of N (32%), SM (36%) and DM (32%)	41 records (340 cycles)	8 kHz	Wavelet based 32 features	GAL and MLP-BP NN	Acc: 98.50 (using GAL with dataset2)	Normal, systolic and diastolic murmurs
2007	[55]	Segmentation and feature extraction using wavelets	WT	Database from [19]		8012 Hz	Wavelet based 64 features	NN	S_p: 85.00, S_e: 54.00, Acc: 70.0	Normal and aortic regurgitation heart sounds
2007	[165]	Wavelet analysis for automated auscultation	TFD	113 normal and 50 pathological	Each 6 cycles	-	Time-frequency	ANN	S_p: 96.5, S_e: 90.0	Normal and pathological heart sound classification
2006	[68]	Spectral analysis using SPWVD	FFT	40 patients	8s each	8 kHz	Time-frequency features	MLP-NN and SPWVD	S_p: 86.40, S_e: 85.10, Acc: 86.4	FHSs and murmurs
2006	[95]	RQA feature and ANN classifier	TD, TFD and WT	36 patients	12 cycles each of 15s	44.1 kHz	207 complexity features	NN	Acc: 86 (MI, AS and PM)	Systolic heart murmur classification

TABLE 5. ***(Continued.)*** **Summary of heart sounds classifiers and their performance comparison.**

2006	[166]	A three-layered ANN for twelve types of cardiac abnormalities detection	TD and FD	49 patients with murmurs	Doppler ECG and PCG signals for 8 sites	-	-	NN	Acc: 68% (overall)	VSD (AS, AR) and PDA not correctly diagnosed
2005	[167]	Wavelet analysis and ANN	WT	Database from [35]		8 and 16 kHz	PCA	ANN	S_p: 70.5, S_e: 64.7 Acc: 70.2	Normal and abnormal heart sounds classification
2005	[168]	Cardiac auscultation in pediatrics	FFT	88 (IM) and 153 pathological murmurs	Each 10-15s	44.1 kHz	Frequency, using Fisher's method	ANN	S_p: 90.00, S_e: 83.00	Innocent and pathological murmur (such as VSD) classification
2004	[21]	WD and classification using NN based classifier	WT	Normal, MVP, coarctation of the aorta, VSD, PS	4096 sample segments	8 kHz	WD based 256 features	NN	Acc: 100.0 (for signals with SNR above 31 dB)	Normal and abnormal sound from coarctation of the aorta and split sounds
2003	[81]	MLP with FFNN	TFD	123 subjects	AV (62 N & 80 AN) & MV (38 N & 66 AN), DHSs	-	Wavelet entropies based 12 features	FFNN	Acc: 84 (N) and 96 (AN)	Aortic and mitral valve diseases
2003	[69]	WPD and wavelet packet entropy	WT	95 (N) and 120 (AN)	215 samples (Doppler heart sounds)	20 kHz	Wavelet packet energy based 256 features	WPNN	Acc: 94.0 (N) and 94.5 (AN)	Normal and abnormal sounds, no murmurs
2003	[169]	Classification of wavelet-based features using ANN	WT	28 subjects, 28 records with 12 periods of HSs in each	4096 discrete data	5512.5 Hz	Wavelet based 672 features	GAL network and LVQ network	Acc: 99.0	AS, MR, MS, PS, AR, SG and normal sounds
2002	[170]	MLP and RBF-NN	FFT	-	36 recordings (each ~ 30 s)	44 kHz	FFT and Levinson-Durbin auto regression	MLP and RBF-NN	Acc: 84.00 (MLP) & 88.00 (RBF)	Normal, NRMR, MVP, BAV, AS, SCAS, AR, aortic/mitral valve, MS, ASD, VSD, LVI, PMD, DC, and aortic incompetence
1995	[171]	Backpropagation based NN classifier (along with ECG)	TD	Database from [39], 48 records (18 (N) and 30 (AN)) from 3 & 6 subjects, respectively		2 kHz	Average correlations & Euclidean distance features	NN	Acc: 95.0	MS, split of S_1 and S_2, aortic/mitral insufficiency, MS, and mitral insufficiency with prolapse
1994	[172]	Wavelet-based fuzzy-NN	FWT	112 patients, 30 selected (15 (N) and 15 (AN)	10 samples from each patient	4 kHz	Wavelet features (mean, variance, skewness, kurtosis)	Fuzzy-NN	Acc: 88.8 (N) & 85.45 (AN)	Coronary artery diseases
HMM-based classifier										
2018	[118]	ANFIS and HMM	WT	Normal and pathological	150 (N) and 80 (AN) records	-	TD and FD based 8 features	ANFIS and HMM	Acc: 98.7	Normal sounds and valve disorders (MS, MR and AR)
2012	[149]	PCA-Discrete HMM	DFT	40 (N), 40 (PS) and 40 (MS) (55M/65F, Age 4-65 y)	80 training set and 187 test set	8 kHz	TD, FD	PCA-DHMM	S_p: 93.30, S_e: 70.30, Acc: 72.2 (SPECTF data)	Classification of normal, MS and PS cardiac sounds
2008	[133]	MFCC-based HMM	TD and STFT	20 (N), 6 (CM), 4 (DM), 11 (SM)	1381 signals	8 kHz	TD, STFT & MFCC features	HMM	Acc: 95.7 (CM), 96.25 (SM), 90.0 (DM)	Normal sounds, ejection clicks, opening snaps, split S_1, split S_2, S_3, S_4, continuous, diastolic and systolic murmurs
2007	[132]	Modified HMM (MHMM)	TD, FD and STFT	41 subjects (21 N and 21 CM, SM and DM)	1398 records	8 kHz	TD, STFT and MFCC	MHMM	S_p: 95.30, S_e: 95.20	Classification of normal sounds, continuous, diastolic and systolic murmurs
2007	[150]	Continuous hidden Markov model (CHMM) based classifier	WT and STFT	132M/83F, mean age 48 years	215 samples (54 (NAHV), 56 (ANAHV), 66 (ANMHV), 39 (NMHV), Doppler ultrasounds	20 kHz	Wavelet and time-frequency domain features	CHMM (FCM/*k*-means algorithms) & ANN	S_p: 92.0, S_e: 97.26 (FCM-*k*-means/CHMM) & S_p: 94.0, S_e: 95.89 (ANN)	Classification of normal and abnormal sounds from mitral and aortic valves
Nearest Neighbor Classifier										
2018	[182]	Nearest neighbor (NN) classifier with Euclidean distance	WT	Six different datasets including PhysioNet database [14]	4000 samples (20 s each)	44 kHz and 2 kHz	Wavelet and filter bank, 34 features	NN with Euclidean distance	S_p: 99.00, S_e: 93.00, Acc: 98, (for dataset E)	Classification of normal and abnormal heart sounds including murmurs
2013	[47]	Feature extraction and Shannon energy using S-transform	T, F and TFD using S-transform	40 (N) and 40 (pathological)	80 records	8 kHz	Best results with the TFD features, total 70 features	*k*-NN classifier	S_e: 95.0, S_p: 97.0 (using TFD features)	Classification of S_1 and S_2

TABLE 5. ***(Continued.)*** **Summary of heart sounds classifiers and their performance comparison.**

2010	[151]	Dynamic features based on various energy distributions	STFT and CWT	22 adults (16 (N) and 6 (SM))	22 PCGs (each ≈ 12 s)	44.1 kHz	TD, FD, TFD based 53 features	*k*-NN	Acc: 98.00	Murmurs detection
2010	[152]	Feature extraction from TFR	TFD	45 adults (26 N and 19 pathological)	45 PCGs (each ≈ 12 s)	44.1 kHz	TVAR, 851 features	*k*-NN	Acc: 99.06±0.06 (best case)	Murmur detection
2009	[94]	*k*-NN with fractal features	STFT, Gabor Transform, WVD, WT	81 (N) and 83 with murmurs	164 records	44.1 kHz	T varying & TF, perceptual and fractal, 149 features	*k*-NN	Acc: 97.17 (using fractal features)	Murmur detection
2008	[153]	Hybrid classifier with AIS and *k*-NN	WT and STFT	132M/83F (Age: 15-80 y)	AV: 110 (54 N & 56 AN), MV: 105 (66 N & 39 AN)	-	WD, STFT and Wavelet entropy based 91 features	AIS and fuzzy *k*-NN	S_p: 96.00, S_e: 95.90	Classification of normal and abnormal sounds from mitral and aortic valves
1998	[123]	CWD based spectrum analysis	TFD and DWT	45 native and 23 aortic Carpentier-Edwards valve	-	2 kHz	Morphological and DWT based 9 features	*k*-NN	Acc: between 61 to 96 (based on the feature selection)	Classification of native and bioprosthetic heart valve sounds
Other classifiers/Hybrid classifiers										
2017	[64]	Empirical wavelet transform (EWT)	EWT	Databases from [32], [14], [34], [37], [33], [38] and HSs, Littmann HSs, Washington HSs and murmurs (WHSM) (total 278 records)			Timing, area and interval based features	Decision rule based classifier	S_e: 97.9, PPV: 97.7, Acc: 95.7 (Noise free)	S_1, S_2, S_3, S_4, split sounds, systolic murmurs (early, mid, late, pan) and diastolic murmurs (early, mid, late, pan) & continuous murmurs
2017	[90]	Probability analysis for feature extraction	TFD	Normal and abnormal HSs from PhysioNet database [14]		2 kHz	Statistical properties of envelope, 53 features	Extension to Naïve Bayes classifier	S_p: 91.25, S_e: 76.96, Acc: 84.11	Classification of normal and abnormal heart sounds including murmurs
2017	[103]	Ensemble of classifiers	TFD	Normal and abnormal HSs from PhysioNet database [14]		1 kHz (resampling)	Time, frequency, wavelet and statistical domain, 131 features	Ensembles of 20 two-step classifiers	S_p: 80.6, S_e: 79.6 (hidden test set), overall: 96.30/90.18 (standard/outlier signals)	Classification of normal and abnormal heart sounds including murmurs
2017	[183]	Wavelet entropy and spectral amplitude based classifier	WT	2408 (N) and 630 (AN) records from PhysioNet database [14] [31]		-	Spectral and wavelet features	DT based classifier	Acc: 76% (mean of S_e 98% and S_p 54%) for wavelet entropy	Classification of normal and abnormal heart sounds including murmurs
2015	[46]	Acoustic features for CAD detection	TFD	133 subjects for 435 records	231 (Non-CAD) and 204 (CAD)	4 kHz	Spectral features, signal complexity features, total 5029 features	Multivariate classifier	S_p: 65.20, S_e: 72.0 (for CAD detection)	Identification of coronary artery (CAD) diseases
2015	[75]	Detection of heart murmurs (PI & TI)	CWT	-	92 cardiac cycles (38 (PI) and 54 (TI))	8 kHz	36 dimensional features	RWNN classifier with EKF algorithm	Acc: 98.84±4.49 (ELM) and 98.04±045 (RWNN)	Pulmonary insufficiency and tricuspid insufficiency murmur detection
2015	[191]	Coiflet wavelets based features and its selection using BPSO	WT	150 (N), 75 (MVP), 50 (VSD), 50 (PS)	-	-	Coiflet wavelet features	Naïve Bayes, *k*-NN, C4.5 and SVM classifier	Acc: 92.31% (highest with SVM)	Classification of normal, MVP, VSD, and PS heart sounds
2012	[175]	Entropy of the wavelet packets as a classification feature	WT	50 (N), 80 (MR), 100 (AS), 50(AR), 70 (MS)	350 records	4 kHz	Wavelet entropy, 32 features	DT, *k*-NN, BayesNet, MLP and SVM	95.45 (DT), 95.78 (*k*-NN), 96.94 (BayesNet), 95.53 (MLP) & 95.33 (SVM)	Classification of AR, MR, AS and MS sounds
2012	[184]	Feature selection using PCA, GA, GP and GDA	WT	-	120 cardiac cycles of AS, MS, MR	44.1 kHz	TD, wavelet and entropy features, 32 features	MLP, RBF and SVM classifier	Acc: 99.47 (best with RBF using GA feature selection)	Diagnosis of AS, MS and MR heart valve diseases
2012	[185]	Matrix decomposition	CWT	-	15 IM, 28 organic murmurs (380 segments)	-	CWT, SVD and QRD features, 83 features	CART	S_p: 83.00, S_e: 94.00, Acc: 90.00	Murmur classification
2009	[186]	Divergence analysis	WT	Data from 2 patients, online and a CD book	140 HSs periods of 14 different types	2 kHz	50 wavelet features	MLP	Acc: 99% & 95% (based on feature extraction)	VSD, MR, LSM, early systolic, opening snap, diastolic rumble, AR, AS, MS, Ebsteins anomaly, summation gallop, venus hum, normal FCG and aortic insufficiency

TABLE 5. ***(Continued.)*** **Summary of heart sounds classifiers and their performance comparison.**

2009	[66]	Hierarchical clustering approach	TD, FD and TFD using STFT	12 subjects 11 subjects	10 records of 40s each 30-45 minutes	20-250 Hz (band pass)	TD, FD, TFD, WVD and CVD based approx. 3500 features	*k*-NN and DA	Acc: 82±7% (k-NN) Acc: 86±7% (DA)	Only classification of S_1 sounds
2007	[26]	Phono-spectrographic analysis	STFT	807 pediatric patients	88 (WM), 447 (IM), 272 (PM)	8-44.1 kHz	Phono-spectrographic features	-	S_p: 91.00, S_e: 90.00	classification of innocent and pathological murmurs in children
2004	[174]	Time-frequency based decision tree	TFD	-	84 (AS: 41 and MR: 43)	-	Time-frequency based 100 features	DT	Acc: 90 (overall), 91.6 (AS), 88.5 (MR)	Classification of FHSs, AS and MR sounds
2013	[192]	Multifractal analysis	-	49 healthy and 48 children with PMV	97 PCG records (each 8s)	8 kHz	Multifractals features	Discrimination threshold	Acc: 96.91	Normal and MVP heart sounds
1987	[99]	Energy spectrum	FFT (TD and FD)	5 healthy, 20 patients	47 records	1024 Hz	Energy curve, spectrum & distribution coefficients	No definite classifier	-	Systolic and diastolic murmur classification

Abbreviation: AN: abnormal heart sounds, Acc: accuracy, TD: time-domain, FD: frequency-domain, TFD: time-frequency domain: TFD, SS-PLSR: scaled spectrogram and partial least squares regression, SVM-DM: SVM-diffusion maps, SS-TD: scaled spectrogram and tensor decomposition, CHF: chronic heart failure, SHM: systolic heart murmurs, HOC: higher-order cumulants, LPCC: linear predictive coding coefficients, VSD: ventricular septal defects, SVM-MCS: SVM-modified Cuckoo search, AHV: aortic heart valve, NAHV: normal AHV, ANAHV: abnormal AHV, MHV: mitral heart valve, NMHV: normal MHV, ANMHV: abnormal MHV, EBP: error back-propagation, AIS: artificial immune system, SM: systolic murmurs, DM: diastolic murmurs, CM: continuous murmurs, MLP-BP: multi-layer perceptron back-propagation, CART: classification and regression trees, BP-ANN: back-propagation artificial neural network, IM: innocent murmurs, PI: pulmonary insufficiency, TI: tricuspid insufficiency, MHMM: modified HMM, RBF: radial basis function, RBF-NN: radial basis function neural network, TVAR: time-varying auto-regression, CR: classification rate, PM: pathological murmurs, NM: no murmurs, IM: innocent murmurs, VHD: valvular heart disease, DA: discriminant analysis, WPD: wavelet packet decomposition, TGNN: time-growing neural network, OMS-WPD: optimum multi-scale wavelet packet decomposition, AWN: additive white noise, HSA: heart sounds analysis, NPV: negative predictive value, WM: without murmurs, CT_LDB: cumulant-based trapezoidal local discriminant basis, FCM: fuzzy *C*-means, RWNN: radial wavelet neural network, EKF: extended Kalman filter, PNN: probabilistic neural network, ANFIS: adaptive-neuro fuzzy inference system, FWT: fast wavelet transform, FFM: frequency feature matrix, GRKF: Gaussian radial basis kernel function, LKF: linear kernel function, PKF: polynomial kernel function, SKF: sigmoid kernel function, GTSVM: growing time support vector machine, VIM: Viola integral method, EEMD: ensemble Empirical mode decomposition, MLBS: multi-level bias selection, MFCC: mel-frequency cepstral coefficient, GSVM: genetic-SVM, CQA: cycle quality assessment, DNN: deep neural network, MFSC: mel-frequency spectral coefficients, SEC: systolic ejection click, ISOM: incremental self-organizing map, WVD: Wigner-Ville distribution, SPWVD: smoothed pseudo WVD, RQA: recurrence quantification analysis, WD: wavelet decomposition, FFNN: feed-forward neural network, WPNN: wavelet packet neural network, CAD: coronary artery disease, CWD: Choi–Williams distribution, ELM: extreme learning machine, PMV: prolapsed mitral valve, BPSO: binary particle swarm optimization, SVD: singular value decomposition, DT: decision trees, TRF: time-frequency representation, ERBF: exponential radial basis function, MWKF: Morlet wavelet kernel function, SG: summation gallop, PDA: patent ductus arteriosus, BAV: bicuspid aortic valve, LVI: left ventricular impairment, PMD: papillary muscle dysfunction, NRMR: non-rheumatic mitral regurgitation, SCAS: severe calciphic aortic stenosis, LSM: late systolic murmur, DC: dilated cardiomyopothy, LBBB: left bundle branch block, CNN: convolutional neural network, DHSs: Doppler heart sounds.

not included in the data synthesis because of a limited number of articles available.

The performance of algorithms focusing on the segmentation and classification of heart sounds was synthesized as the accuracy measures in Table 6. Segmentation of S_1 (FHSD) reported in [25], [29], [45], [47], [52], [57], [64], [87]–[89], [92], [94], [96], [100], [104], and [113], achieved mean accuracy of 94.54 ± 5.15% in correct identification of S_1 at the event level, while mean classification accuracy achieved was 89.77 ± 4.53% in [66], [90], [97], [106], and [111]. Similarly, identification of S_2 (SHSD) at the event level, was reported in [25], [29], [45], [47], [52], [57], [64], [87]–[89], [92], [94], [96], [100], and [104], achieving a mean accuracy of 93.96 ± 5.01%; while the mean classification accuracy reported in [90], [106], and [111] was 90.82 ± 6.58%. Pathological heart sounds detection (PHSD) at the event level reported in [29], [64], [65], [67], and [112], achieved mean accuracy of 88.50 ± 5.93%, while pathological heart sounds classification (PHSC) reported in [64], [69], [75], [78], [95], [105], [110], [140], [142], [145], [146], [155], [157], [158], [162]–[164], [167], [170], [183], [185], and [191], achieved mean classification accuracy of 90.28 ± 7.82%. The mean accuracy in the identification of S_1 at the event level was found to be the highest. However, pathological sounds' detection at the event level achieved the least accuracy.

VI. DISCUSSION

This systematic review provides an overview of the current state-of-the-art in algorithms developed for computerized heart sounds analysis and classification. Algorithms reviewed here investigated advanced signal processing tools and learning based approaches to automate the process. These algorithms were carefully evaluated to understand current challenges. Segmentation and classification of heart sounds were found to be still challenging, mainly because of the noise associated with the acquired signals that affected the quality of analysis. Also, the complexity and non-uniformity associated with heart sounds signals were difficult to model.

Most of the segmentation approaches reviewed utilized adaptive threshold values of peak amplitudes, assumptions related to the systolic and diastolic intervals, and cardiac cycle period, to localize the peaks in the heart sounds signals. These assumptions are not valid for all kinds of subjects. Also, most of the segmentation algorithms fail in case the systole and diastole periods are of nearly equal duration. Thus, the error at the segmentation level may propagate to the next level of analysis. Only a few reviewed articles studied

the noise tolerance while segmenting heart sounds signals [29], [50], [61], [64], [96], [112]. Recently suggested probabilistic models by Springer *et al* [80] and Schmidt *et al* [45] achieved good segmentation accuracy even for noisy signals.

From the results synthesized, it was found that identification of fundamental heart sounds S_1 and S_2 achieved higher accuracy compared to the pathological sounds' identification during the segmentation process: ($94.54 \pm 5.15\%$) and ($93.96 \pm 5.01\%$), respectively, versus ($88.50 \pm 5.93\%$). While most of the articles identified S_1 and S_2 heart sounds at the event level, the identification of S_1 sounds achieved higher accuracy compared to the S_2 sounds.

Among the articles reviewed here, only a few articles aimed to identify pathological heart sounds at the event level. These articles include detection of S_3 ([64], [65]), S_4 ([64], [65]) and murmurs [29], [64], [67], [112]). The Hilbert-Huang Transform was suggested for identification of S_3 and S_4 [65]. However, the selection of intrinsic mode functions (IMFs) required in the model was challenging because of the varying temporal-spectral characteristics of heart sounds. More recently, the Empirical wavelet transform was also suggested as a decomposition approach to segment heart sounds and to detect S_1, S_2, S_3 and murmurs [64]. Though these results appear to indicate that pathological sounds can be identified at the event level during the segmentation, most of the studies performed classification to diagnose pathologies. A few studies also suggested to segment cardiac signals directly into cardiac cycles rather than identifying the peak locations [56], [79], [91], [114], [158]. In these approaches, initial localization of S_1 and S_2 was skipped if prior knowledge of cardiac cycles was available.

From the data summarized in Table 6, it can be found that different characterization measurements are evaluated based on the classification problems. Statistical features are mostly extracted to identify the fundamental heart sounds and systole and diastole intervals in a cardiac cycle. Additionally, morphological, spectral, perceptual, fractal features, wavelet features, higher-order statistics and other time-varying and time-frequency domain discriminative features are recommended to distinguish pathological sounds. These features take into account the dynamics of heart sounds under pathological conditions. Most of the features yielded promising results for classification between normal and abnormal heart sounds. Only a few reviewed articles reported features to identify particular cardiac pathologies which are discussed in the following paragraphs.

Reported characterization measurements are extracted using various heart sounds signal transformations and decompositions suggested. Among them, wavelet-based decomposition and reconstruction methods to obtain signal characteristics in both, time and frequency domains, for feature extraction were suggested in most of the recent articles [91], [175], [193]. The coefficients of mother wavelet transform are also evaluated as promising features. Some articles presented a comparative study of mother wavelets and suggested continuous wavelet transform using a Morlet wavelet as a potential transformation to extract features for detection of cardiac abnormalities - such as S_3, S_4, aortic stenosis, mitral regurgitation, midsystolic click, ventricular septal defect, atrial septal defect, mitral stenosis and aortic regurgitation [104], [130]. While others suggested the Daubechies wavelet for heart sounds analysis [67], [79], [150], [194].

Mel-frequency spectral coefficients (MFSCs) and Mel-Frequency Spectral Coefficients (MFSCs) have yielded promising results, compared to time-domain and short-time Fourier transform based features [132], [133], [155], in classification of fundamental heart sounds, S_3, S_4, ejection click, opening snap and diastolic and systolic murmurs [133]. However, MFCCs are not efficient in murmur classification with large energy lobes [118]. Hence, in addition to time-frequency domain features (such as STFT, wavelet transform, *etc.*), perceptual features (such as MFCCs), non-linear and chaos based features (such as recurrence quantification analysis and higher order statistics) and fractal features (such as correlation dimension, Largest Lyapunov Exponent and Hurst exponent) are recommended for identification of valve disorders [94], [102]. Other features included multi-fractal spectrum [192], that achieved 96.91% accuracy in identifying prolapsed mitral valve; and multi-level basis selection [70] which yielded 97.56% accuracy in identification of aortic stenosis, mitral insufficiency, and atrial insufficiency. Similarly, along with time-domain based features, the center of gravity and the width of the frequency distribution extracted using a moving windowed Hilbert transform, reported up to 98.40% accuracy for identification of ventricular septal defects. Identification of systolic ejection click using spectral analysis with a time growing window also reported promising results (97.00% accuracy). Other than this, instantaneous frequency and amplitude of decomposed signal were found to be useful for the identification of splitting of fundamental heart sounds [22].

Reviewed articles also suggested other features extraction methods - partial least squares regression method [79], matching pursuit based methods [97], sparse coefficient matrix [138] and multivariate matching pursuit [93] - for which extracted features achieved promising results in classifying normal and abnormal heart sounds. In general, temporal, statistical, wavelet coefficients, spectral and instantaneous amplitude, and frequency based features were extracted for abnormality detection.

Most of the recent studies classified pathological heart sounds using learning based approaches (Artificial Neural Network (ANN) or Support Vector Machine (SVM)). Articles also suggested modified support vector machines (such as Genetic SVM (G-SVM) [145], Least-Square Support Vector Machine (LS-SVM) [124], [195], Growing Time Windows based Support Vector Machine (GTSVM) [140], Support Vector Machine and Modified Cuckoo search (SVM-MCS) [111]), and validated the classification performance of SVM using different kernel functions in identification of normal and pathological sounds. It was found

TABLE 6. Accuracy measure of heart sounds' detection and classification approaches.

	First heart sounds detection (FHSD) (%)	Second heart sounds detection (SHSD) (%)	Pathological heart sounds detection (PHSD) (%)	First heart sounds classification (FHSC) (%)	Second heart sounds classification (SHSC) (%)	Pathological heart sounds classification (PHSC) (%)
	98.60 [25]	98.60 [25]	97.47 [29]	86.00 [66]	84.10 [90]	95.50 [64]
	97.47 [29]	97.47 [29]	94.21 [64]	84.10 [90]	91.12 [106]	94.50 [69]
	98.60 [45]	98.60 [45]	90.40 [65]	93.00 [97]	97.25 [111]	98.84 [75]
	95.00 [47]	95.00 [47]	85.50 [65]	91.12 [106]		99.60 [78]
	94.86 [52]	95.92 [52]	85.47 [67]	94.63 [111]		86.00 [95]
	98.53 [57]	98.31 [57]	86.47 [67]			85.60 [105]
	91.92 [64]	91.92 [64]	80.00 [112]			95.00 [110]
	93.60 [87]	93.60 [87]				91.50 [158]
	88.20 [88]	88.20 [88]				76.70 [157]
	93.00 [89]	93.00 [89]				84.15 [155]
	97.00 [92]	94.00 [92]				92.31 [191]
	92.00 [94]	92.00 [94]				79.00 [183]
	100.00 [96]	97.00 [96]				98.33 [162]
	96.90 [100]	96.50 [100]				90.00 [185]
	79.30 [104]	79.30 [104]				94.74 [146]
	97.80 [113]					94.52 [145]
						94.42 [163]
						88.00 [170]
						84.00 [140]
						70.20 [167]
						94.00 [164]
						99.39 [142]
Mean accuracy	94.54	93.96	88.50	89.77	90.82	90.28
Standard deviation	5.15	5.01	5.93	4.53	6.58	7.82

that the Gaussian Radial Basis Kernel Function (GRKF) produced the best results in classifying normal, aortic stenosis, pulmonary stenosis, tricuspid insufficiency and mitral insufficiency heart sounds compared to Linear Kernel Function (LKF), Polynomial Kernel Function (PKF) and Sigmoid Kernel Function (SKF)) [107]. Also, the least-square support vector machine (LS-SVM) classifiers were found promising in identifying normal, valvular defects, septal defects and other defects [139], with Morlet wavelet kernel function. Least square SVM was also suggested for identifying cases of chronic heart failure [73]. This achieved similar results to the back-propagation artificial neural network (BP-ANN) and hidden Markov models (HMM) and required less training time compared to its counterpart [148]. Other classification approaches such as decision trees [174], were also reported for the classification of fundamental heart sounds, aortic stenosis and mitral regurgitation. However, these methods are not suitable for complex feature classification [56].

Most of the studies reported methods to identify murmurs as systolic or diastolic murmurs. However, the classification of these murmurs into various sub-classes was not found in general. In a recent study, it was found that wavelet-based features and coefficients such as entropy, achieved promising results using a decision-based classification algorithm in classifying murmurs into systolic murmurs (early, mid, late, pan) and diastolic murmurs (early, mid, late, pan) and continuous murmurs [64]. Murmurs of valvular defects, mainly because of the stenosis, regurgitation and insufficiency, were mostly investigated. Wavelet transformation and wavelet coefficients such as entropy, were found useful to classify normal, aortic stenosis, aortic regurgitation, mitral stenosis and mitral regurgitation [64], [70], [147]. Another method based on murmur likelihood computation and SVM classifier was found useful in classifying normal, aortic stenosis, mitral regurgitation, ventricular septal defect, aortic regurgitation, mitral stenosis, and mitral valve prolapse [105]. SVM classifier based approaches were also extended to diagnose ventricular septal defects and atrial fibrillation and achieved satisfactory results in abnormalities classification [78], [85]. Other diagnostic heart sounds such as gallop rhythm were also classified using an SVM based classifier after pre-processing signals using the optimum multi-scale wavelet packet decomposition [143].

Other than these sounds, splitting of fundamental heart sounds has also been identified as a pathological event. While a limited number of articles investigated the splitting of second heart sounds (S_2) at the event level, no quantitative measurement of splitting of the first heart sounds (S_1) was found. The split identification was found to be obscured mainly because of the overlap of the components (M_1 and T_1 of S_1 and A_2 and P_2 of S_2). In the articles reviewed here, it was not possible to ascertain the accuracy level in detecting the splitting of fundamental heart sounds due to the lack of articles available and the lack of quantitative analysis. Apart from these diagnostic sounds, a large amplitude of S_3 or S_4

and the presence of extra peaks in the cardiac cycle may reflect valvular malfunctioning or abnormalities, but these have not been investigated.

Although existing approaches reported promising results, algorithms were specifically developed for identification and classification of certain types of pathological sounds. In some cases, the accuracy of the algorithm was greatly dependent on the disease being investigated. Thus, these results cannot be interpolated to analyze other heart sounds that may be present in a cardiac cycle. Other than this, in some of the studies, the class of murmurs was not specified.

Data acquisition systems and databases used by the reviewed studies were also examined, coming to the conclusion that databases available for the validation of the algorithms are limited. In addition, demographics of the subjects and protocols followed when performing signal acquisition were not always fully specified. Sensors locations were also generally missing. Only a few studies validated the proposed algorithm with a database containing normal and abnormal heart sounds [111]. As most of the algorithms for the heart sounds analysis were validated with limited duration of recordings, the performance of these algorithms is not statistically significant. Thus, the robustness of algorithms still needs to be validated using large databases and with signals obtained from different subjects populations, including wider age ranges, and in real use scenarios. This is even more important considering that heart sounds are very sensitive to noise and interference, and different databases show different levels of data corruption. Furthermore, libraries of auscultatory recordings containing sounds signals from all possible auscultation sites from different subjects have not been reported. The analysis should be extended to test the robustness of the algorithms against the placement of the sensor (auscultation positions) while performing the signal acquisition. In relation to this, acquisition systems and noise reduction techniques should be developed in parallel, since different acquisition systems respond differently to artifacts, which consequently might affect the performance of specific noise reduction algorithms.

Overall, existing algorithms show satisfactory results in classifying heart sounds in controlled conditions. However, it is not possible to extrapolate from this how they would operate in long-term continuous monitoring of signals in real life environments, mostly when subject-specific training is not an option.

VII. STUDY LIMITATIONS

When evaluating the accuracy measurements, the differences in the databases utilized for the verification and validation of algorithms had to be neglected. Approaches for data collection and feature extraction were not included in the data synthesis due to the lack of standardized methods and proper indexes for performance comparison. Lack of large databases in the studies makes it difficult to assess the primary outcome and to establish a proper comparison. Also, in some cases, it was hard to determine the accuracy level because of the missing performance metrics.

VIII. CONCLUSION

The key objective of this systematic review was the identification of methodological approaches for computerized heart sounds analysis and classification. This included the review of databases used for testing of the different algorithms, methods for segmentation, feature extraction and classification of heart sounds. A cost-effective system with precise automatic analysis of heart sounds may assist in early diagnosis and to improve the outcomes of cardiovascular diseases. However, extraction and analysis of these signals is a challenging task because of their complex non-stationary nature as well as the noise and interference corruption due to the limitations associated with the acquisition systems. Algorithms for automated analysis of the acoustic cardiac signals have been reported but with limited capabilities. There is a large variation in data in terms of accuracy of some of the studied algorithms. Evaluation with universally standardized databases still needs to be carried out for a proper comparison, and if the algorithms are intended to be used with wearable systems, the design and validation needs to take into account the practical challenges associated to the specific wearable.

APPENDIX

Preferred reporting items provide on the PRISMA 2009 Checklist [13] document with the page number indicating the reported items in this systematic review.

REFERENCES

[1] World Health Organization. (2015). *Media Centre-Cardiovascular Diseases (CVDs) Fact Sheet*. Accessed: May 1, 2017. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs317/en/

[2] D. Mozaffarian *et al.*, "Heart disease and stroke statistics-2015 update: A report from the American heart association," *Circulation*, vol. 131, no. 4, pp. e29–e322, 2015.

[3] L. H. Schwamm *et al.*, "Recommendations for the implementation of telehealth in cardiovascular and stroke care: A policy statement from the American heart association," *Circulation*, vol. 135, no. 7, pp. e24–e44, 2017.

[4] J. Hu *et al.*, "Portable microfluidic and smartphone-based devices for monitoring of cardiovascular diseases at the point of care," *Biotechnol. Adv.*, vol. 34, no. 3, pp. 305–320, 2016.

[5] J. S. Shinbane and L. A. Saxon, "Digital monitoring and care: Virtual medicine," *Trends Cardiovascular Med.*, vol. 26, no. 8, pp. 722–730, 2016.

[6] Z. Jiang and S. Choi, "A cardiac sound characteristic waveform method for in-home heart disorder monitoring with electric stethoscope," *Expert Syst. Appl.*, vol. 31, no. 2, pp. 286–298, 2006.

[7] S. Mangione and L. Z. Nieman, "Cardiac auscultatory skills of internal medicine and family practice trainees: A comparison of diagnostic proficiency," *JAMA*, vol. 278, no. 9, pp. 717–722, 1997.

[8] L.-G. Durand and P. Pibarot, "Digital signal processing of the phonocardiogram: Review of the most recent advancements," *Crit. Rev. Biomed. Eng.*, vol. 23, nos. 3–4, pp. 163–219, 1995.

[9] A. K. Bhoi, K. S. Sherpa, and B. Khandelwal, "Multidimensional analytical study of heart sounds: A review," *Int. J. Bioautomat.*, vol. 19, no. 3, pp. 351–376, 2015.

[10] G. D. Clifford *et al.*, "Recent advances in heart sound analysis," *Physiol. Meas.*, vol. 38, no. 8, pp. E10–E25, 2017.

[11] R. M. Rangayyan and R. J. Lehner, "Phonocardiogram signal analysis: A review," *Crit. Rev. Biomed. Eng.*, vol. 15, no. 3, pp. 211–236, 1998.

[12] M. Nabih-Ali, E. S. A. El-Dahshan, and A. S. Yahia, "A review of intelligent systems for heart sound signal analysis," *J. Med. Eng. Technol.*, vol. 41, no. 7, pp. 553–563, 2017.

[13] D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *PLoS Med.*, vol. 6, no. 7, p. e1000097, 2009.

[14] C. Liu *et al.*, "An open access database for the evaluation of heart sound algorithms," *Physiol. Meas.*, vol. 37, no. 12, pp. 2181–2213, 2016.

[15] S. Leng, R. S. Tan, K. T. C. Chai, C. Wang, D. Ghista, and L. Zhong, "The electronic stethoscope," *Biomed. Eng. OnLine*, vol. 14, no. 66, pp. 1–66, 2015.

[16] A. Leatham, *Auscultation of the Heart and Phonocardiography*, vol. 10. London, U.K.: J. & A. Churchill, 1970.

[17] S. M. Debbal and F. Bereksi-Reguig, "Time-frequency analysis of the second cardiac sound in phonocardiogram signals," *Med. Phys.*, vol. 32, no. 9, pp. 2911–2917, 2005.

[18] M. Jabloun, P. Ravier, O. Buttelli, R. Lédée, R. Harba, and L.-D. Nguyen, "A generating model of realistic synthetic heart sounds for performance assessment of phonocardiogram processing algorithms," *Biomed. Signal Process. Control*, vol. 8, no. 5, pp. 455–465, 2013.

[19] D. Mason, *Listening to the Heart: A Comprehensive Collection of Heart Sounds and Murmurs*, 2nd ed. Philadelphia, PA, USA: Hahnemann University, 2000.

[20] Y. D. Shin *et al.*, "The correlation between the first heart sound and cardiac output as measured by using digital esophageal stethoscope under anaesthesia," *Pakistan J. Med. Sci.*, vol. 30, no. 2, p. 276, 2014.

[21] T. R. Reed, N. E. Reed, and P. Fritzson, "Heart sound analysis for symptom detection and computer-aided diagnosis," *Simul. Model. Pract. Theory*, vol. 12, no. 2, pp. 129–146, 2004.

[22] S. Barma, B.-W. Chen, K. L. Man, and J.-F. Wang, "Quantitative measurement of split of the second heart sound (S2)," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 12, no. 4, pp. 851–860, Jul. 2015.

[23] J. Xu, L. G. Durand, and P. Pibarot, "Nonlinear transient chirp signal modeling of the aortic and pulmonary components of the second heart sound," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 10, pp. 1328–1335, Oct. 2000.

[24] L.-J. Thoms, G. Colicchia, and R. Girwidz, "Phonocardiography with a smartphone," *Phys. Educ.*, vol. 52, pp. 023004-1–023004-4, Jan. 2017.

[25] H. Naseri and M. R. Homaeinezhad, "Detection and boundary identification of phonocardiogram sounds using an expert frequency-energy based metric," *Ann. Biomed. Eng.*, vol. 41, no. 2, pp. 279–292, 2012.

[26] A.-L. Noponen, S. Lukkarinen, A. Angerla, and R. Sepponen, "Phonospectrographic analysis of heart murmur in children," *BMC Pediatrics*, vol. 7, no. 1, p. 23, 2007.

[27] J. Grayzel, "Gallop rhythm of the heart: I. Atrial gallop, ventricular gallop and systolic sounds," *Amer. J. Med.*, vol. 28, no. 4, pp. 578–592, 1960.

[28] C. E. Lok, C. D. Morgan, and N. Ranganathan, "The accuracy and interobserver agreement in detecting the 'gallop sounds' by cardiac auscultation," *Chest*, vol. 114, no. 5, pp. 1283–1288, 1998.

[29] S. Ari, P. Kumar, and G. Saha, "A robust heart sound segmentation algorithm for commonly occurring heart valve diseases," *J. Med. Eng. Technol.*, vol. 32, no. 6, pp. 456–465, 2008.

[30] *PhysioNet*. Accessed: Jan. 2017. [Online]. Available: https://physionet.org/

[31] G. D. Clifford *et al.*, "Classification of normal/abnormal heart sound recordings: The PhysioNet/computing in cardiology challenge 2016," in *Proc. Comput. Cardiol.*, vol. 43, Sep. 2016, pp. 609–612.

[32] P. Bentley, G. Nordehn, M. Coimbra, S. Mannor, and R. Getz. (2011). *The PASCAL Classifying Heart Sounds Challenge 2011 (CHSC2011)*. Accessed: Mar. 3, 2017. [Online]. Available: http://www.peterjbentley.com/heartchallenge/

[33] R. D. Judge and R. Mangrulkar. (2015). The open michigan heart sound & murmur library (OMHSML). University of Michigan. Accessed: Mar. 26, 2017. [Online]. Available: http://www.med.umich.edu/lrc/psb/heartsounds/

[34] eGeneral Medical. *Cardiac Auscultation of Heart Murmurs Database*. Accessed: May 27, 2017. [Online]. Available: http://www.egeneralmedical.com/listohearmur.html

[35] ThinkLabs. *Heart Sound Library*. Accessed: May 26, 2017. [Online]. Available: http://www.thinklabs.com/heart-sounds-old

[36] J. M. Wilson and R. J. Hall. Heart sounds laboratory: Heart sounds podcast series. Texas Heart Institute. Accessed: Jan. 2017. [Online]. Available: http://feeds.texasheart.org/HeartSoundsPodcastSeries

[37] *Frontiers in Bioscience: Normal and Abnormal Heart Sounds*. [Online]. Available: http://int-prop.lf2.cuni.cz/heart_sounds/h14/sound.htm

[38] The Johns Hopkins University School of Medicine, Helen B. Taussig Children's Heart Center. (2015). *Cardiac Auscultatory Recording Database*. Accessed: May 26, 2017. [Online]. Available: http://murmurlab.org/card6/

[39] M. E. Tavel, R. W. Campbell, and M. E. Gibson, *Heart Sounds and Murmurs: An Audio Visual Presentation*. Chicago, IL, USA: Year Book Medical Publisher, 1973.

[40] M. Malik *et al.*, "Heart rate variability: Standards of measurement, physiological interpretation, and clinical use," *Eur. Heart J.*, vol. 17, no. 3, pp. 354–381, 1996.

[41] C. Liu, D. Springer, and G. D. Clifford, "Performance of an open-source heart sound segmentation algorithm on eight independent databases," *Physiol. Meas.*, vol. 38, no. 8, pp. 1730–1745, 2017.

[42] Z. H. Syed, "MIT automated auscultation system," M.S. thesis, Massachusetts Inst. Technol., Cambridge, MA, USA, 2003.

[43] Z. Syed, D. Leeds, D. Curtis, F. Nesta, R. A. Levine, and J. Guttag, "A framework for the analysis of acoustical cardiac signals," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 4, pp. 651–662, Apr. 2007.

[44] H. Naseri, M. R. Homaeinezhad, and H. Pourkhajeh, "Noise/spike detection in phonocardiogram signal as a cyclic random process with non-stationary period interval," *Comput. Biol. Med.*, vol. 43, no. 9, pp. 1205–1123, 2013.

[45] S. E. Schmidt, C. Holst-Hansen, C. Graff, E. Toft, and J. J. Struijk, "Segmentation of heart sound recordings by a duration-dependent hidden Markov model," *Physiol. Meas.*, vol. 31, no. 4, pp. 513–529, 2010.

[46] S. E. Schmidt, C. Holst-Hansen, J. Hansen, E. Toft, and J. J. Struijk, "Acoustic features for the identification of coronary artery disease," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 11, pp. 2611–2619, Nov. 2015.

[47] A. Moukadem, A. Dieterlen, N. Hueber, and C. Brandt, "A robust heart sounds segmentation module based on S-transform," *Biomed. Signal Process. Control*, vol. 8, no. 3, pp. 273–281, May 2013.

[48] A. Moukadem, A. Dieterlen, N. Hueber, and C. Brandt, "Localization of heart sounds based on S-transform and radial basis function neural network," in *Proc. NBC Biomed. Eng. Med. Phys.*, vol. 34, 2011, pp. 168–171.

[49] C. D. Papadanil and L. J. Hadjieontiadis, "Efficient heart sound segmentation and extraction using ensemble empirical mode decomposition and kurtosis features," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 4, pp. 1138–1152, Jul. 2014.

[50] H. Tang, T. Li, Y. Park, and T. Qiu, "Separation of heart sound signal from noise in joint cycle frequency–time–frequency domains based on fuzzy detection," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 10, pp. 2438–2447, Oct. 2010.

[51] H. Tang, T. Li, and T. Qiu, "Noise and disturbance reduction for heart sounds in cycle-frequency domain based on nonlinear time scaling," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 2, pp. 325–333, Feb. 2010.

[52] H. Tang, T. Li, T. Qiu, and Y. Park, "Segmentation of heart sounds based on dynamic clustering," *Biomed. Signal Process. Control*, vol. 7, no. 5, pp. 509–516, 2012.

[53] T. Li, H. Tang, T. Qiu, and Y. Park, "Best subsequence selection of heart sound recording based on degree of sound periodicity," *Electron. Lett.*, vol. 47, no. 15, pp. 841–843, 2011.

[54] R. Sameni and M. Samieinasab, "Fetal phonocardiogram extraction using single channel blind source separation," in *Proc. 23rd Iran. Conf. Elect. Eng.*, May 2015, pp. 78–83.

[55] H. Nazeran, "Wavelet-based segmentation and feature extraction of heart sounds for intelligent PDA-based phonocardiography," *Methods Inf. Med.*, vol. 46, pp. 1–7, Aug. 2007.

[56] W. Zhang, J. Han, and S. Deng, "Heart sound classification based on scaled spectrogram and tensor decomposition," *Expert Syst. Appl.*, vol. 84, pp. 220–231, Oct. 2017.

[57] S. Sun, Z. Jiang, H. Wang, and Y. Fang, "Automatic moment segmentation and peak detection analysis of heart sound pattern via short-time modified Hilbert transform," *Comput. Methods Programs Biomed.*, vol. 114, no. 3, pp. 219–230, 2014.

[58] S. Sun, "An innovative intelligent system based on automatic diagnostic feature extraction for diagnosing heart diseases," *Knowl.-Based Syst.*, vol. 75, pp. 224–238, Feb. 2015.

[59] D. Boutana, M. Benidir, and B. Barkat, "Segmentation and identification of some pathological phonocardiogram signals using time-frequency analysis," *IET Signal Process.*, vol. 5, no. 6, pp. 527–537, 2011.

[60] M. S. Manikandan and K. P. Soman, "Robust heart sound activity detection in noisy environments," *Electron. Lett.*, vol. 46, no. 16, pp. 1100–1102, 2010.
[61] V. N. Varghees and K. I. Ramachandran, "A novel heart sound activity detection framework for automated heart sound analysis," *Biomed. Signal Process. Control*, vol. 13, pp. 174–188, Sep. 2014.
[62] S. Patidar and R. B. Pachori, "Segmentation of cardiac sound signals by removing murmurs using constrained tunable-Q wavelet transform," *Biomed. Signal Process. Control*, vol. 8, no. 6, pp. 559–567, 2013.
[63] *Texas Heart Institute Database*. Accessed: Jan. 2017. [Online]. Available: https://www.texasheart.org/
[64] V. N. Varghees and K. I. Ramachandran, "Effective heart sound segmentation and murmur classification using empirical wavelet transform and instantaneous phase for electronic stethoscope," *IEEE Sensors J.*, vol. 17, no. 12, pp. 3861–3872, Jun. 2017.
[65] Y.-L. Tseng, P.-Y. Ko, and F.-S. Jaw, "Detection of the third and fourth heart sounds using Hilbert-Huang transform," *Biomed. Eng. OnLine*, vol. 11, no. 8, pp. 1–13, 2012.
[66] G. Amit, N. Gavriely, and N. Intrator, "Cluster analysis and classification of heart sounds," *Biomed. Signal Process. Control*, vol. 4, no. 1, pp. 26–36, 2009.
[67] C. N. Gupta, R. Palaniappan, S. Swaminathan, and S. M. Krishnan, "Neural network classification of homomorphic segmented heart sounds," *Appl. Soft Comput.*, vol. 7, no. 1, pp. 286–297, 2007.
[68] F. Javed, P. A. Venkatachalam, and M. H. A. Fadzil, "A signal processing module for the analysis of heart sounds and heart murmurs," *J. Phys.*, vol. 34, no. 1, pp. 1098–1105, 2006.
[69] I. Turkoglu, A. Arslan, and E. Ilkay, "An intelligent system for diagnosis of the heart valve diseases with wavelet packet neural networks," *Comput. Biol. Med.*, vol. 33, no. 4, pp. 319–331, 2003.
[70] F. Safara, S. Doraisamy, A. Azman, A. Jantan, and A. R. A. Ramaiah, "Multi-level basis selection of wavelet packet decomposition tree for heart sound classification," *Comput. Biol. Med.*, vol. 43, no. 10, pp. 1407–1414, Oct. 2013.
[71] P. Banerjee and A. Mondal, "An irregularity measurement based cardiac status recognition using support vector machine," *J. Med. Eng.*, vol. 2015, Oct. 2015, Art. no. 327534.
[72] A. Iwata, N. Ishii, N. Suzumura, and K. Ikegaya, "Algorithm for detecting the first and the second heart sounds by spectral tracking," *Med. Biol. Eng. Comput.*, vol. 18, no. 1, pp. 19–26, 1980.
[73] Y. Zheng, X. Guo, J. Qin, and S. Xiao, "Computer-assisted diagnosis for chronic heart failure by the analysis of their cardiac reserve and heart sound characteristics," *Comput. Methods Programs Biomed.*, vol. 122, no. 3, pp. 372–383, 2015.
[74] W. Zhang, X. Guo, Z. Yuan, and X. Zhu, "Heart sound classification and recognition based on EEMD and correlation dimension," *J. Mech. Med. Biol.*, vol. 14, no. 4, pp. 1450046-1–1450046-17, 2014.
[75] J. E. Guillermo, L. J. R. Castellanos, E. N. Sanchez, and A. Y. Alanis, "Detection of heart murmurs based on radial wavelet neural network with Kalman learning," *Neurocomputing*, vol. 164, pp. 307–317, Apr. 2015.
[76] M. Elgendi *et al.*, "Spectral analysis of the heart sounds in children with and without pulmonary artery hypertension," *Int. J. Cardiol.*, vol. 173, no. 1, pp. 92–99, 2014.
[77] K. Hassani, K. Bajelani, M. Navidbakhsh, D. J. Doyle, and F. Taherian, "Heart sound segmentation based on homomorphic filtering," *Perfusion*, vol. 29, no. 4, pp. 351–359, 2014.
[78] S. Choi and Z. Jiang, "Cardiac sound murmurs classification with autoregressive spectral analysis and multi-support vector machine technique," *Comput. Biol. Med.*, vol. 40, no. 1, pp. 8–20, 2010.
[79] W. Zhang, J. Han, and S. Deng, "Heart sound classification based on scaled spectrogram and partial least squares regression," *Biomed. Signal Process. Control*, vol. 32, pp. 20–28, Feb. 2017.
[80] D. B. Springer, L. Tarassenko, and G. D. Clifford, "Logistic regression-HSMM-based heart sound segmentation," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 4, pp. 822–832, Apr. 2016.
[81] I. Turkoglu, A. Arslan, and E. Ilkay, "A wavelet neural network for the detection of heart valve diseases," *Expert Syst.*, vol. 20, no. 1, pp. 1–7, 2003.
[82] H. Uğuz, "A biomedical system based on artificial neural network and principal component analysis for diagnosis of the heart valve diseases," *J. Med. Syst.*, vol. 36, no. 1, pp. 61–72, 2012.
[83] S. Kang, R. Doroshow, J. McConnaughey, and R. Shekhar, "Automated identification of innocent Still's murmur in children," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 6, pp. 1326–1334, Jun. 2017.
[84] P. Sharma, S. A. Imtiaz, and E. Rodriguez-Villegas, "An algorithm for heart rate extraction from acoustic recordings at the neck," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 1, pp. 246–256, Jan. 2019.
[85] S. Sun, H. Wang, Z. Jiang, Y. Fang, and T. Tao, "Segmentation-based heart sound feature extraction combined with classifier models for a VSD diagnosis system," *Expert Syst. Appl.*, vol. 41, pp. 1769–1780, Mar. 2014.
[86] Z. Yan, Z. Jiang, A. Miyamoto, and Y. Wei, "The moment segmentation analysis of heart sound pattern," *Comput. Methods Programs Biomed.*, vol. 98, no. 2, pp. 140–150, 2010.
[87] A. A. Sepehri, A. Gharehbaghi, T. Dutoit, A. Kocharian, and A. Kiani, "A novel method for pediatric heart sound segmentation without using the ECG," *Comput. Methods Programs Biomed.*, vol. 99, no. 1, pp. 43–48, 2010.
[88] S. Choi and Z. Jiang, "Comparison of envelope extraction algorithms for cardiac sound signal segmentation," *Expert Syst. Appl.*, vol. 34, no. 2, pp. 1056–1069, 2008.
[89] H. Liang, S. Lukkarinen, and I. Hartimo, "Heart sound segmentation algorithm based on heart sound envelogram," in *Proc. Comput. Cardiol.*, vol. 24, Sep. 1997, pp. 105–108.
[90] F. Plesinger, I. Viscor, J. Halamek, J. Jurco, and P. Jurak, "Heart sounds analysis using probability assessment," *Physiol. Meas.*, vol. 38, no. 8, pp. 1685–1700, 2017.
[91] S. Yuenyong, A. Nishihara, W. Kongprawechnon, and K. Tungpimolrut, "A framework for automatic heart sound analysis without segmentation," *Biomed. Eng. OnLine*, vol. 10, no. 13, pp. 1–23, 2011.
[92] A. Gharehbaghi, T. Dutoir, A. Sepehri, P. Hult, and P. Ask, "An automatic tool for pediatric heart sounds segmentation," in *Proc. Comput. Cardiol.*, Sep. 2011, pp. 37–40.
[93] S. Jabbari and H. Ghassemian, "Modeling of heart systolic murmurs based on multivariate matching pursuit for diagnosis of valvular disorders," *Comput. Biol. Med.*, vol. 41, no. 9, pp. 802–811, 2011.
[94] E. Delgado-Trejos, A. F. Quiceno-Manrique, J. I. Godino-Llorente, M. Blanco-Velasco, and G. Castellanos-Dominguez, "Digital auscultation analysis for heart murmur detection," *Ann. Biomed. Eng.*, vol. 37, no. 2, pp. 337–353, 2009.
[95] C. Ahlstrom *et al.*, "Feature extraction for systolic heart murmur classification," *Ann. Biomed. Eng.*, vol. 34, no. 11, pp. 1666–1677, 2006.
[96] M. El-Segaier, O. Lilja, S. Lukkarinen, L. Sörnmo, R. Sepponen, and E. Pesonen, "Computer-based detection and analysis of heart sound and murmur," *Ann. Biomed. Eng.*, vol. 33, no. 7, pp. 937–942, 2005.
[97] W. Wang, Z. Guo, J. Yang, Y. Zhang, L.-G. Durand, and M. Loew, "Analysis of the first heart sound using the matching pursuit method," *Med. Biol. Eng. Comput.*, vol. 39, pp. 644–648, Nov. 2001.
[98] M. W. Groch, J. R. Domnanovich, and W. D. Erwin, "A new heart-sounds gating device for medical imaging," *IEEE Trans. Biomed. Eng.*, vol. 39, no. 3, pp. 307–310, Mar. 1992.
[99] R. J. Lehner and R. M. Rangayyan, "A three-channel microcomputer system for segmentation and characterization of the phonocardiogram," *IEEE Trans. Biomed. Eng.*, vol. BME-34, no. 6, pp. 485–489, Jun. 1987.
[100] D. Gill, N. Gavrieli, and N. Intrator, "Detection and identification of heart sounds using homomorphic envelogram and self-organizing probabilistic model," in *Proc. Comput. Cardiol.*, vol. 32, Sep. 2005, pp. 957–960.
[101] A. D. Ricke, R. J. Povinelli, and M. T. Johnson, "Automatic segmentation of heart sound signals using hidden Markov models," in *Proc. Comput. Cardiol.*, Sep. 2005, pp. 953–956.
[102] M. Abdollahpur, A. Ghaffari, S. Ghiasi, and M. J. Mollakazemi, "Detection of pathological heart sounds," *Physiol. Meas.*, vol. 38, no. 8, pp. 1616–1630, 2017.
[103] M. N. Homsi and P. Warrick, "Ensemble methods with outliers for phonocardiogram classification," *Physiol. Meas.*, vol. 38, no. 8, pp. 1631–1644, 2017.
[104] E. Kay and A. Agarwal, "DropConnected neural networks trained on time-frequency and inter-beat features for classifying heart sounds," *Physiol. Meas.*, vol. 38, no. 8, pp. 1645–1657, 2017.
[105] C. Kwak and O.-W. Kwon, "Cardiac disorder classification by heart sound signals using murmur likelihood and hidden Markov model state likelihood," *IET Signal Process.*, vol. 6, no. 4, pp. 326–334, 2012.
[106] T.-E. Chen *et al.*, "S1 and S2 heart sound recognition using deep neural networks," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 2, pp. 372–380, Feb. 2017.

[107] Y. Zheng, X. Guo, and X. Ding, "A novel hybrid energy fraction and entropy-based approach for systolic heart murmurs identification," *Expert Syst. Appl.*, vol. 42, no. 5, pp. 2710–2721, 2015.

[108] V. Nigam and R. Priemer, "Accessing heart dynamics to estimate durations of heart sounds," *Physiol. Meas.*, vol. 26, no. 6, pp. 1005–1018, 2005.

[109] S. Sanei, M. Ghodsi, and H. Hassani, "An adaptive singular spectrum analysis approach to murmur detection from heart sounds," *Med. Eng. Phys.*, vol. 33, no. 3, pp. 362–367, 2011.

[110] Z. Dokur and T. Ölmez, "Heart sound classification using wavelet transform and incremental self-organizing map," *Digit. Signal Process.*, vol. 18, pp. 951–959, Nov. 2008.

[111] G. Redlarski, D. Gradolewski, and A. Palkowski, "A system for heart sounds classification," *PLoS One*, vol. 9, no. 11, p. e112673, 2014.

[112] V. Nigam and R. Priemer, "A simplicity-based fuzzy clustering approach for detection and extraction of murmurs from the phonocardiogram," *Physiol. Meas.*, vol. 29, no. 1, pp. 33–47, 2008.

[113] T. Oskiper and R. Watrous, "Detection of the first heart sound using a time-delay neural network," in *Proc. Comput. Cardiol.*, vol. 29, Sep. 2002, pp. 537–540.

[114] S.-W. Deng and J.-Q. Han, "Towards heart sound classification without segmentation via autocorrelation feature and diffusion maps," *Future Gener. Comput. Syst.*, vol. 60, pp. 13–21, Feb. 2016.

[115] A. Haghighi-Mood and J. N. Torry, "A sub-band energy tracking algorithm for heart sound segmentation," in *Proc. Comput. Cardiol.*, Sep. 1995, pp. 501–504.

[116] J. Herzig, A. Bickel, A. Eitan, and N. Intrator, "Monitoring cardiac stress using features extracted from S1 heart sounds," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 4, pp. 1169–1178, Apr. 2015.

[117] R. Abbasi-Kesbi, A. Valipour, and K. Imani, "Cardiorespiratory system monitoring using a developed acoustic sensor," *Healthcare Technol. Lett.*, vol. 5, no. 1, pp. 7–12, 2018.

[118] H. M. Fahad, M. U. G. Khan, T. Saba, A. Rehman, and S. Iqbal, "Microscopic abnormality classification of cardiac murmurs using ANFIS and HMM," *Microsc. Res. Techn.*, vol. 81, no. 5, pp. 449–457, 2018.

[119] *Online Database 3M Littmann*. Accessed: Jan. 2017. [Online]. Available: www.littmann.in

[120] Y. Soeta and Y. Bito, "Detection of features of prosthetic cardiac valve sound by spectrogram analysis," *Appl. Acoust.*, vol. 89, pp. 28–33, Mar. 2015.

[121] M. S. Obaidat, "Phonocardiogram signal analysis: Techniques and performance comparison," *J. Med. Eng. Technol.*, vol. 17, no. 6, pp. 221–227, 1993.

[122] N. E. Huang *et al.*, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. Roy. Soc. London A, Math., Phys. Eng. Sci.*, vol. 454, no. 1971, pp. 903–995, Mar. 1998.

[123] P. M. Bentley, P. M. Grant, and J. T. E. McDonnell, "Time-frequency and time-scale techniques for the classification of native and bioprosthetic heart valve sounds," *IEEE Trans. Biomed. Eng.*, vol. 45, no. 1, pp. 125–128, Jan. 1998.

[124] S. Ari, K. Hembram, and G. Saha, "Detection of cardiac abnormality from PCG signal using LMS based least square SVM classifier," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 8019–8026, 2010.

[125] S. M. Debbal and F. Bereksi-Reguig, "Analysis of the second heart sound using continuous wavelet transform," *J. Med. Eng. Technol.*, vol. 28, no. 4, pp. 151–156, 2004.

[126] S. M. Debbal and F. Bereksi-Reguig, "Filtering and classification of phonocardiogram signals using wavelet transform," *J. Med. Eng. Technol.*, vol. 32, no. 1, pp. 53–65, 2008.

[127] O. Rioul and P. Flandrin, "Time-scale energy distributions: A general class extending wavelet transforms," *IEEE Trans. Signal Process.*, vol. 40, no. 7, pp. 1746–1757, Jul. 1992.

[128] M. Akay, "Wavelet applications in medicine," *IEEE Spectr.*, vol. 34, no. 5, pp. 50–56, May 1997.

[129] S. M. Debbal and F. Bereksi-Reguig, "Detection of differences of the phonocardiogram signals by using the continuous wavelet transform method," *Biomed. Soft Comput. Hum. Sci.*, vol. 18, no. 2, pp. 73–81, 2013.

[130] B. Ergen, Y. Tatar, and H. O. Gulcur, "Time–frequency analysis of phonocardiogram signals using wavelet transform: A comparative study," *Comput. Methods Biomech. Biomed. Eng.*, vol. 15, no. 4, pp. 371–381, 2012.

[131] S. M. Debbal and A. M. Tani, "Heart sounds analysis and murmurs," *Int. J. Med. Eng. Inform.*, vol. 8, no. 1, pp. 49–62, 2016.

[132] P. Wang, C. Lim, S. Chauhan, J. Foo, and V. Anantharaman, "Phonocardiographic signal analysis method using a modified hidden Markov model," *Ann. Biomed. Eng.*, vol. 35, no. 3, pp. 367–374, 2007.

[133] S. Chauhan, P. Wang, C. S. Lim, and V. Anantharaman, "A computer-aided MFCC-based HMM system for automatic auscultation," *Comput. Biol. Med.*, vol. 38, no. 2, pp. 221–233, 2008.

[134] P. Lubaib and K. V. A. Muneer, "The heart defect analysis based on PCG signals using pattern recognition techniques," *Procedia Technol.*, vol. 24, pp. 1024–1031, Jan. 2016.

[135] J. E. Jacobs, K. Horikoshi, and M. L. Petrovick, "Feasibility of automated analysis of phonocardiogram," *J. Audio Eng. Soc.*, vol. 17, no. 1, pp. 49–54, 1969.

[136] T. H. Joo, J. H. McClellan, R. A. Foale, G. S. Myers, and R. S. Lees, "Pole-zero modeling and classification of phonocardiograms," *IEEE Trans. Biomed. Eng.*, vol. BME-30, no. 2, pp. 110–118, Feb. 1983.

[137] P. D. Stein, H. N. Sabbah, J. B. Lakier, S. R. Kemp, and D. J. Magilligan, "Frequency spectra of the first heart sound and of the aortic component of the second heart sound in patients with degenerated porcine bioprosthetic valves," *Amer. J. Cardiol.*, vol. 53, no. 4, pp. 557–561, 1984.

[138] B. M. Whitaker, P. B. Suresha, C. Liu, G. Clifford, and D. Anderson, "Combining sparse coding and time-domain features for heart sound classification," *Physiol. Meas.*, vol. 38, pp. 1701–1713, Jul. 2017.

[139] S. Patidar, R. B. Pachori, and N. Garg, "Automatic diagnosis of septal defects based on tunable-Q wavelet transform of cardiac sound signals," *Expert Syst. Appl.*, vol. 42, no. 7, pp. 3315–3326, 2015.

[140] A. Gharehbaghi, M. Borga, B. J. Sjöberg, and P. Ask, "A novel method for discrimination between innocent and pathological heart murmurs," *Med. Eng. Phys.*, vol. 37, no. 7, pp. 674–682, 2015.

[141] A. Gharehbaghi, I. Ekman, P. Ask, E. Nylander, and B. Janerot-Sjoberg, "Assessment of aortic valve stenosis severity using intelligent phonocardiography," *Int. J. Cardiol.*, vol. 198, pp. 58–60, Nov. 2015.

[142] F. Safara, "Cumulant-based trapezoidal basis selection for heart sound classification," *Med. Biol. Eng. Comput.*, vol. 53, no. 11, pp. 1153–1164, 2015.

[143] Y. Wang, W. Li, J. Zhou, X. Li, and P. Yifei, "Identification of the normal and abnormal heart sounds using wavelet-time entropy features based on OMS-WPD," *Future Gener. Comput. Syst.*, vol. 37, pp. 488–495, Jul. 2014.

[144] T. Gokhale, "Machine learning based identification of pathological heart sounds," in *Proc. Comput. Cardiol.*, vol. 43, Sep. 2016, pp. 553–556.

[145] E. Avci, "A new intelligent diagnosis system for the heart valve diseases by using genetic-SVM classifier," *Expert Syst. Appl.*, vol. 36, no. 7, pp. 10618–10626, 2009.

[146] I. Maglogiannis, E. Loukis, E. Zafiropoulos, and A. Stasis, "Support vectors machine-based identification of heart valve diseases using heart sounds," *Comput. Methods Programs Biomed.*, vol. 95, no. 1, pp. 47–61, 2009.

[147] S. Choi, "Detection of valvular heart disorders using wavelet packet decomposition and support vector machine," *Expert Syst. Appl.*, vol. 35, no. 4, pp. 1679–1687, 2008.

[148] E. Çomak, A. Arslan, and İ. Türkoğlu, "A decision support system based on support vector machines for diagnosis of the heart valve diseases," *Comput. Biol. Med.*, vol. 37, no. 1, pp. 21–27, 2007.

[149] R. Saraçoğlu, "Hidden Markov model-based classification of heart valve disease with PCA for dimension reduction," *Eng. Appl. Artif. Intell.*, vol. 25, no. 7, pp. 1523–1528, 2012.

[150] H. Uğuz, A. Arslan, and İ. Türkoğlu, "A biomedical system based on hidden Markov model for diagnosis of the heart valve diseases," *Pattern Recognit. Lett.*, vol. 28, no. 4, pp. 395–404, 2007.

[151] A. F. Quiceno-Manrique, J. I. Godino-Llorente, M. Blanco-Velasco, and G. Castellanos-Dominguez, "Selection of dynamic features based on time–frequency representations for heart murmur detection from phonocardiographic signals," *Ann. Biomed. Eng.*, vol. 38, no. 1, pp. 118–137, 2010.

[152] L. D. Avendaño-Valencia, J. I. Godino-Llorente, M. Blanco-Velasco, and G. Castellanos-Dominguez, "Feature extraction from parametric time–frequency representations for heart murmur detection," *Ann. Biomed. Eng.*, vol. 38, no. 8, pp. 2716–2732, 2010.
[153] A. Sengur and I. Turkoglu, "A hybrid method based on artificial immune system and fuzzy k-NN algorithm for diagnosis of heart valve diseases," *Expert Syst. Appl.*, vol. 35, no. 3, pp. 1011–1020, 2008.
[154] F. Beritelli, G. Capizzi, G. Lo Sciuto, C. Napoli, and F. Scaglione, "Automatic heart activity diagnosis based on Gram polynomials and probabilistic neural networks," *Biomed. Eng. Lett.*, vol. 8, no. 1, pp. 77–85, 2018.
[155] V. Maknickas and A. Maknickas, "Recognition of normal–abnormal phonocardiographic signals using deep convolutional neural networks and mel-frequency spectral coefficients," *Physiol. Meas.*, vol. 38, no. 8, pp. 1671–1684, 2017.
[156] H.-L. Her and H.-W. Chiu, "Using time-frequency features to recognize abnormal heart sounds," in *Proc. Comput. Cardiol.*, vol. 43, Sep. 2016, pp. 1145–1148.
[157] S.-K. Teo, B. Yang, L. Feng, and Y. Su, "Power spectrum analysis for classification of heart sound recording," in *Proc. Comput. Cardiol.*, vol. 43, Sep. 2016, pp. 1169–1172.
[158] M. Zabihi, A. B. Rad, S. Kiranyaz, M. Gabbouj, and A. K. Katsaggelos, "Heart sound anomaly and quality detection using ensemble of neural networks without segmentation," in *Proc. Comput. Cardiol.*, vol. 43, Sep. 2016, pp. 613–616.
[159] C. Potes, S. Parvaneh, A. Rahman, and B. Conroy, "Ensemble of feature-based and deep learning-based classifiers for detection of abnormal heart sounds," in *Proc. Comput. Cardiol.*, vol. 43, Sep. 2016, pp. 621–624.
[160] M. Tschannen, T. Kramer, G. Marti, M. Heinzmann, and T. Wiatowski, "Heart sound classification using deep structured features," in *Proc. Comput. Cardiol.*, vol. 43, Sep. 2016, pp. 565–568.
[161] A. Gharehbaghi, T. Dutoit, P. Ask, and L. Sörnmo, "Detection of systolic ejection click using time growing neural network," *Med. Eng. Phys.*, vol. 36, no. 4, pp. 477–483.
[162] H. Uğuz, "Adaptive neuro-fuzzy inference system for diagnosis of the heart valve diseases using wavelet transform with entropy," *Neural Comput. Appl.*, vol. 21, no. 7, pp. 1617–1628, 2012.
[163] S. Babaei and A. Geranmayeh, "Heart sound reproduction based on neural network classification of cardiac valve disorders using wavelet transforms of PCG signals," *Comput. Biol. Med.*, vol. 39, no. 1, pp. 8–15, 2009.
[164] A. A. Sepehri, J. Hancq, T. Dutoit, A. Gharehbaghi, A. Kocharian, and A. Kiani, "Computerized screening of children congenital heart diseases," *Comput. Methods Programs Biomed.*, vol. 92, pp. 186–192, Nov. 2008.
[165] J. P. D. Vos and M. M. Blanckenberg, "Automated pediatric cardiac auscultation," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 2, pp. 244–252, Feb. 2007.
[166] K. Higuchi, K. Sato, H. Makuuchi, A. Furuse, S. Takamoto, and H. Takeda, "Automated diagnosis of heart disease in patients with heart murmurs: Application of a neural network technique," *J. Med. Eng. Technol.*, vol. 30, no. 2, pp. 61–68, 2006.
[167] N. Andrisevic, K. Ejaz, F. Rios-Gutierrez, R. Alba-Flores, G. Nordehn, and S. Burns, "Detection of heart murmurs using wavelet analysis and artificial neural networks," *J. Biomed. Eng.*, vol. 127, no. 6, pp. 899–904, 2005.
[168] S. R. Bhatikar, C. DeGroff, and R. L. Mahajan, "A classifier based on the artificial neural network approach for cardiologic auscultation in pediatrics," *Artif. Intell. Med.*, vol. 33, no. 3, pp. 251–260, 2005.
[169] T. Ölmez and Z. Dokur, "Classification of heart sounds using an artificial neural network," *Pattern Recognit. Lett.*, vol. 24, pp. 617–629, Jan. 2003.
[170] R. Folland, E. L. Hines, P. Boilot, and D. Morgan, "Classifying coronary dysfunction using neural networks through cardiovascular auscultation," *Med. Biol. Eng. Comput.*, vol. 40, no. 3, pp. 339–343, 2002.
[171] I. Cathers, "Neural network assisted cardiac auscultation," *Artif. Intell. Med.*, vol. 7, no. 1, pp. 53–66, 1995.
[172] Y. M. Akay, M. Akay, W. Welkowitz, and J. Kostis, "Noninvasive detection of coronary artery disease," *IEEE Eng. Med. Biol. Mag.*, vol. 13, no. 5, pp. 761–764, Nov. 1994.
[173] R. C. King, E. Villenueve, R. J. White, R. S. Sherratt, W. Holderbaum, and W. S. Harwin, "Application of data fusion techniques and technologies for wearable health monitoring," *Med. Eng. Phys.*, vol. 42, pp. 1–12, Apr. 2017.
[174] S. Pavlopoulos, A. C. H. Stasis, and E. N. Loukis, "A decision tree–based method for the differential diagnosis of aortic stenosis from mitral regurgitation using heart sounds," *Biomed. Eng. OnLine*, vol. 3, no. 1, p. 21, 2004.
[175] F. Safara, S. Doraisamy, A. Azman, A. Jantan, and S. Ranga, "Wavelet packet entropy for heart murmurs classification," *Adv. Bioinf.*, vol. 2012, Oct. 2012, Art. no. 327269.
[176] L.-G. Durand, M. Blanchard, G. Cloutier, H. N. Sabbah, and P. D. Stein, "Comparison of pattern recognition methods for computer-assisted classification of spectra of heart sounds in patients with a porcine bioprosthetic valve implanted in the mitral position," *IEEE Trans. Biomed. Eng.*, vol. 37, no. 12, pp. 1121–1129, Dec. 1990.
[177] L. Atallah, B. Lo, R. King, and G.-Z. Yang, "Sensor positioning for activity recognition using wearable accelerometers," *IEEE Trans. Biomed. Circuits Syst.*, vol. 5, no. 4, pp. 320–329, Aug. 2011.
[178] A. M. Mannini and A. Sabatini, "Machine learning methods for classifying human physical activity from on-body accelerometers," *Sensors*, vol. 10, no. 2, pp. 1154–1175, 2010.
[179] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.
[180] Y.-J. Son, H.-G. Kim, E.-H. Kim, S. Choi, and S.-K. Lee, "Application of support vector machine for prediction of medication adherence in heart failure patients," *Healthcare Inform. Res.*, vol. 16, no. 4, pp. 253–259, 2010.
[181] Y.-L. Tseng, K.-S. Lin, and F.-S. Jaw, "Comparison of support-vector machine and sparse representation using a modified rule-based method for automated myocardial ischemia detection," *Comput. Math. Methods Med.*, vol. 2016, Jan. 2016, Art. no. 9460375.
[182] M. Hamidi, H. Ghassemian, and M. Imani, "Classification of heart sound signal using curve fitting and fractal dimension," *Biomed. Signal Process. Control*, vol. 39, pp. 351–359, Jan. 2018.
[183] P. Langley and A. Murray, "Heart sound classification from unsegmented phonocardiograms," *Physiol. Meas.*, vol. 38, pp. 1658–1670, Jul. 2017.
[184] M. Rouhani and R. Abdoli, "A comparison of different feature extraction methods for diagnosis of valvular heart diseases using PCG signals," *J. Med. Eng. Technol.*, vol. 36, no. 1, pp. 42–49, 2012.
[185] Y. Chen, S. Wang, C.-H. Shen, and F. K. Choy, "Matrix decomposition based feature extraction for murmur classification," *Med. Eng. Phys.*, vol. 34, no. 6, pp. 756–761, 2012.
[186] Z. Dokur and T. Ölmez, "Feature determination for heart sounds based on divergence analysis," *Digit. Signal Process.*, vol. 19, no. 3, pp. 521–531, 2009.
[187] K. Altun, B. Barshan, and O. Tunçel, "Comparative study on classifying human activities with miniature inertial and magnetic sensors," *Pattern Recognit.*, vol. 43, no. 10, pp. 3605–3620, Oct. 2010.
[188] N. Bicocchi, M. Mamei, and F. Zambonelli, "Detecting activities from body-worn accelerometers via instance-based algorithms," *Pervasive Mobile Comput.*, vol. 6, no. 4, pp. 482–495, Aug. 2010.
[189] Z. Wang, Z. Yang, and T. Dong, "A review of wearable technologies for elderly care that can accurately track indoor position, recognize physical activities and monitor vital signs in real time," *Sensors*, vol. 17, no. 2, p. 341, 2017.
[190] B. Al-Naami, J. Al-Nabulsi, H. Amasha, and J. Torry, "Utilizing wavelet transform and support vector machine for detection of the paradoxical splitting in the second heart sound," *Med. Biol. Eng. Comput.*, vol. 48, no. 2, pp. 177–184, 2010.
[191] G. V. H. Prasad and P. R. Kumar, "Wavelet Feature Selection Approach for Heart Murmur Classification," *Int. J. Med., Heal., Biomed., Bioeng. Pharmaceutical Eng.*, vol. 9, no. 3, pp. 315–322, 2015.
[192] A. Gavrovska, G. Zajić, I. Reljin, and B. Reljin, "Classification of prolapsed mitral valve versus healthy heart from phonocardiograms by multifractal analysis," *Comput. Math. Methods Med.*, vol. 2013, Apr. 2013, Art. no. 376152.
[193] M. Abo-Zahhad, M. Farrag, S. N. Abbas, and S. M. Ahmed, "A comparative approach between cepstral features for human authentication using heart sounds," *Signal, Image Video Process.*, vol. 10, no. 5, pp. 843–851, 2016.
[194] C. Ahlstrom, T. Länne, P. Ask, and A. Johansson, "A method for accurate localization of the first heart sound and possible applications," *Physiol. Meas.*, vol. 29, no. 3, pp. 417–428, 2008.
[195] G. E. Güraksın and H. Uğuz, "Classification of heart sounds based on the least squares support vector machine," *Int. J. Innov. Comput., Inf. Control*, vol. 7, no. 12, pp. 7131–7144, 2011.

AMIT KRISHNA DWIVEDI (GS'14) received the B.Tech. degree in electronics from the Vishveshwarya Institute, India, in 2012, and the M.E. degree in electronics from the Birla Institute of Technology, Mesra, India, in 2015. He received the Certificate of Academic Excellence for the academic years 2009–2010, 2010–2011, and 2011–2012 for his top academic performances. He also secured first positions in both the bachelor's and master's degrees. He was a recipient of the GATE Scholarship from AICTE, Government of India, for the academic years 2013–2015, and the Visvesvaraya Scholarship, Ministry of Electronics and Information Technology, Government of India, for the academic year 2015–2016.

He is currently a President's PhD Scholar, and pursuing the Ph.D. degree with the Department of Electrical and Electronic Engineering, Imperial College London, London, U.K. From 2015 to 2016, he was a Research Scholar with the Department of Electrical Engineering, IIT Delhi, India. His research interests include biomedical circuits and systems focused toward low-power electronics and its applications. He is the author or co-author of more than 25 research papers in reputed journals and international conferences, and book chapters.

SYED ANAS IMTIAZ (S'07–M'16) received the B.Eng. degree from the National University of Sciences and Technology, Islamabad, Pakistan, in 2008, and the M.Sc. and Ph.D. degrees from the Imperial College London, London, U.K., in 2009 and 2015, respectively.

From 2009 to 2010, he was a Digital Design Engineer with Imagination Technologies, Kings Langley, U.K. He is currently a research fellow and focuses on creating novel wearable technologies to aid in the long-term monitoring and diagnosis of different medical conditions. His current research interests include developing low-complexity signal processing algorithms and their low-power mixed-signal circuit design, particularly for use in sleep medicine and epilepsy monitoring.

ESTHER RODRIGUEZ-VILLEGAS (SM'08) received the Ph.D. degree from the University of Seville, Spain, in 2002. Since 2002, she has been a Faculty Member with the Imperial College London. Since 2015, she holds the Chair of Low Power Electronics with the Department of Electrical and Electronic Engineering. She is also the Director of the Wearable Technologies Lab. She has trained over 700 engineers from all over the world at the M.S. or Ph.D. levels in ultralow-power electronic design. She is also the Chief Scientific Officer of TainiTec, Ltd., and the Co-Chief Executive Officer of Acurable, Ltd., which she founded. She has received a number of awards and honors, including being recognized as the Top Young Scientist/Engineer in Spain, in 2009 (the Complutense Award); the Institution of Engineering and Technology (United Kingdom) Innovation Award, in 2009; being recognized twice by the European Research Council as a Research Leader in Europe (Starting and Consolidator Awards, in 2010 and 2016); and the XPRIZE (United States) Award, in 2014.