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TOPICAL REVIEW

Automated System for the Detection of Heart Anomalies Using Phonocardiograms: A Systematic Review

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ABSTRACT Phonocardiogram (PCG) signals generated by the heart contain information about heart conditions. This review examines how PCG analysis identifies and diagnoses heart issues. We studied traditional signal processing and artificial intelligence techniques and provided a complete picture of the current state of this field. Adhering to the systematic review guidelines, our comprehensive review covers 103 studies from reputed journals. It includes Machine Learning (ML) and Deep Learning (DL) techniques used to develop the computer-aided diagnostic tools using PCG signals. This review evaluates the strengths and weaknesses of various ML and DL methods, emphasizing their effectiveness in diagnosing several abnormalities. Additionally, we examine the obstacles and challenges limiting the widespread adoption of PCG-based diagnostic systems in clinical settings. We outline a plan for future research to develop improved versions of PCG analysis models. These models will be more robust, precise, and user-friendly. They will improve cardiovascular care by enabling machines to screen for problems automatically and intelligently.

INDEX TERMS Computer-aided diagnostic tool, deep learning, heart sound classification, heart diseases, phonocardiogram.

I. INTRODUCTION

Cardiovascular Disease (CVD) is one of the leading causes of death worldwide. The World Health Organization estimated that about 17.9 million deaths were due to CVD in 2019, accounting for 32% of all deaths globally. Among these, 85% of them died due to heart attack and stroke.[1] The imperative for risk stratification, screening, diagnosis, and prompt management of these cardiac ailments is underscored within the global health sector. The assessment of heart sounds, within the context of a patient's clinical profile, holds pivotal significance in the physical examination

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[1]https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

conducted by clinicians. Abnormal heart sounds can indicate underlying pathological processes or identify patients at risk of cardiovascular disease [1].

Auscultation forms a foundational aspect of cardiac examination during patient evaluation and assessment. Detection of abnormal heart sounds serves to uncover structural or functional cardiac irregularities. While echocardiography is recognized as a viable diagnostic method for various cardiac conditions, auscultation remains crucial as the frontline assessment tool, particularly in cases involving acutely ill patients or where other diagnostic modalities are unavailable. Conventionally, heart sounds comprise S1 and S2 components, representing atrioventricular and semilunar valve closures, respectively. Additionally, physiological S3 and S4 diastolic gallop rhythms may manifest during specific phases of the cardiac cycle [2], [3], [4].

Various pathological conditions, such as valvular abnormalities, intracardiac shunts, impaired cardiac function, and arrhythmias, can generate abnormal heart sounds and murmurs [5], [6], [7]. These sounds are characterized based on their timing, intensity, pitch, shape, location, radiation, rhythm, and response to positional changes and dynamic maneuvers. This characterization aids in distinguishing between physiological and pathological heart sounds [2], [7]. Consequently, the diagnosis of cardiac diseases via auscultation necessitates subjective interpretation, reliant upon extensive clinical expertise and experience.

Phonocardiogram (PCG), a graphical depiction of the recorded heart sound signal, provides an objective, detailed and permanent readout that can be used to analyse valve function and heart health. While it reduces some operator variability, PCG still requires expert interpretation and manual analysis can be onerous and subject to human biases. Heart sound examination includes evaluating S1 and S2 heart sounds, understanding their frequency and pitch, and assessing their regularity (refer to Figure 1). Clinical auscultation can identify changes in heart sounds, the presence of murmurs, and rubs. Heart sounds are brief, and transient sounds are heard during valve closure and opening. Based on the timings, these can be divided into diastolic and systolic sounds. Murmurs are sounds heard due to turbulent blood flow across the valves, chambers, or vessels and are typically longer in duration than heart sounds. They can be classified as systolic, diastolic, or continuous murmurs based on their timing [8].

Accurate identification of cardiac pathologies via auscultation necessitates clinical expertise. Although advanced imaging modalities like echocardiography offer precise diagnosis and severity assessment of cardiac lesions, auscultation retains significance, particularly in resource-constrained settings lacking access to advanced equipment [8]. Thus, there is a growing need for automated methods to identify abnormal heart sounds and murmurs using PCG signals, providing an objective approach to evaluating cardiac abnormalities.

Valvular heart diseases often present with abnormal heart sounds and murmurs. Mitral Stenosis (MS) can cause loud or soft S1 sounds and a mid-diastolic murmur due to obstruction [9], [10]. Mitral Regurgitation (MR) typically results in a soft S1 and a systolic murmur, varying by severity and presence of Mitral Valve Prolapse (MVP) [9], [11]. Aortic Stenosis features a soft S2 with an ejection systolic murmur, while Aortic Regurgitation (AR) also has a soft S2 but a diastolic murmur [12], [13]. Congenital defects like Ventricular Septal Defect (VSD) and Atrial Septal Defect (ASD) produce distinctive murmurs and abnormal heart sounds based on their specific conditions [14], [15]. Patients with Coronary Artery Disease (CoAD) may have S3 heart sounds from left ventricular failure and a valve-related murmur with MR [16]. In addition, pulmonary hypertension can cause a loud P2 component of S2 [17], while extrasystole leads to irregular, diminished heart sounds due to premature beats [18].

Accurate detection of cardiac pathology using auscultation requires experience and clinical skills. Although advanced imaging modalities such as echocardiography can accurately reveal the diagnosis and severity of cardiac lesions, heart sound examination may still be the primary assessment tool in remote areas without advanced echocardiographic equipment, where the clinician's expertise is essential for a provisional diagnosis. This underscores the need for automated identification of abnormal heart sounds and murmurs using automated methods for assessing PCG signals, providing an objective way of evaluating heart sounds and their abnormalities.

A. MOTIVATION

Evaluation of abnormal heart sounds through serial examination helps determine dynamic changes in the heart's hemodynamics, especially following acute injury or complications to the heart. These changes may result from disease pathology or procedural complications during interventions. Therefore, clinicians with good auscultatory skills and knowledge of heart disease pathology are essential. In this context, using automated models to evaluate abnormal heart sounds through PCG signals can aid clinicians in understanding underlying heart pathology, particularly in the absence of echocardiographic diagnostic systems or remote healthcare centres. This approach significantly impacts the identification of diseases and risk stratification of patients with cardiac-related complications. To date, only a few review or survey articles have summarised the existing detection methods for heart anomalies using PCG signals. Table 1 shows the summary of the existing review papers. From the table and our examination, it is evident that no systematic reviews have been conducted on the classification of heart sounds to detect heart abnormalities using PCG signals. Hence, a systematic review is proposed in this area, along with further research challenges for emerging researchers.

B. CONTRIBUTION

The major contribution of the current study is outlined as follows:

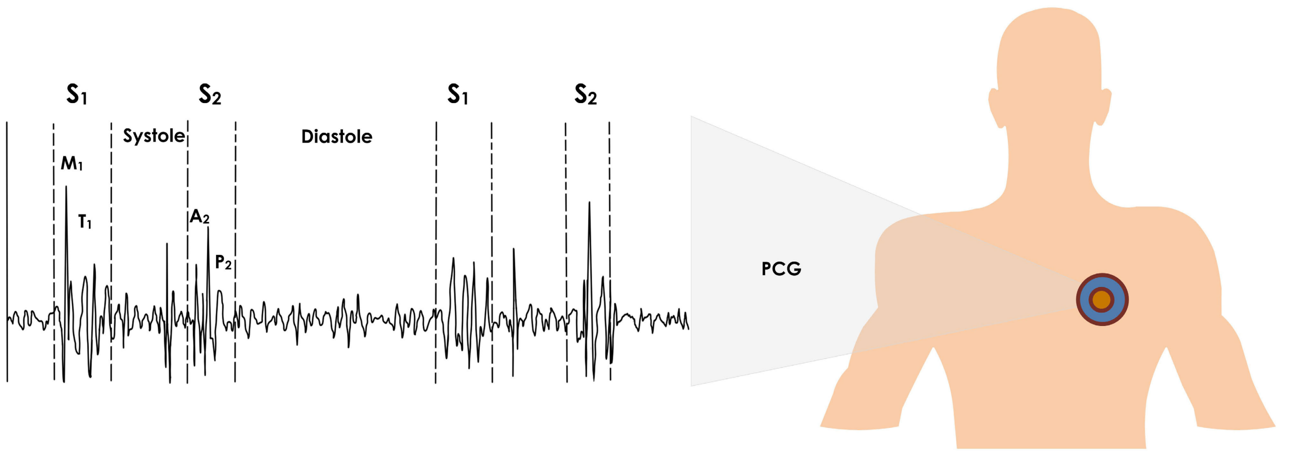

FIGURE 1. PCG recording of heart sound from PhysioNet[2].

TABLE 1. Summary of the review papers recently used for the analysis of PCG papers.

Paper/Year	PCG datasets used	Methods used	Evaluation metrices	Discussion
[19]/2018	Public and private (more than 4)	Time and frequency representation, wavelet domains are used for the detailed analysis of PCG signals	Results are summarized using accuracy, sensitivity, specificity, PPV etc.	• Localization and classification techniques are summarised. • Study showed wavelets and Empirical Mode Decomposition (EMD) are a better choice for noisy signals.
[20]/2019	Public (one)	Convolutional Neural Networks (CNN) are used for the analysis of PCG signals	Accuracy	• Showed the application of DL approaches using various signal (e.g. PCG and Electrocardiogram (ECG)) and imaging (e.g. CT, MRI etc.) modalities. • Fewer papers are considered for PCG analysis.
[21]/2022	Public (two)	ML and CNN approaches	Sensitivity	• Review performed using 60 papers (2008-2020). • Only 2 papers pertaining to PCG were considered for the analysis.
Proposed	**Public and private (more than 4)**	**Various ML and DL approaches are utilised for the detailed analysis of PCG signal.**	**Results are summarized using accuracy, sensitivity, specificity, F1-score, G-mean etc.**	• **Review is carried out as a function of state-of-the-art ML and DL techniques, which includes features extraction, classification, hybrid approaches (i.e., combination of ML and DL) etc.** • **Performed systematic review by using 103 Q1 papers (2013-2023).** • **Proposes certain future directions of the research as most viable for real-time use.**

- We have performed a systematic review [22] and categorized existing mythologies for automated classification of heart abnormalities using PCG signals in traditional/Machine Learning (ML) and Deep Learning (DL) architectures.
- We have investigated these methods by analysing their techniques, dataset used, and performance metrics. We have also summarised all the existing models for a better perspective.
- We catalogue numerous unsolved challenges and trace the pathway that can be followed to progress the existing methods.

The paper is organized as follows: Section I provides the introduction, motivation and contributions of the study. The details of the search strategy are presented in Section II. Section III describes the datasets, preprocessing techniques, and performance metrics employed in various studies. Sections IV and V present studies utilizing ML and

[2]https://www.physionet.org/content/challenge-2016/1.0.0/training-a/#files-panel

DL techniques. Finally, the discussion and conclusion are presented in Sections VI and VII. Further, for the sack of clarity the organization of the paper is portrayed in Figure 2.

II. SEARCH STRATEGY

We searched IEEE Xplore, ScienceDirect, PubMed, and Google Scholar for articles published between 1 January 2013 and 31 Dec 2023 on the application of Artificial Intelligence (AI) methods for Computer-Aided Diagnosis (CAD) based on PCG using keyword combinations (refer to Table 2). We included only English articles published in Q1 tier journals, and excluded animal studies, human studies on fetal, neonatal and pediatric subjects, conference papers, review articles, and academic thesis. The percentage of paper downloaded and selected from various reputed databases is shown in Figure 3.

The initial search yielded 635 articles and 89 duplicate articles based on title and author names were discarded. Abstracts of articles were manually reviewed by authors for relevance, reducing the number to 287. Among these, 103 had been published in Q1 journals, and were included into our analysis (refer to Figure 4), with the following inclusion and exclusion criteria,

Inclusion:

- Articles must be in English.
- Only the articles present in the Q1 journal are selected.
- Papers based on PCG signals or PCG with other signals for the classification of heart sound in only considered.

Exclusion:

- Study on animals is not considered.
- Studies purely on the fetal and neonatal, children are not considered.
- Articles published in conferences are not considered.
- Review papers are not considered.
- Thesis is not considered.
- Articles purely-based on devices (not using CAD tools) are not considered.

III. AUTOMATED SYSTEM: DATASET, PREPROCESSING, AND ANALYSIS

CAD utilizes computer algorithms and software to scrutinize physiological signals [23], [24], [25] and medical images [26], [27], [28]. CAD systems are engineered to refine the precision and efficiency of physiological signal interpretation by providing supplementary insights or pinpointing areas of potential anomalies. These paradigms have found widespread applications in various medical domains, including radiology, pathology, ophthalmology, and neurology. Employing sophisticated methodologies such as traditional approach and DL, these systems extract pertinent features and patterns from PCG signals, thereby bolstering clinical decision-making. CAD has emerged as a robust adjunct in physiological signals, aiding healthcare professionals in the identification, diagnosis, and monitoring of various medical conditions [23], [24], [25], [26], [27], [28].

Two primary paradigms have gained significant traction in the domain of abnormality detection heart sound: The traditional approach (i.e., ML-based techniques and unsupervised statistical techniques) and DL approaches. The first paradigm encompasses ML-based techniques and unsupervised statistical methods. These approaches rely on extracting relevant features from PCG signals and utilizing algorithms to identify patterns and make predictions. Unsupervised statistical techniques, such as clustering [29] and anomaly detection [30], can aid in identifying potential abnormalities without the need for labelled data. However, in ML-based techniques, handcrafted features from the PCG signals are classified using methods such as K- Nearest Neighbor (KNN), Support Vector Machine (SVM), ensemble model, etc. The second paradigm involves DL techniques, revolutionizing computer vision and medical image analysis. DL models, such as CNNs [31], U-Net architectures [32], and Recurrent Neural Network (RNN) [33], have demonstrated remarkable performance in tasks like image segmentation, classification, and detection.

Figure 5 illustrates the schematic depiction of the methodology commonly adopted across numerous studies to detect heart abnormalities using PCG signals. The initial segments delineate many learning methodologies, including Neural Networks (NNs), autoencoders, and DL models, used for feature extraction and classification. These methodologies operate on the PCG Signal derived from the afflicted organ, namely the heart. Subsequently, another segment, "Model Generation," was tasked with discerning the optimal model among a selection of candidates and ranking based on their performance in distinguishing between normal and abnormal cases.

A. DATASETS

The datasets play a significant role in validating the systems that identify cardiac disorders with state-of-the-art techniques. The heart sound recognition/ classification task is carried out by classifying abnormal and normal heart sound (i.e., 2-class classification), and multi-class categorization is performed by categorizing heart sound into multiple disorders. It is observed from systematic literature that some popular datasets are publicly available to encourage research on identifying abnormalities in the heart. Detailed descriptions of these datasets are given below.

PhysioNet/ Computing in Cardiology Challenge dataset [34]: It comprises 6 sets, namely training-a to training-f. It is referred to as PhNetDB in this paper and is available in Classification of Heart Sound Recordings: The PhysioNet/Computing in Cardiology Challenge 2016 v1.0.0[3]. It consists of a total raw recording of 3240 (Normal: 2575 and Abnormal: 665). The abnormal or pathological class includes diseases such as Aortic Stenosis (AS), MR, Aortic Regurgitation (AR), etc. In challenging data, Train data comprises 764 patients/ subjects with heart sound

[3]https://www.physionet.org/content/challenge-2016/1.0.0/

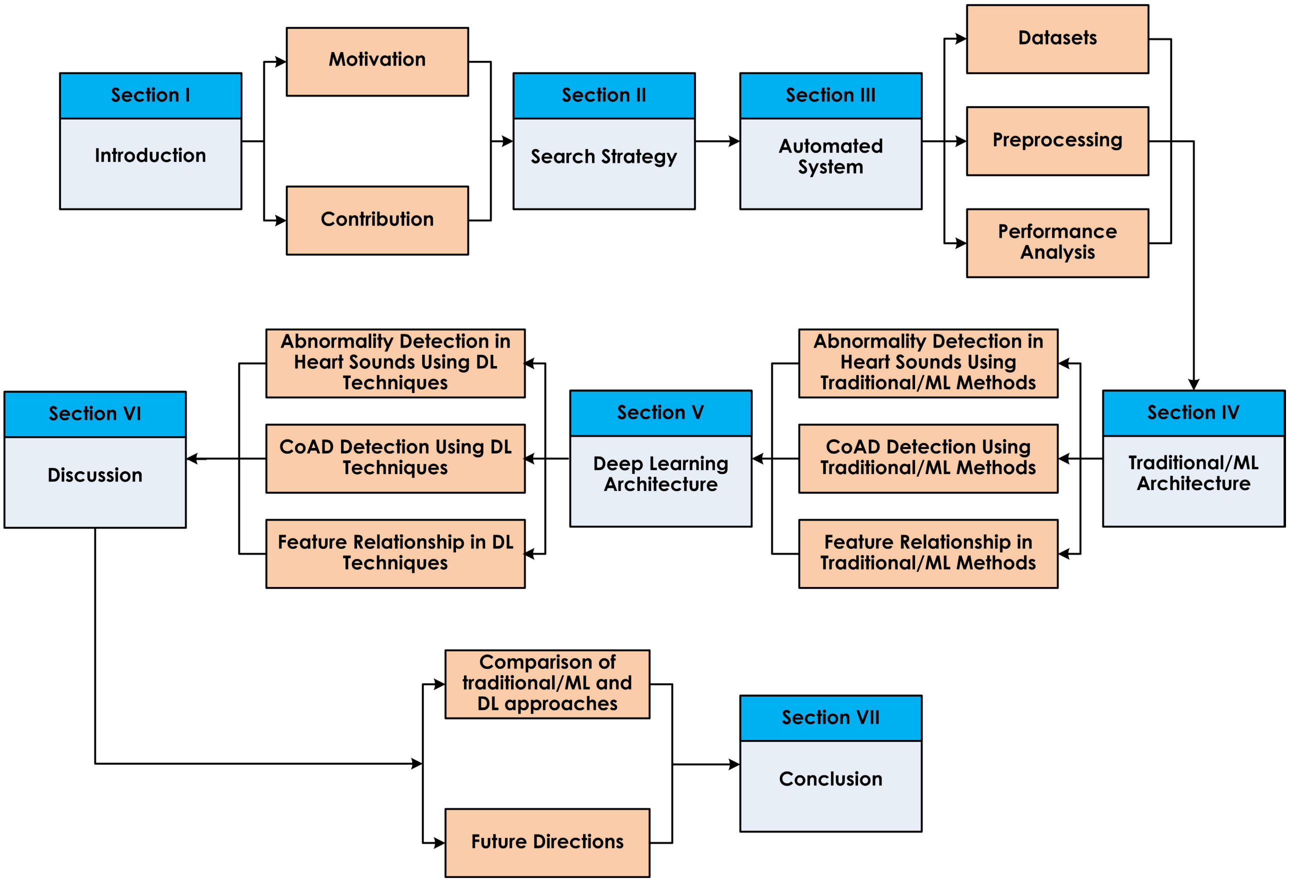

FIGURE 2. Organization of this paper.

TABLE 2. Search query or string used in the current study.

Search query or string
(Phonocardiogram) AND (Machine Learning) (Phonocardiogram) AND (Deep Learning) (Phonocardiogram) AND (artificial intelligence)
(heart valve disorder) AND (phonocardiogram) OR (pcg) AND (machine learning) (heart valve disorder) AND (phonocardiogram) OR (pcg) AND (deep learning) (heart valve disorder) AND (phonocardiogram) OR (pcg) AND (artificial intelligence)
(abnormal heart sounds) AND (phonocardiogram) OR (pcg) AND (deep learning) (abnormal heart sounds) AND (phonocardiogram) OR (pcg) AND (artificial intelligence) (abnormal heart sounds) AND (phonocardiogram) OR (pcg) AND (machine learning)
(cardiac disease) AND (phonocardiogram) OR (pcg) AND (artificial intelligence) (cardiac disease) AND (phonocardiogram) OR (pcg) AND (machine learning) (cardiac disease) AND (phonocardiogram) OR (pcg) AND (deep learning)

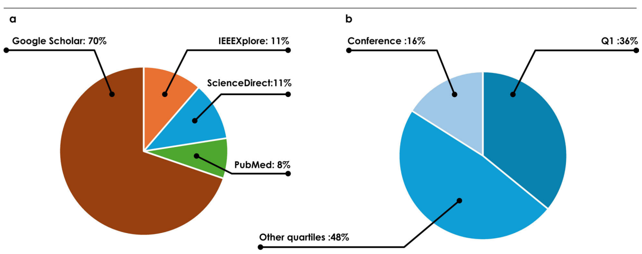

FIGURE 3. a) Articles downloaded from reputed databases, b) quartile categories.

recording of 3153, with a duration of 5 s to 120 s. Test data: 30 patients/subjects with heart sound recording of 1277 having duration 6 s to 104 s. All PCGs were resampled to 2000 Hz. The sample signals are shown in Figure 6.

The PASCAL[4] dataset was released for the segmentation and classification of heart sounds challenge using PCG signals and is referred to as PSDB in this paper. For the classification task, data were collected from two sources using: i) stethoscope Pro iPhone app, i.e., Dataset A (DS A), and ii) digital stethoscope DigiScope, i.e., Dataset B (DS B). Dataset A and Dataset B consist of 176 and 656 auscultations, respectively. In DS A, class/count is given as normal (NR)/31, murmur (MU)/34, extra heart sound (EHS)/19, the

[4]https://istethoscope.peterjbentley.com/heartchallenge/index.html

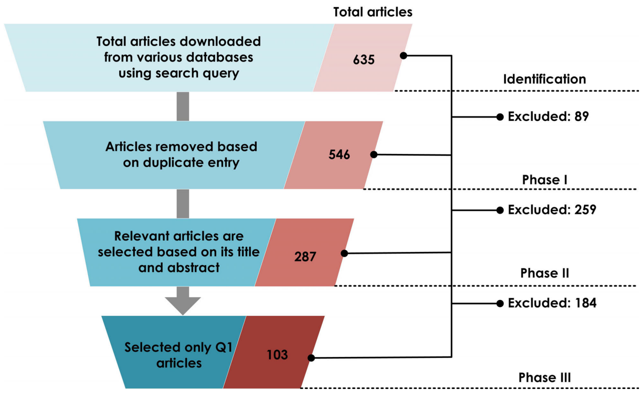

FIGURE 4. Search strategy used in current study.

artifact (AR)/40, and unlabelled test/ 52. Likewise, in DS B, class/count is given as normal (NR)/320, murmur (MU)/95, extra-systole (ES)/46, and unlabelled test/195.

Yaseen et al. [35]: The authors have collected PCG from 48 various sources and made available at https://github.com/yaseen21khan/Classification-of-Heart-Sound-Signal-Using-Multiple-Features-/blob/master/README.md; it is referred to as YDB in this paper. They eliminated the data with high noise, and the signals were sampled at 8000Hz. It comprises 5 classes/counts NR/200, AS/200, MS/200, MR/200, and MVP/200. A total of 1000 files for NR and AB categories in *.wav* format.

B. PREPROCESSING

The heart sound can be graphically represented by using PCG signals. However, along with useful information, these also contain noise. Noise could be due to the surrounding environment or the recording instrument itself. Although these noises are controllable, they cannot be eliminated. Hence, it is very essential to use certain de-noising techniques to highlight the required sound range [36]. Studies have used Butterworth filters in the range varying from 20 Hz upto 500 [36], [37], [38], [39] or wavelet transform [40], adaptive finite impulse response notch filter and a high-pass Butterworth filter [41] for preprocessing the PCG signals.

Further, PCG signals are separated into systole and diastole states of cardiac cycles. This helps in the classification of the abnormalities. This separation into cardiac cycles can be performed with or without using ECG as reference signals [42], [43]. A study by [42] used Springer's improved version of Schmidt's segmentation algorithm for cardiac cycle separation, which doesn't require ECG signals as a reference. A study by [44] used amplitude and frequency-based segmentation techniques. Studies also use envelop extraction [45], [46]. A study by [45] performed homomorphic filtering on the preprocessed PCG signals. In this stage, the non-linear combination of signals is converted into linear combinations using logarithmic transformation. Further, the peaks were identified. Shannon entropy envelopes are used in [47]. Segmentation of the signals is also done using Hidden Semi-Markov Models (HSMM) as these techniques can give good results even for the noisy PCGs [39], [42], [48], [49], [50], [51]. The performance of these models is ensured with the help of Viterbi algorithm [39], [49], [50].

C. PERFORMANCE ANALYSIS

The major aspect is how the performance of traditional/ ML methods and DL methods are analyzed. For classification, Accuracy (AC), Precision (PR), or PPV: Positive Predictive Value, Specificity (SP), Sensitivity (SE) or Recall (RE), and F1-score or F-measures (FM) are calculated using a confusion matrix [27]. The Mean Accuracy (MAC) is calculated based on the SE and SP, which reflects the overall performance of the predictive model [34], [52]. The balanced performance between 2 classes is calculated using G-mean [53]. All are described using T_p*:true positive*, T_n*:true negative*, F_p*:false positive*, and F_n*:false negative*. Parameters such as the F1-score and Area Under Curve (AUC) are used to compare the performance of the system and classifier efficiency, respectively [28], [29]. Another parameter, such as Matthew's Correlation Coefficient (MCC), ranges from $0 - 1$; the higher the MCC better the classifier performance [54]. These performance measures reflects the ability of diagnostic system for identifying abnormalities in heart sounds. These parameters of the diagnostic tools should be at greatest possible to exhibits its correctness towards specific task. The figures of merits are shown in the Table 3.

IV. TRADITIONAL/ML ARCHITECTURE

Multiple studies are carried out using various traditional approaches to classify PCG signals into binary and multi-class. In this review, different traditional methods used for classification are summarized and shown in Figure 7. Traditional Architecture (TA)/ ML architecture generally follows preprocessing, feature extraction, feature reduction/ranking and classification. Further, these methods are classified into supervised learning and unsupervised learning approaches for the detection of heart abnormalities using PCG signals.

Unsupervised: This type of learning approach supports the classification job by using an unlabelled dataset. Data preprocessing, feature selection and extraction are commonly performed using unsupervised learning [139]. It also employed for clustering, feature dimensionality reduction, density estimation etc. [140].

Supervised: This learning is widely used for regression i.e., to fit the data and classification for separating the data. It uses the labelled dataset to predict the classes [140]. For example, supervised learning is text recognition [141], traffic sign recognition [142] etc.

A. ABNORMALITY DETECTION IN HEART SOUNDS

Studies have considered both unsupervised and supervised techniques for the classification of binary and multi-class heart abnormalities using PCG signals. Spectral clustering is

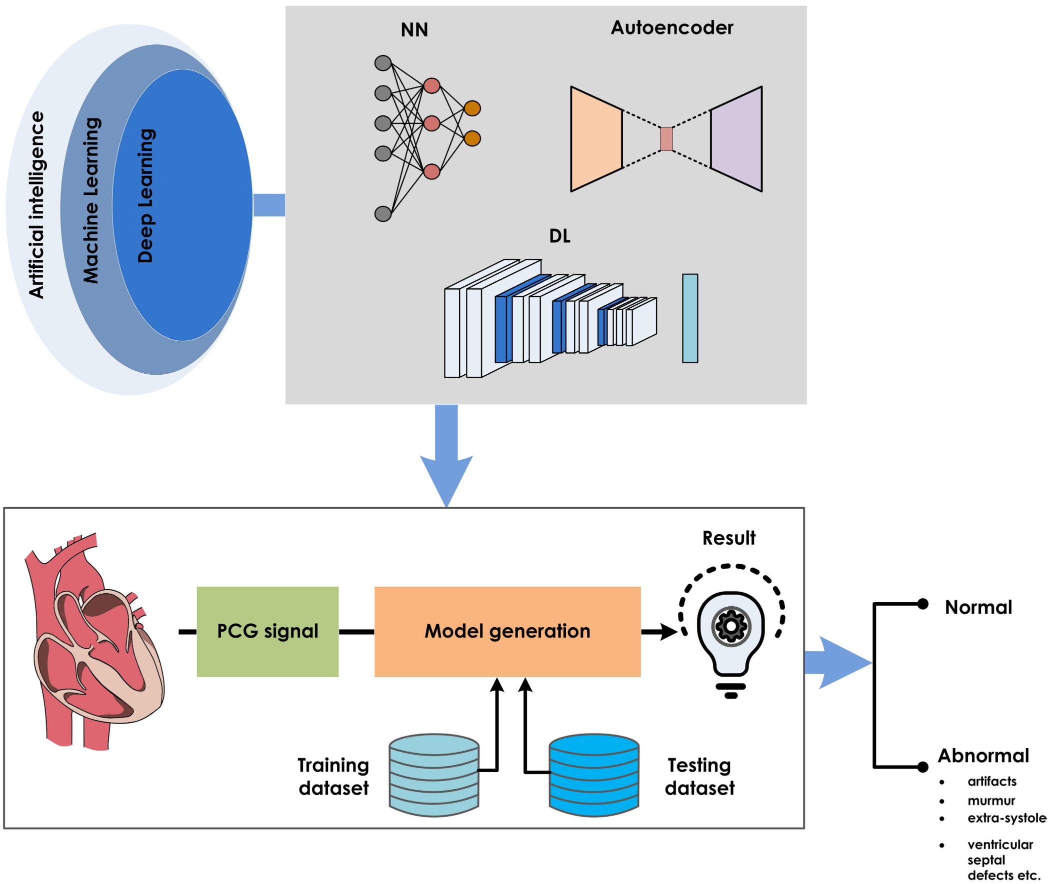

FIGURE 5. Graphical illustration of various approaches for detecting heart anomalies (as targeted application) with fundamental purpose.

TABLE 3. The metrics that reflects the system performance.

Sl.No	Evaluation Metric	Range	Equation
1	AC:Accuracy	0-100%	$(T_p + T_n)/(T_p + F_p + T_n + F_n)$
2	SE:Sensitivity or RE:Recall	0-100%	$T_p/(T_p+F_n)$
3	SP:Specificity	0-100%	$T_n/(T_n+F_p)$
4	MAC:Mean accuracy	0-100%	$(SE + SP)/2$
5	PR:Precision	0-100%	$T_p/(T_p+F_p)$
6	FM: F-measure, F1-Score (also known F measure)	0-100%	$(2 \times PR \times RE)/(PR + RE)$
7	GM:G-mean	0-100%	$\sqrt{(SE \times SP)}$

used to classify the unlabelled data set. The affinity matrix is created by considering the similarity values of two feature vectors, and the eigenvector of this affinity matrix is then used to cluster the similar feature vectors [29]. A study by [55] proposed a privacy-based approach for PCG signals analysis using F-test.

Studies have also used various supervised classifiers such as SVM ([35], [37], [42], [43], [51], [56], [57], [58], [59], [60], [61], [62], [63], [64], KNN ([35], [42], [43], [60], [62], [63], [65]), logistic regression [43], ensemble techniques [38], [42], [43], random forest ([60], [61], [64], [65]) for binary and multi-class classification. Some studies have used variation in SVM to attain better classification rates. A study by [66] has used a Twin SVM (TWSVM) on various features and attained an accuracy of 90.4%. A study by [67] has used Least Square SVM (LSSVM) to achieve an accuracy of 86.718%. A study by [44] used five types of artificial neural networks, namely narrow, medium, wide, bilayered, and trilayered for training the extracted spectral features. They modelled various combination of features with the different networks and individual features spectral spread, and spectral slope attained maximum accuracy, sensitivity, specificity, precision and F1-score each of 99.9% for the medium, wide, narrow, bilayered, and trilayered neural networks.

B. CoAD DETECTION USING TRADITIONAL/ML METHODS:

A study extracted time-domain, frequency-domain, entropy, and cross-entropy features. The study has used a statistical analysis technique called the generalized linear mixed model.

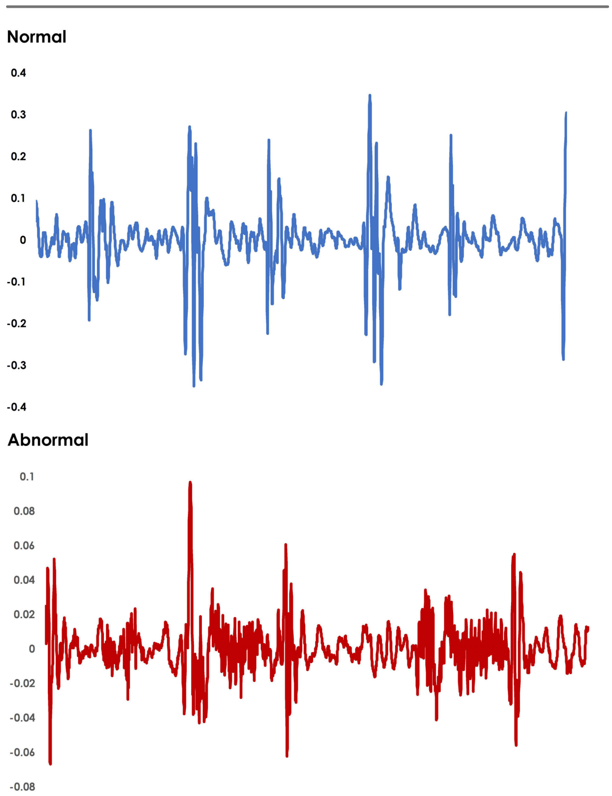

FIGURE 6. Example of PCG signal normal (a0007.wav) and abnormal (a0002.wav) with 3500 values[2].

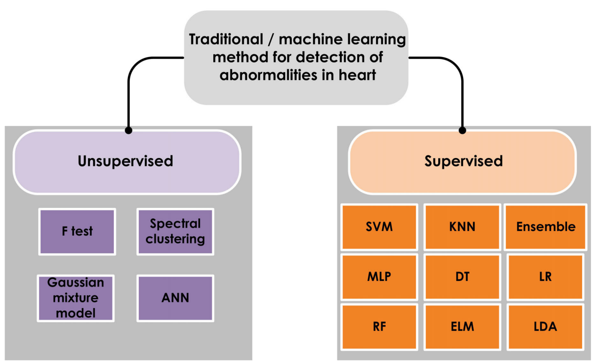

FIGURE 7. Various Traditional/ ML models applied to detect heart abnormalities using PCG signal.

To reduce the dimensionality of the features, the study has used two feature selection techniques: information gain and SVM–Recursive Feature Elimination (SVM-RFE). For the top 30 features selected by SVM-RFE, the study attained a maximum accuracy of 90.92% using the SVM classifier [68]. A study by [69] used a synchro-squeezing transform to detect CoAD in heart signals. For the fusion of spectral features on a multi-channel framework, they observed an accuracy of 83.48%.

C. FEATURE RELATIONSHIP IN TRADITIONAL/ML METHODS

Features are extracted from PCG signals either from 1D CNN signals or from 2D images. 1D CNN .wav files of PCG signals are converted into 2D Cochleagram [29], chromagram [58] and spectrogram images [58]. A study has extracted Local Binary Patterns (LBP) from these 2D images to extract the textual descriptors. LBPs are used because of their resistance to grayscale variance and are not computationally complex [58]. A study has extracted Mel-Frequency Cepstral Coefficients (MFCC) and Discrete Wavelet Transform (DWT) features from PCG signals and fed them as input to various models. They found that a combination of both features provides good results [65].A study has considered Fractional Fourier Transform-Based Mel-Frequency Spectral Coefficients (FrFT-MFSC) features. The fractional Fourier transform highlights the signal rotation in the time-frequency domain. These are more suitable for the representation of signals that are not stationary [42]. It is observed that wavelet-based features could capture the otherwise neglected features on an inhomogeneity scale. The study has utilized features at wavelet coefficients at levels 3 and 4 and approximation coefficients at level 4, thus making a total of 900 wavelet-based features. This study also captured various statistical features [49].

Spectral-based feature extraction has also proven to be a good approach for the classification of PCG signals [44]. A study has extracted various spectral features, namely spectral kurtosis, spectral skewness, spectral roll-off point, spectral slope and spectral spread and by using the combination of these features with the ANN classifier, has achieved a better accuracy of 99% [44]. Another study has extracted features from multiple domains such as time, frequency, state amplitude, energy, spectrum-domain, cepstrum-domain, cyclostationary features, High-order statistical features, entropies, etc. Their analysis of various feature domains indicated that frequency, energy, and entropy domains outperformed the other domain features [51].

In [30], the local and global statistical features are extracted from a windowed PCG signal. The authors have considered the static features of MFCC, Perceptual Linear Prediction (PLP) and Linear Predictive Cepstral Coefficients (LPCC) with logarithmic energy and their first and second derivative. Further, to reduce the dimensionality of the features extracted, they applied a mutual information-based feature selection approach. A study by [29] has used Cochleagram features by considering the first 20 gamma tone filter bank energy as effective features.

Time and wavelet-based features are utilized for multi-class classification by [67]. They used Daubechies-2 wavelets to extract wavelet coefficients from PCG signals. Studies have also used a combination of various types of features for multi-class classification. In [71], the MFCC and LPCC from 1D CNN PCG signal are extracted. They converted the 1D PCG to 2D using Continuous Wavelet Transform (CWT) and deep spatial features are obtained using various deep CNNs. The features are selected using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) [71].

Studies have also used a combination of features by extracting time and frequency domain features from DWT, Wavelet Packet Transform (WPT), Perceptual WPT and EMD methods and deep features from various pretrained models such as VGG16, ResNet-50 and MobileNetV2 [60]. A Multilayer Extreme Learning machine (ML-ELM) is used for the PCG scalogram. Further, to identify the most unique feature, the recursive feature elimination technique is used [60].

It is observed that, initially EMD is used to denoise the raw PCG signals. Further, for the representation of various classes of signals, one-dimensional Local Ternary Patterns (LTPs) and MFCCs were extracted. These features were then fused and fed to the SVM classifier for classification [59].

Since the PCG signals are non-stationary, a study by [61] used Fourier-Bessel Series Expansion-based Empirical Wavelet Transform (FBSE-EWT) for the decomposition of the signals. However, this produces a different number of intrinsic mode functions to maintain uniformity. The study has used strategies based on signal energy, statistical analysis, and signal similarity measures. The dimensionality is reduced by using Salp Swarm Optimization Algorithm (SSOA), Emperor Penguin Optimization Algorithm (EPOA), and Tree Growth Optimization Algorithm (TGOA).

A study by [62] has generated 768 features from the one-dimensional binary pattern with three kernels. Further, the feature set is reduced by Neighbourhood Component Analysis (NCA) based on weights. Features were also generated by using a graph-based technique named Petersen Graph Pattern (PGP), which is combined with tent pooling for decomposition. Then, the features were selected by using Iterative NCA [63].

To reflect the major correlation energy of a template signal, a study by [64] first constructed a wavelet group. Next, the target signals' fuzzy characteristics are acquired by convolving them using the best possible wavelet collection. Lastly, matching features between the template and target signals are computed using fuzzy features. Self-matching features in the frequency domain, mutual matching features in the frequency domain, and self-matching features in the time domain were extracted in their work. Further, they also extracted MFCC features from PCG signals and observed that combining Fuzzy Matching Feature Extraction (FMFE) with MFCC attained the maximum accuracy of 99% for SVM classifiers. Table 4 shows the used traditional/ML approaches, datasets, classes, and performances of the studies analysed using PCG signal and Table 5 shows the traditional methods used for detecting CoAD.

V. DEEP LEARNING ARCHITECTURE

In the literature, it is observed that most of the work significantly uses the DL architecture (namely 1D CNN, 2D CNN, RNN, and Autoencoders Neural Network (AEN)) to characterise the heart anomalies using PCG signal. The signal-based or image-based inputs are fed into the various models. As a result of the present study, we have organized all the various nomenclature of DL architecture around the related work, as shown in Figure 8. Here, we describe briefly an overview of the various DL approaches used to identify heart abnormalities using PCG signal.

CNNs: The advancement in the feed-forward NN eventually introduces CNNs as next- generation neural computation approach in computer vision area. CNNs are widely used in various applications, to name a few: speech recognition [143], text classification [144] etc. In CNNs, the layers referred to as convolutional stacked together with pooling layers followed by fully connected layers are used for classification tasks. In the ImageNet classification competition, a new CNN-based architecture called AlexNet [145] achieved unrivaled performance. Further to enhance the overall accuracy ResNet was introduced by Microsoft researchers [146]. Herein residual blocks and skip-connection networks concepts are introduced. Another model, i.e., VGG is introduced by Simonyan and Zisserman [147] with a depth of 16 to 19 weight layers having a convolutional layer (3×3) to achieve promising results.

RNNs: RNNs are designed to process sequential information form text, videos, and audio [148]. Long-Term Memory Networks (LSTMs) are variants of RNN and comprise recurrent memory blocks [149]. Further, Bidirectional Long Short-Term Memory (BiLSTM) shows better performance, when compared to RNN and LSTM for classification tasks [150]. Here, two LSTM layers are used for information processing in both directions [151].

AEN: AEN comprise three layers: input, hidden (coding), and output (decoding). It is an unsupervised learning method, used for dimensionality reduction [152]. Its learning efficiency is increased as it converts the input into lower-dimensional feature vectors. Another variant of autoencoder i.e., denoising autoencoder is proposed to enhance the robustness of the model [153].

A. ABNORMALITY DETECTION IN HEART SOUNDS

The temporal statistics and dynamics are captured efficiently from the heartbeat sequences using RNNs [33]. BiLSTM performs 1.3% better than Gated Recurrent Units (GRU) [33]. In [82], the capability of the 1D CNN model is improved when compared with 2D CNN model. However, three VGGNets are used to construct the promising predictive model [83].

In [84], AEN, CNN, Deep Neural Network (DNN), ANNs, and SVM are compared and AEN showed better results. The CNN architecture achieved a promising performance using transition blocks and stacked clique [31]. The time and frequency domain features are extracted using GRU and CNN, respectively and fused to get Heart Sounds Parallel Feature fusion classification Network (HSPFN) [85]. The Large Kernel Network (LKNet) is proposed in [36], and multiple LKNets are fused to enhance the accuracy of the transfer learning model. The authors have studied various attention modules and data-balancing techniques to evaluate the effectiveness of the DsaNet [86]. In [86], the DsaNet result is improved by 2.37% when using a 2-stage training

TABLE 4. Summary of the traditional/ML approaches in terms of their characteristics and results used to detect heart abnormalities.

Sl.No.	Ref	Year	Methods	Results	Database	Count	Class
			Binary class classification				
1	[46]	2012	Gaussian Smoothing Filter + Correlation-based Technique	SE: 99%, PPV;98.6%	Private		S1, S2
2	[51]	2018	Multi-domain features + SVM	SE: 88% , SP:87%, overall score: 0.88	PhNetDB		NR, AB
3	[45]	2018	Envelope extraction using homomorphic envelogram+SVM with RBF	AC:91%	PSDB		S1, S2
4	[66]	2019	Wavelet fractal+ TWSVM	AC: 90.4%, SE: 94.6%, SP: 85.5%, F1 score: 95.2%	PhNetDB		NR, AB
5	[55]	2019	F-test	AC: 80%	MIT Physionet		NR, AB
6	[72]	2019	STGNN and MTGNN (Static and the Moving Time-Growing Neural Network) + Repeated random sub-sampling	84.20%	Private	Children:140 Elderly patients: 50 (university hospital)	NR, AB
7	[42]	2020	FrFT-MFSC + classifiers (SVM, KNN , ensemble)	Score: 0.92, SE: 87.35%, SP: 96.66% for SVM	PhNetDB		NR, AB
8	[49]	2020	Wavelet + statistical features + Classifiers (bagging +boosting)	AC: 86.6%	PhNetDB		NR, AB
9	[29]	2020	Cochleagram features + Spectral clustering	F1-score: 98% normal, F1-score: 92.5% abnormal	PhNetDB	NR: 589, AB:586	NR, AB
10	[73]	2020	ANN with Multilayer Perceptron (MLP)	ROC:94%	PSDB		NR, AB
11	[37]	2021	Wavelet scattering+ SVM	AC:92.23%, SE:96.62%, SP:90.65%, Mean AC:93.64%	PhNetDB	Recording: 3240 (NR: 2575, AB: 665)	NR, AB
12	[74]	2021	TQWT + Fano factor + Gradient boosting framework	SE:89.30%,SP:91.20%, overall score: 90.25% , SMOTE:- SE:86.32%,SP: 99.44% ,overall score: 92.88%	DB1: PhNetDB , DB2: PSDB		NR, AB
13	[58]	2023	LBP,Adaptive LBP, Ring LBP+SVM	Mean AC:94.87%, PR:93.11%, F1-score:95.273%	PhNetDB	Recording: 3240	NR, AB
14	[75]	2021	Various Decompo-	SE:97.73%, SP:98.05%,	PhNetDB		NR, AB

TABLE 4. *(Continued.)* **Summary of the traditional/ML approaches in terms of their characteristics and results used to detect heart abnormalities.**

			sition Techniques + Dynamical estimators consisting of neural networks	Overall Score: 97.89%, AC: 97.89%			
15	[44]	2022	Fusion of spectral features + ANN	AC: 99.99% for Spectral Spread.	Private	NR:231, AB:230	NR, AB
16	[65]	2022	DWT + MFCC + classifiers (KNN, RF, XGB)	AC: 89.53%, F1 score: 0.9, AUC: 0.95	DB1: PhNetDB , DB2: PSDB	DB1: AB:816, NR 2725, DB2: AB:231, NR:100	NR, AB
17	[57]	2023	ABS-GP, BS-GP+ FCM + various classifiers	AC: 95.39% - SVM	PhNetDB	Recording: 3153 (NR:2488, AB: 665)	NR, AB
18	[43]	2023	Fast Fourier Transform (FFT) + Hybrid structured sparse learning+ various classifiers	AC:96.64 - Azad3, 98.02 - PhNetDB, and 84.7 - PSDB	DB1: PhNetDB , DB2: PSDB, DB3: AZAD3		NR, AB
19	[30]	2023	Statistical feature +KNN, Gaussian mixture models	AC:94.97%	PSDB	recording:176	NR, AB
20	[76]	2022	Doubechies wavelet transform+ Shannon energy + FFT+Classification	Se:99.5%, Sp:99.6%, AC.:99.6%, FP:0.388%	PhNetDB		NR,AB
				Multi-class classification			
21	[59]	2020	One-dimensional LTPs + MFCC +SVM	AC:95.24% - 3 class, AC: 95.63% -2 class	private	NR:140, ASD:85, VSD:55	NR,ASD, VSD
22	[77]	2023	Statistical Rule-Based Models (RBM) + DT	AC:100% RBM	YDB		Early Systolic Click (ESC), ESC with murmur (ESCM), and mid-SC with murmur (MSCM)
23	[78]	2020	Chirplet transform + Multi-class composite classifier	SE:99.44%-AS, SE:98.66%-MS, SE:96.22%- MR	YDB	NR:200, AS:200, MR:200, MS:200	MR,MS,AS,NR
24	[67]	2010	Time and wavelet feature + LSSVM	AC: 86.718%		Recording: 64	5
25	[50]	2016	HSMM + logistic regression	F1 score: 95.63±0.85%,	Private	NR:38, MVP:37, benign murmur:36, aortic:5, other: 7	NR, MVP, benign murmur, aortic, other

TABLE 4. ***(Continued.)*** **Summary of the traditional/ML approaches in terms of their characteristics and results used to detect heart abnormalities.**

26	[47]	2017	Empirical Wavelet Transform (EWT) + Shannon entropy envelope extraction	AC: 95.5%, SE: 98%, PPV: 97.4%,	Multiple datasets		Multi-class
27	[35]	2018	MFCC, DWT+SVM, Deep Neural Network (DNN), displacement-based KNN	AC: 97%	YDB		NR, AS, MR, MS, and MVP
28	[79]	2018	MFCC and Hidden Markov Model.	AC: 92.68%			NR + 13 type heart murmur
29	[70]	2021	EMD + RFE + KNN	AC:94%	Private		NR, AS, MR, MS, and MVP
30	[62]	2021	1D CNN binary pattern+ NCA + KNN, SVM	AC: 99.5% - KNN, AC:98.30% - SVM	YDB	NR:200, AS:200, MR:200, MS:200, MVP:200	NR, AS, MR, MS, and MVP
31	[63]	2021	PGP + Iterative NCA + Various classifiers	AC: 100% - KNN	YDB		NR, AS, MR, MS, and MVP
32	[80]	2021	TQWT + Fast and Adaptive Multivariate EMD (FA-MVEMD) +Shannon energy envelope + RBF NN	AC: 97.75 % - 2 class, AC: 98.69% - 4 class, AC: 98.48% - 5 class			2 class:NR, AB, 5 class: NR, AS, MR, MS, and MVP
33	[60]	2022	Multiple features + RFE Feature Selection + Various classifiers (KNN,SVM, RF, ML-ELM)	AC:99.4%, MCC:99.3%, G-mean: 99.3%.	DB1: YDB, DB2: PhNetDB	DB1: NR:200, AB:800 DB2:NR: 2575, AB:665	NR, AS, MR, MS, and MVP
34	[61]	2022	FBSE-EWT + Feature selection (SSOA, EPOA, TGOA) +ML classifiers (ANN, SVM, RF)	AC: 98.53% - 5 class, AC: 98.44% - 4 class, AC: 99.07% - 3 class, AC: 99.70% - 2 class	YDB	NR:200, AS:200, MR:200, MS:200, MVP:200	5 class: NR, AS, MR, MS, and MVP, 4 class: NR, AS, MS, MVP+MR, 3 class:NR, AS, MS+ MVP+MR, 2 class:NR, AS+MS+ MVP+MR
35	[38]	2022	Burg's autoregressive model + Ensembled bagged trees	AC: 93.46 - PhNetDB, AC: 99.28% - YDB	DB1: PhNetDB, DB2: YDB		NR, AS, MR, MS, and MVP
36	[39]	2022	Hilbert Envelope Feature (HEF)-RF,	AC: 94.78% (±2.63), SE: 87.48 %(±6.07),	DB1: YDB, DB2: Private	DB1. NR:200,	NR, AS, MR, MS, and MVP

TABLE 4. ***(Continued.)*** **Summary of the traditional/ML approaches in terms of their characteristics and results used to detect heart abnormalities.**

			HEF-ResNet-INTERSPEECH 2009 EMOTION CHALLENGE (IS09)-RF, HEF-ResNet-IS09-SVC	SP: 96.87% (±1.51) F1: 87.47% (±5.94),		AS:200, MR:200, MS:200, MVP:200, DB2. 364	
37	[64]	2022	MFCC+FMFE+SVM	AC:99%, SE:99.4%, SP:99.7% -	YDB		NR, AS, MR, MS, and MVP
38	[81]	2022	Numerical and graphical features + ML and DL classifiers	AC: 100% for ML, AC: 99.17% for CNN	PSDB	NR:462, Murmur:200, Artifact:80, Extra heart sound:38, Extrasystole:92	NR, Murmur, Artifact, Extra heart sound, Extra systole
39	[71]	2023	MFCC + deep CNN + PSO and GA + Vision Transformer (ViT)	AC: 99.90%, F1: 99.95%	YDB	NR:200, AB:800	NR, AS, MR, MS, and MVP

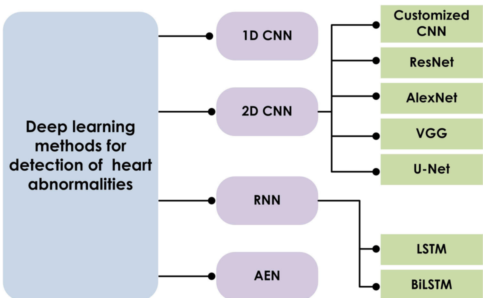

FIGURE 8. **Various DL models applied to detect heart abnormalities using the PCG signal.**

approach. The stacked autoencoder-based DNN is developed [87]. Recently, 1D CNN has been utilized to construct an Attentional Multi-Scale Temporal Network (AmtNet), and a Convolutional Block Attention Module (CBAM) has been used to improve the feature map [88]. In [89], the Wasserstein autoencoder-based model reconstructs the PCG signals. In addition, various deep Generative Adversarial Networks (GAN) are also evaluated [89].

The usage of enhanced MFCC features with ResNet has increased the efficiency of the classification when classifying 3-class data [90]. For 3-class classification, AEN outperforms, with a significance level of 5 % when compared to other methods [84]. The generative model such as WaveNet is used in [91], for multi-class categorization, which comprises a residual block with activated function as gated. In [92], the cardiac auscultation is detected using lightweight CRNN model called CardioXNet. The two-phase learning structure of CardioXNet handles 2-class and 5-class problems efficiently.

A novel log MFSC features are used, which is the distinctive form of MFCC [93]. It addresses the four-class classification problems, i.e.,ASD, VSD, Patent Ductus Arteriosus (PDA), and normal. In [94], a combination of Stationary Wavelet Transform (SWT) and Hierarchical Long Short-Term Memory (HLSTM) is utilized for binary and multi-class categorization. For multi-class categorization of the heart sound, the features were extracted using MFCC, spectrogram, and chromagram with CNNs and referred to as Feature-based Fusion Network (FDC-FS) [95]. Recently, Continuous Wavelet Transform (CWT) with Noise Robust Cardio net (NRC-Net), a type of CRNN, has better accuracy when compared to the visual geometry group with 16 layers VGG16 [96].

B. CoAD DETECTION USING DL TECHNIQUES

The heart irregularities due to coronary artery disease are captured using a PCG and ECG. It is very difficult to identify CoAD using these modalities due to its lower diagnostic sensitivity [53]. Hence, multi-domain features are integrated under the CNN framework to detect CoAD by using ECG and PCG [53], The researchers have collected data, with the subjects having stenosis ≥50% in the left circumflex, left anterior descending, and right coronary artery [53]. In [97], the FFT and P-Welch Sub-Band Moments (SBMs) give a multichannel accuracy of 82.57% by using channels closer to the inferior, anterior, and apex of the heart.

C. FEATURE RELATIONSHIP IN DL TECHNIQUES

The features extracted from the autoencoder are better than the MFCC [82]. To obtain more discriminative features, a *t-test* is applied to SBM features and are selected based on the *p-value* [97]. In [98], the feature dimensions are effectively reduced and selected using principal component analysis and correlation methods. It is observed that the greater significant difference between non-CoAD and CoAD

TABLE 5. Summary of the traditional approaches in terms of their characteristics and results used to detect CoAD.

Sl.No	Ref	Year	Methods	Results	Database	Count
1.	[69]	2020	Synchro Squeezing Transform (SST) + spectral features + SVM, KNN	AC:83.48%, SE:85.37%, kappa:0.67	Private	CoAD: 40, No CoAD: 40
2	[68]	2021	Multiple features + feature selection (IG, SVM-RFE) +SVM	AC:90.92%	Private	CoAD: 21, No CoAD:15

is achieved with a principal component of the greater correlation [98]. Modified gaussian window-based stockwell transform is used to obtain the Time-Frequency Representation (TFR) of PCG signals [87]. The TF entropy features are extracted from each segmented FHS component of the PCG signal, and significant features have been selected using the ANOVA test [87]. Also, the authors have utilised SHapley Additive exPlanations (SHAP), values to analyse the model deeply [52], [99]. It shows the positive and negative effects of the features on the performance of the classifier [99]. To identify Diastolic Dysfunction (DD), the dimensions of the deep features are reduced by using Linear Discriminant Analysis (LDA) [41].

The extraction of power spectrogram i.e., Short-Time Fourier Transform (STFT), picks up the discriminative features from PCG for disease identification [100]. The fusion of LPCCs and MFCC provide complementary features to detect heart valve diseases [101]. The usage of triple spectrograms was made in [102], which led to acceptable results for noisy data. The features such as DWT, CWT, and MFCC have shown competitive results for binary and multi-class classification [103]. The features such as time-frequency domain and deep features using CNN are fused, and features are selected using variance [104]. The methods such as STFT, log-mel transformation, Hilbert-Huang transformation, wavelet transformation, MFCC, and Stockwell transformation are explored in [52]. In [54], Rational Dilation Wavelet Transform (RDWT) which is decomposed into sub-bands and is selected as discriminant features. It is observed that SWT depicts fundamental heart sounds efficiently when compared to DWT [94]. The DL visualization is performed locally and globally to indicate the prominence of the features for correct prediction [105]. The various 2D features are extracted for sound classification, and it found that for time domain features, transfer learning has increased the result by 2% [40]. Table 6 shows the DL approaches, datasets, classes, and performances of the studies analysed using PCG signal. Table 7 summarizes the state-of-the-art DL methods to detect CoAD using PCG.

VI. DISCUSSION

We reviewed 103 Q1 papers that highlight the significance of using PCG signals to identify heart abnormalities in recent years. The distribution of the papers used in the current study is shown in Figure 9. It was observed that IEEE, Elsevier, Springer, and others (MDPI, Wiley, etc.) contributed 21.35%, 48.54%, 12.56%, and 17.47% of TA/ML and DL architecture techniques, respectively. These techniques vary based on the type of modality (signal or image) used as input to the architecture.

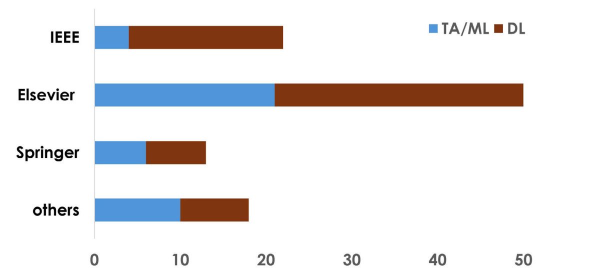

FIGURE 9. Selected papers from various standard journals.

The authors used publicly available and private datasets to evaluate their models. Some models utilized multiple datasets for binary and multi-class classification [105], [126], [130], [131]. For instance, as shown in Table 6, the authors favored the 2D CNN model for both binary and multi-class classification. From Tables 4-7, it is observed that accuracy, sensitivity, specificity, and F1-score are commonly used metrics, while AUC, MCC, and G-mean are used to a lesser extent. In some cases, the overall score of the developed system is calculated using the values of sensitivity and specificity. However, TA/ML and DL methods show homogeneity in performance measures. Tables 4 and 6 show that most of the multi-class categorization is performed by considering only two of the datasets. The usage of the database across various methods is shown in Figure 10.

Various studies have been conducted using supervised and unsupervised traditional or ML techniques. It is observed that TA has used (dataset/work): PhNetDB/25.64%, PSDB/10.25%, YDB/17.94%, Others/28.20%, and Multiple datasets/17.94%, for heart sound identification. From the literature, it is observed that a study by [76] attained the maximum sensitivity and specificity of 99.5% and 99.6%, respectively. In this study, after the preprocessing stage, the output of the wavelet transform was used to evaluate the Shannon energy, which highlights the low energy values. This emphasizes the medium energy level and preserves high peaks. Further, a threshold-based technique is used to binary classify heart abnormalities using PCG signals. A study by [64] attained the highest sensitivity and

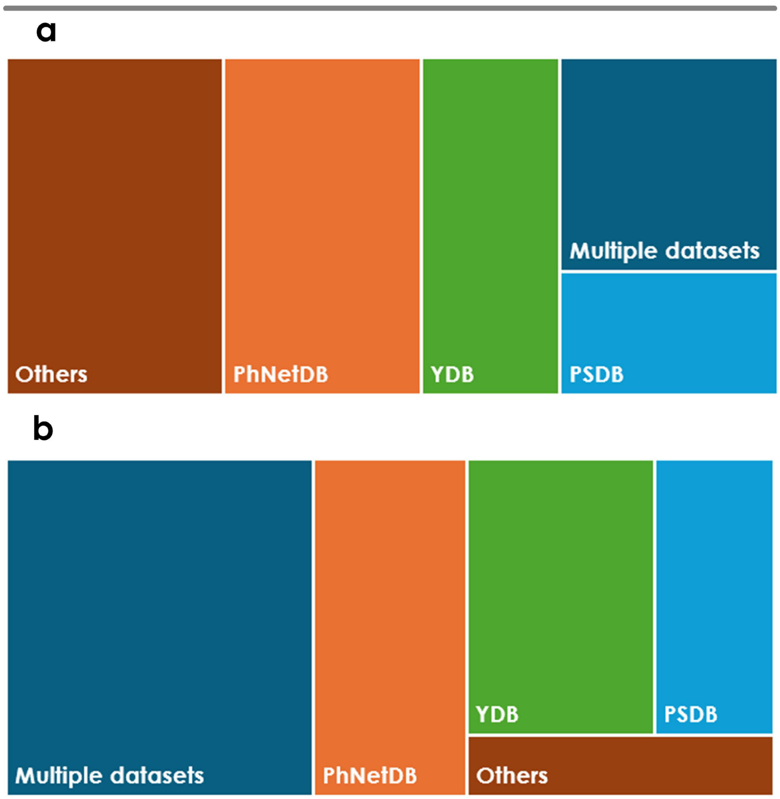

FIGURE 10. The distribution of the datasets a) TA/ML methods and b) DL methods used by various authors.

specificity of 99.4% and 99.7% for multi-class classification for combining MFCC with FMFE with an SVM classifier. This study has evaluated the performance of FMFE features with various classifiers and noted that incorporation of MFCC features drastically improves the performance of the model [64]. It is observed that different studies have used SVM and variation in SVM and attained good results for binary classification [37], [42], [45], [58], [66]. However, for multi-class abnormality detection models with KNN [62], [63], [70], or RF ([60], [61], [81]), classifiers have outperformed compared to other methods.

Out of all, DL approaches have contributed 60.19% work and used: PhNetDB/20%, PSDB/10%, YDB/21.81%, Others/7.2%, and Multiple datasets/40% for heart sound identification. The maximum number of the work have used multiple datasets to show the robustness of the method (refer to Table 6). It is noted that 2D CNN has achieved better results than 1D CNN and avoids the segmentation of PCG signals. It is observed that 2 papers such as [87] and [106] have achieved better sensitivity for binary classification. However, the specificity achieved by [87] is 99.26% and 98.32%, for different datasets, which is better compared to other results. Since the combination of CNN-SVM has achieved a high recognition rate in image classification/ recognition tasks, the same has been expected in PCG classification [129]. For multi-class classification, the YDB dataset is used extensively (refer to Figure 11). In [92], a combination of CNN and BiLSTM are used to extract the efficient features to achieve remarkable performance. It is also observed that 1D CNN is developed to obtain the accuracy of 99.5% [123]. It is observed that [94], have achieved an accuracy of 99.47 ± 0.42 using YDB dataset. They have also concentrated on 2- class classification. Herein, SWT and HLSTM acquire the fundamental and temporal variations in heart sounds respectively. Hence, it effectively helps to discriminate against heart valve diseases. The Chirplet Z transform(CZT) with pretrained networks and multiple training are also achieved better results [56]. Recently, it has been observed that YAM-Net has achieved a specificity of 99.9% and authors have considered various SNRs to analyze the PCG signal in different noise environments [130]. It is also observed that, AEN has been practically used to observe the condition of the heart [84]. However, for MR, AS, MS, and MVP, an accuracy of 100% is achieved using [125] using LOOCV strategy.

It is also observed that [40], [56], [84], [88], have used more than 2 databases for the analysis of PCG signals. Only a few works, such as [47] and [56], have worked on more than 5 class categorizations using PCG signals. Hence it is difficult to compare it with other methods. Some papers, such as [113], have combined PCG and ECG, wherein the predicting model extracts more information.

PCG can assist the clinician in the cardiac disease diagnosis by providing information on the phase of the cardiac cycle affected. This information, along with the clinical background and provisional diagnosis, can be made with the suspicion of underlying cardiac pathology. Although echocardiography is the best method for structural heart diseases and the severity of valve stenosis or regurgitation, PCG can assist physicians in stratifying the patients with the presence of heart diseases using abnormal heart sound patterns along with the details of patient's signs and symptoms.

A. COMPARISON OF TRADITIONAL/ML AND DL APPROACHES

Tables 4 and 6, indicate that most of the work has performed multi-class categorization of heart abnormalities using PCG signal. Figure 12 shows the distribution of these work with respect to number classes using ML and DL approaches.

It is observed that, the majority of the work addresses the 5-class classification problems, i.e., 58% and 71% using traditional/ML and DL approaches respectively. Since the evaluation protocols of the various studies are different, the performance parameter such as accuracy is considered for the comparison (refer to Figure 12). By using the discriminable structure of the proposed methodology, the approaches present in [63], [81], [92], [125], [128], and [130] have shown promising results i.e., approximately 100% accuracy.

The selection of the methods under ML or DL depends on the discretion of the research group. In the ML approach, the generation of the hand-crafted features is based on the empirical way or researcher experience, which may produce false positives during diagnosis. Hence, DL methods are selected to perform feature extraction and classification automatically [128]. The DL approaches provide the end-to-end structureand avoids manual extraction of features. In [125], deep CNN has shown its ability to categorise each class to 100% accuracy, when compared to TL models such as VGG16 and ResNet-50. A CardioXNet lightweight CRNN is designed to be comparable computational requirement [92]. The TL based on YAM-Net with 86 layers is utilised to classify heart sounds [130]. The authors have utilised the complementary features of ML and DL, i.e., feature generation is performed by multilevel networks and classification is performed by using KNN classifier to achieve an accuracy of 100% [63]. Though the performance of the DL approaches is exciting, it requires more training time and computational power due huge number of features that are fed to DL models [61].

B. FUTURE DIRECTIONS

CoAD is a prevalent and serious health condition that affects millions of people worldwide. Early and accurate diagnosis is crucial for effective treatment and prevention of complications. Many researchers have proposed predicting models using PCG signals. However, the development of CAD tools using PCG signals faces several challenges. For the benefit of public health, we presented the following future directions for the researchers to improve the efficacy of the CAD tool, which can thus be deployed in real-world scenarios. It is represented in 5-fold, with the pictorial representation shown in Figure 13.

1) MULTICENTRIC, MULTIMODALITY, AND SPECIAL AI STRUCTURE

One significant challenge is the lack of multi-regional patient data for robust model prediction and better inter-regionality samples. CoAD manifestations can vary across different populations, and a diverse dataset from multiple regions is essential to develop generalizable and reliable models. Additionally, the absence of a comprehensive database for multi-class samples hinders the ability to train models for accurately classifying various heart conditions. Furthermore, the unavailability of a database for multi-modality signals limits the potential for extracting complementary features from various bio-signals, such as ECG, PCG, and imaging data (e.g. heart ultrasound). Hence, there is a need for a multicentric study to collect the multimodality data. It can be possible with two or more international research collaborative groups associated with various hospitals. Combining the information from multiple modalities could enhance the diagnostic capabilities of CAD tools. Ensemble models leverage the strengths of different approaches, including ML, DL, and signal processing techniques, to provide more reliable and accurate diagnoses. Further, the ensemble of DL models (such as bagging, stacking and boosting [26]), can be utilised to integrate the various data modalities in heterogeneous domains. In addition, data fusion models such as joint modeling, independent modeling, and guided modeling fusion can be further explored to improve classification accuracy [154]. It is observed that the research community lacks benchmark performance of ML and DL architectures for the publicly available datasets using unified evaluation parameters. Hence, the area is in need of a benchmark among the various ML and DL approaches published for heart abnormality detection using various modalities. The integration of multiple prediction models with multiple feature extraction using deep layers will surely provide new intuition to explore the significance of each model that affect heart abnormalities. Thus, it is able to establish a special AI structure for the detection of heart abnormalities in the future.

2) INTERNET OF THINGS (IOT)

The IoT block in the image suggests an integrated system where data from various sources, such as medical devices and sensors, is collected and uploaded to the cloud. This centralized data repository is valuable for training advanced AI models, specifically ensemble models. Ensemble models are employed to leverage their ability to extract important features from diverse and multifaceted data. By combining

TABLE 6. Summary of the DL approaches in terms of its characteristics and results used to detect heart abnormalities.

S.No.	Ref	Year	Methods	Results	Database	Count	Class
				Binary class classification			
1	[33]	2018	RNNs	Mean AC:98.61%, SE:98.86%, SP:98.36%	PhNetDB	Records: 3240	NR, AB
2	[83]	2019	Spectrograms, Mel spectrograms and MFCC + CNN	Mean AC: 89.81%, SE:91.73%, SP:87.90%	PhNetDB	Records: 3240	NR, AB
3	[82]	2019	Denoising autoencoder + 1D CNN	AC:99.01%, F1-score:99.10%	Private+PhNetDB	DB1:45 patients, DB2: Recordings-4430	NR, AB
4	[31]	2020	CNN	AC:93%, SP:95%, SE:86%, F1-score:91%	PhNetDB	3153	NR, AB
5	[32]	2020	EWT + U-Net	AC:91.17%	PhNetDB+ Littmann's lung Sound Library +private	74-Private	Combination of heart, lung, speech
6	[106]	2020	MFCC+DNN	AC:97.10%, SE:99.26%, SP:94.84%	DB1:Michigan Heart Sound and Murmur Library and DB2: PhNetDB	DB1:Recordings-23, DB2:Recordings-3240	NR, AB
7	[107]	2020	1D CNN	Reduces misclassification	PhNetDB	Records:1200 (high SNR) & 1008 (low SNR)	NR, AB
8	[108]	2020	STFT+ Temporal attentive pooling-Convolutional Recurrent Neural Network (CRNN)	SE:96.0%, SP:96.7%	Private	Subjects:76	NR, VSD
9	[111]	2020	RF + ResNet	Score:89.3%, AC:92.9%	PhNetDB		
10	[109]	2021	Cross-wavelet transform (XWT) + CNN (AlexNet)	AC:98%	PhNetDB	3240	NR, AB
11	[110]	2021	CNN	AC:94.80%, SE: 94.29%, SP:95.54%, PR:93.44%, F1-score of 93.84%, AUC: 0.943.	Master of Heart Sound Shower, auscultation medical book and device + PhNetDB	Samples:19847	NR, AB
12	[36]	2021	Multifeature +LKNet Boosting	MAC:92.48%, SE: 96.34%, SP:86.62%	PhNetDB		NR, AB
13	[85]	2021	HSPFN model	AC:95.50%, SE:94.41%, SP:96.98%	PhNetDB	Records: 3240	NR, AB

TABLE 6. *(Continued.)* **Summary of the DL approaches in terms of its characteristics and results used to detect heart abnormalities.**

14	[112]	2022	Cochleagram-DNN	AC: 98.33%, F1-score:98.3%, SE:98.2%, SP:98.45%, PR:98.42%	PhNetDB	2435	NR, HM
15	[86]	2022	DsaNet	AC: 90.70%	PhNetDB	Samples:3240	NR, AB
16	[87]	2022	DNN	DB1:AC:99.55%, SE:99.93%, SP:99.26%, PR: 99.02%, DB2: AC: 95.43%, SE:97.92%, SP:98.32%, PR:97.60%	DB1: Michigan heart sound and murmur database + DB2: PhNetDB	DB1: Recordings-23, DB2: Recordings-2732	NR, AB
17	[88]	2023	AmtNet	4 databases are utilised to evaluate the model			
18	[52]	2023	Modified VGG model	Mean AC: 65.2%, SE:77.5%, SP:52.9%	PhNetDB	Records: 3240	NR, AB
19	[113]	2023	EMD-ResNet18	AC: 96.90%, PR: 97.10%, RE: 97.10%, MCC: 0.9377	Private (ECG & PCG)	MR :56) & without MR: 990	MR & non-MR
20	[40]	2023	Analysed various ML & DL methods		4 datasets are used to generate integrated dataset		
21	[41]	2023	LDA+ CatBoost	AC:88.2%,SE: 82.1%,SP: 92.7%, AUC = 0.911,F1-score: 89.2%	Private	DD:55, without DD:67	With & without DD
				Multi-class Classification			
22	[114]	2019	RNN based on LSTM	AC:80.80%	PSDB	NR:320, MU:95, ES:46 Total: 461	NR, MU, ES
23	[84]	2020	AEN	DB1:AC:100%, SE:100%, SP:100%, F-Measure:100%, G-Means:100% , DB2: 99.80%, SE:99.65%, SP:99.13%, FM:99.67%, GM:99.38% DB3: AC:96.03% (NR), 90.11%(MR), 91.91%(ES)	DB1: PSDB, DB2: PhNetDB DB3: Private	DB1:449, DB2:409, DB3:479	NR, MU, ES
24	[115]	2020	Deep features	AC:98.60%	YDB	Recording:1000	NR, AS, MS, MR, MVP
25	[116]	2020	Various pre-trained CNN models are analysed		PSDB		2 class:NR, AB,3 class:NR, MU, ES
26	[91]	2020	WaveNet model	AC: 97.0%, SE: 92.5%, SP: 98.1%	YDB	Recording:1000	NR, AS, MS, MR, MVP
27	[117]	2020	CNN	AC:89.6%, SE:90.8%, SP:89.6, F1-score:89.9%	YDB	N: 200, AS: 200, MR: 184, MS: 186, MVP: 181	NR, AS, MS, MR, MVP

TABLE 6. *(Continued.)* Summary of the DL approaches in terms of its characteristics and results used to detect heart abnormalities.

28	[118]	2023	CNN	AC:99.6% (higher)	YDB		AS, MR, MS, MVP, NR
29	[92]	2021	CardioXNet	AC:99.6%, RE:99.52%, PR:99.56%,F1-score:99.68%	DB1:YDB, DB2: PhNetDB	DB1:1000	NR, AS, MS, MR, MVP
30	[119]	2021	Hybrid Constant-Q Transform-based (HCQT) + CNN	AC:96.4%, F1-score:94.8%, RE:96.6%, PR:93.4%	PSDB	Total:462	NR, MU, AR, ES, EX
31	[120]	2021	CNN-BiLSTM	Cohen's kappa:97.87%, AC:99.32%, SE:98.30%, SP:99.58%, PR:98.32%, F1-score:98.30%, AUC:0.998 (for DB1) AC:87.31%, AUC:0.900 (for DB2)	DB1: YDB, DB2: PhNetDB	Recording: 1000 (DB1),3240(DB2)	DB1:NR, AS, MS, MR, MVP, DB2:NR, AB
32	[93]	2021	MFSC+CNN	AC:93.89%(2 class), 86.25%(multi-class)	Private	Total:1800	NR, PDA, VSD, ASD
33	[121]	2021	Stacked autoencoder	AC:99.80%, SE:100.0%, SP:100.0%,PR: 99.70%,F1-Score:99.85%	PSDB	Total:449	NR, MU, ES
34	[122]	2021	CNNs	DB1:AC:87%, SE:83%, PR:81%	DB1: PSDB & DB2: PhNetDB		NR, MU, ES
35	[95]	2022	FDC-FS (Fusion + CNN)	AC:97%	PSDB	Recording: 656	Multi-class
36	[123]	2022	MFCC+1D CNN	AC:99.5%	YDB	Recording:1000	NR, AS, MS, MR, MVP
37	[100]	2022	Cardi-Net	AC:98.879%	YDB	Recording:1000	NR, AS, MS, MR, MVP
38	[124]	2022	Spectrogram based 2D CNN	Avg.AC:97.85%, Avg.SE:97.85%, Avg.SP:99.46%, Avg.PR:97.85%, Avg.F1-score:97.85%	YDB	Recording:1000	NR, AS, MS, MR, MVP
39	[125]	2022	Polynomial chirplet transform + Deep CNN	AC:100% (for DB1), 85.16% (for DB2)	DB1: YDB, DB2: PhNetDB	Recording :1000 (DB1), 2871 (DB2)	NR, AS, MS, MR, MVP
40	[101]	2022	Feature Fusion+ Hierarchical LSTM	DB1:AC:98.76± 0.10, RE:99.15± 0.16, PR:99.51± 0.21, F1-score:99.33±0.05, DB2:AC:99.10±	DB1: PhNetDB, DB2: YDB	DB1:3240, DB2:1000	DB1:NR, AB, DB2:NR, AS, MS, MR, MVP

TABLE 6. *(Continued.)* Summary of the DL approaches in terms of its characteristics and results used to detect heart abnormalities.

				0.42, RE:99.17± 0.52, PR:99.06± 0.51, F1-score:99.10±0.45			
41	[102]	2022	SpectroCardioNet	DB1: AC:91.36%, SE:93.33%, SP:89.40%, F1-score:91.50%, AUC:0.92, DB2: AC:97.77%, PR:96.57%, RE:96.66%, F1-score:96.60% (for DB2)	DB1: PhNetDB, DB2: YDB	DB1:2825, DB2:1000	DB1:NR, AB, DB2:NR, AS, MS, MR, MVP
42	[126]	2022	FFT+ CNN-LSTM	DB1: AC: 98.48%, SE: 98.52%, SP: 99.57%, AUC: 0.998, DB2: AC: 93.77%, SE: 99.63%, SP: 92.42%, AUC: 0.951 (for DB2)	DB1: PhNetDB, DB2: YDB	Recording:1000 (DB1)	DB1:NR, AB, DB2:NR, AS, MS, MR, MVP
43	[103]	2022	DWT, MFCCs, CWT + DNN	Multi-class - AC:98.5%, PR, RE, F1-score:95.5%, SP:98.9%, Binary-AC:99.2%	YDB	Recording:1000 (DB1)	NR, AS, MS, MR, MVP
44	[127]	2022	Spectrogram-ResNet50	AC: 87.65%.	PSDB	Tracks:832 (404 used)	AR, NR, MU, ES, EX
45	[128]	2022	DNN features + PCA+ MLP	AC: 99.61% (binary), 99.44%(multi-class)	DB1: PhNetDB & DB2: YBD	DB1:3153, DB2:1000	NR, AB (2 class), NR, AS, MS, MR, MVP (multi-class)
46	[90]	2022	Improved MFCC+ResNet	AC:94.43%, SE:92.32%, SP:95.47%, PR:90.55%	Used 3 datasets		NR, AB, Noise
47	[54]	2023	Teager–Kaiser energy operator (TKEO) +RDWT + 1D CNN	AC:98.10%, SP:99.52%,SE: 98.10%, PPV:98.10%, NPE:99.52%, MCC:0.976,F1-score: 98.10%	YDB	Recording :1000	NR, AS, MS, MR, MVP
48	[104]	2023	Fused features+ XGBoost	AC:87.80%, SE:86.05%, SP:89.74%	Private	Total: 483	NR, CHD, PAH
49	[129]	2023	AlexNet+SVM	AC,PR,RE are more than 95%	PSDB A & B		
50	[130]	2023	YAM-Net	AC:99.83 ± 0.27, SE: 99.59 ± 0.67, SP:99.90 ± 0.17, PR: 99.61 ± 0.63,	DB1:YDB, DB2: PhNetDB	DB1:1000	NR, AS, MS, MR, MVP

TABLE 6. ***(Continued.)*** **Summary of the DL approaches in terms of its characteristics and results used to detect heart abnormalities.**

				F1-score:99.58 ± 0.67, MCC:0.99 ± 0.010, Kappa:0.99 ± 0.010 For binary classification AC:92.23%			
51	[94]	2023	SWT+HLSTM	AC:99.47±0.42(DB1), AC:98.55±0.05, SE:98.04±0.10, SP:99.02±0.10 (for DB2)	DB1:YDB, DB2: PhNetDB	Recording :1000 (DB1), 2871 (DB2)	NR, AS, MS, MR, MVP
52	[56]	2023	CZT + Round based TL	AC:99%	DB1: PSDB A& B, DB2: YDB	Recording: 176,656,1000	Databases are combined to get a maximum of 9 classes
53	[131]	2023	STFT + DNN	AC:91%, SE:85%, SP:85%, F1-score:86% (for DB1), AC, SE, SP, F1-score:100% (DB2)	DB1: PhNetDB, DB2: YDB	Recording: 3240(DB1), 1000(DB2)	DB1:NR, AB, DB2:NR, AS, MS, MR, MVP
54	[105]	2023	CWT + CNN	MeanAC:98.32%, Mean.RE:96.03 MeanPR:95.80% (for DB1), AC: 93.07% (for DB2)	DB1: YDB, DB2: PhNetDB	Recording:1000 (DB1),3240(DB2)	DB1:AS, MR, MS, MVP, NR, DB2:NR, AB
55	[96]	2023	CWT+NRC-Net	AC: 97.40%, SE: 98.10%,SP: 98.90%	YDB	Recording:1000	AS, MR, MS, MVP, NR,
56	[132]	2023	Mel spectrogram + residual neural networks	Avg.SE: 80.4% , F1-score :75.8%	M. A. Reyna et al., "Heart murmur detection from phonocardiogram recordings: The George B Moody physionet challenge," medRxiv, 2022.	802(absent), 153 (soft MU) and 52 (loud MU)	MU:absent, soft, loud

numerous algorithms and techniques, these ensemble models can effectively identify and integrate the most relevant features, enhancing the overall predictive power and accuracy of the system. The trained ensemble models are then utilized to make predictions and generate diagnostic insights. These predictions are subsequently shared across mobile devices, ensuring better availability and accessibility of the diagnostic results to healthcare professionals and patients. This integrated approach not only facilitates the collection and aggregation of data from multiple sources but also harnesses the power of ensemble AI models to extract meaningful insights. By leveraging cloud computing and mobile technologies, the system enables widespread dissemination of diagnostic information, ultimately improving healthcare delivery and patient outcomes.

3) EXPLAINABLE AI (XAI) AND UNCERTAINTY ESTABLISHMENT (UE)

The deployment of advanced AI models, particularly ensemble models, in the domain of CAD using medical signals like PCG underscores the importance of XAI and UE techniques. XAI plays a crucial role in enhancing the transparency, interpretability, and trustworthiness of the diagnostic pre-

TABLE 7. Summary of the DL approaches used to detect CoAD in terms of their characteristics and results.

S.No	Ref	Year	Methods	Results	Database	Count
1.	[99]	2022	MFCC + CNN-LSTM	AC:96.05%, SE:96.12%, SP:96.12% (for DB2) AC:99.02% (for DB2)	DB1: (https://github.com/syxiaobai/PCG-data) DB2: PhNetDB	DB1:CoAD:206 subjects, non-CoAD: 348 subjects
2	[53]	2021	Spectrum, MFCC+CNN	AC:85.82% ± 2.43, SE:91.26% ± 4.55, SP:73.58% ± 8.20, G-mean:81.72% ±(for PPG)	Private	Subjects:60 (non-CoAD) 135 (CoAD)
3	[97]	2019	SBMs	Multi-channel AC:82.57%, SE:85.61%, SP:79.55%	Private	Subjects:66
4	[98]	2020	Multi-domain and DL features + MLP	AC:90.43% ±3.79, SE:93.67% ±3.02, SP:83.36% ± 10.07	Private	Subjects:175 (120 CoAD, 55 non-CoAD)
5	[133]	2022	CNN + Multi kernel learning + SVM	AC:91.19%, G-mean:88.19% ±5.53, Kappa: 0.8238	Private	Normal:40, CoAD:40

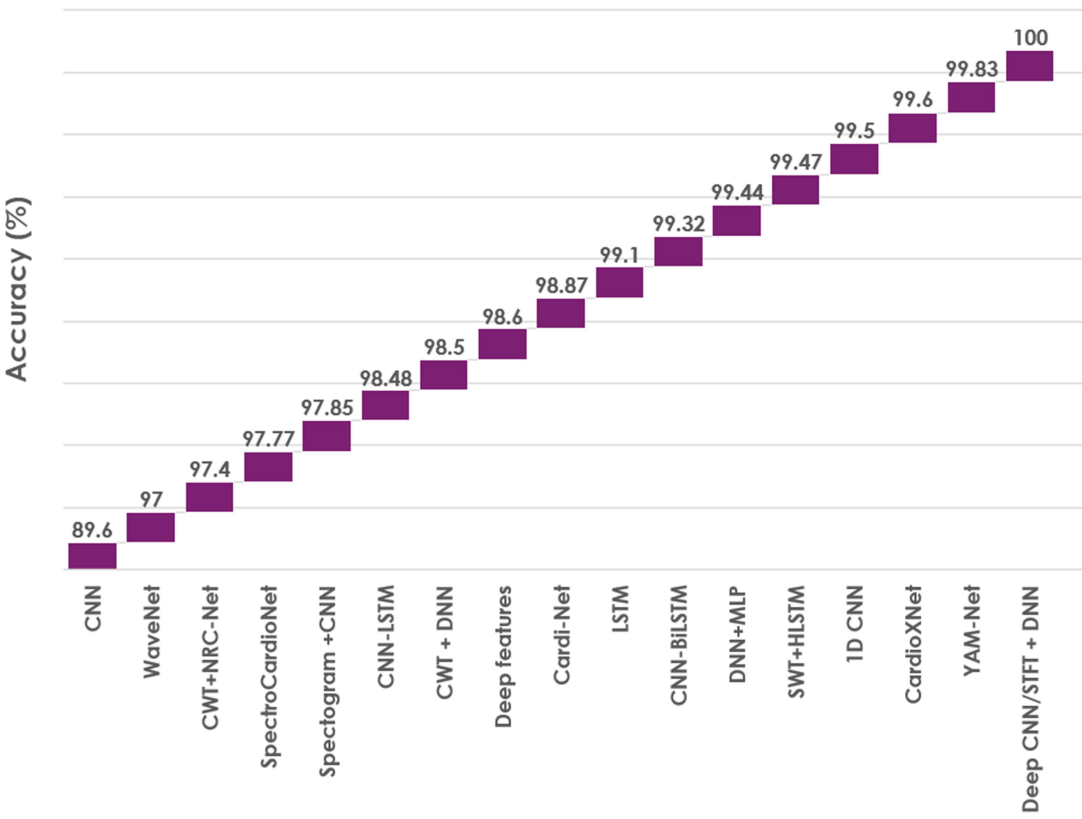

FIGURE 11. Performance of the various approaches using YDB dataset.

dictions made by these complex AI systems [134], [135]. Given the critical nature of medical diagnoses and the potential impact on patient care, it is essential to understand the reasoning behind the model's decisions. The various methods such as Explain like I'm 5 (years old) (ELI5) [155], Local Interpretable Model-Agnostic Explanations (LIME) [156], and SHAP [157] can be utilised to visualise the interpretations by the predicting models. Further, these models are helpful in analyzing the importance of various modalities. The adaptation of these methods in the attention

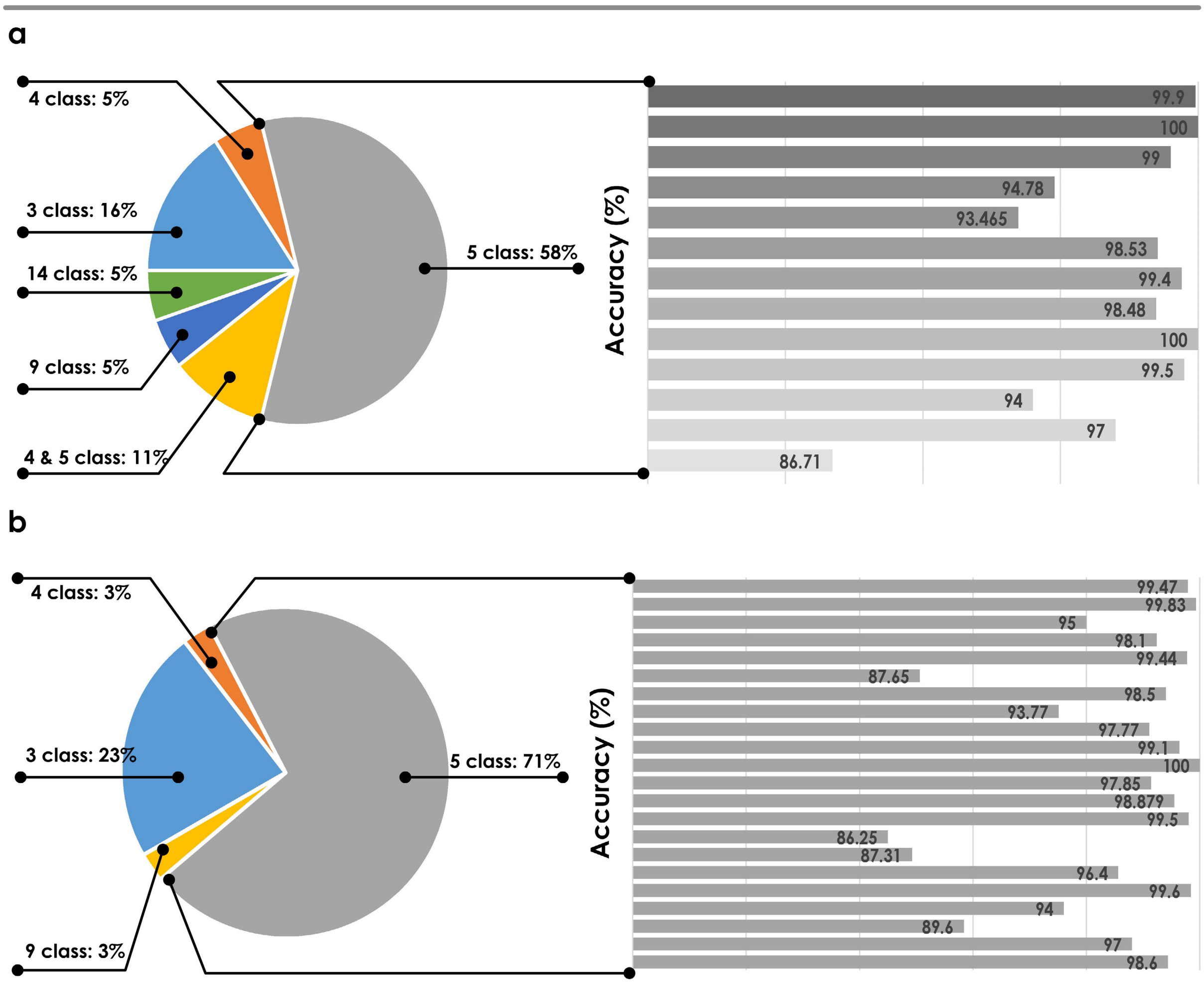

FIGURE 12. Multi-class work distribution using a) traditional/ML approaches and, b) DL approaches.

modules of ensemble DL networks can help to analyse the impact of the various patches or portions of the input image or signals on the classification accuracy. This helps to show the clinical importance of each modality used to build the AI models. By incorporating XAI methods, healthcare professionals can gain valuable insights into the decision-making process of the ensemble models. XAI techniques can highlight the specific features or patterns in the medical signals that contributed most significantly to the diagnostic outcome. This understanding can aid in building confidence in the model's predictions, as well as facilitating more informed clinical decision-making [136].

As DL predictions have become increasingly important, so does the need to estimate uncertainty. Uncertainty arises from two main sources: the data and the model. Data uncertainty stems from noise or imperfections in the input, such as sensor noise in images or videos. Model uncertainty, on the other hand, reflects the model's ability to learn effectively from the training data and make accurate predictions, especially when faced with inputs that differ significantly from the ones it was trained on. In DL and ML, it's crucial to consider uncertainty to ensure reliable predictions and decision-making. There are two main types of uncertainty: Aleatoric (Data) Uncertainty: This stems from the inherent randomness or noise in the data itself. Epistemic (Model) Uncertainty: This arises from the limitations of the model, such as insufficient data or incomplete training [137]. UE aims to measure these uncertainties throughout developing and using DL and ML models, from data selection and evaluation to model training, performance assessment, and deployment, thus improving the confidence level of the model. Hence the researchers can concentrate on the prospective study, which focuses on uncertainty estimation for DL models (correspondingly, Bayesian neural networks, Monte Carlo dropout, bootstrap models, and Gaussian mixture models [138]), to enhance the honesty of clinical practitioners on the detection of heart abnormalities.

Moreover, XAI and UE can help identify potential biases or limitations in the trained models, enabling continu-

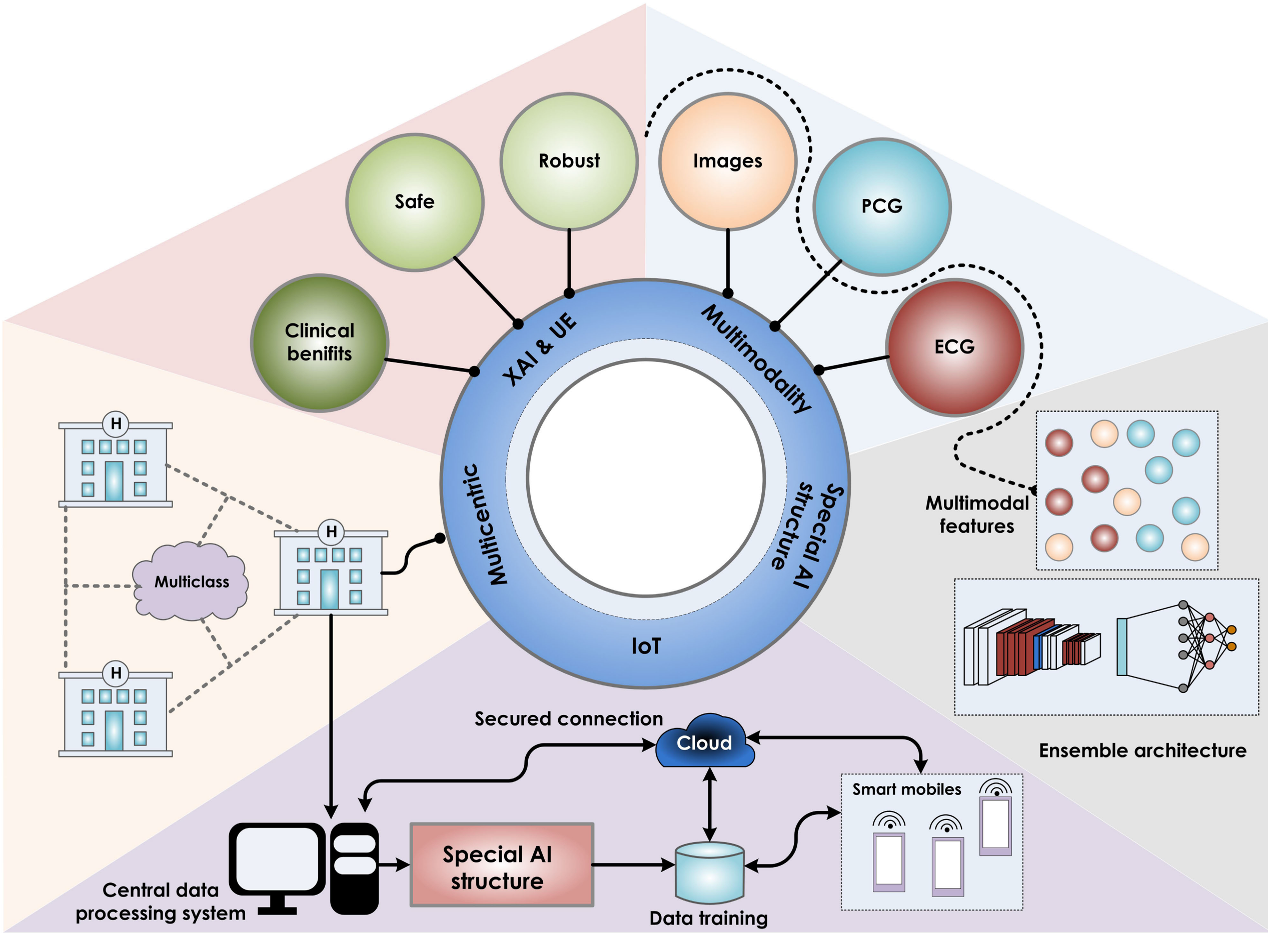

FIGURE 13. General flowchart of challenges in future directions for automated identification of heart pathologies.

ous improvement and refinement of the CAD systems. By shedding light on the model's behaviour healthcare professionals can better assess the reliability and applicability of the diagnostic results, particularly in cases where the predictions deviate from clinical expectations. Ultimately, the integration of XAI and UE in CAD tools leveraging medical bio signals such as ECG, PCG, and various imaging modalities, not only enhances the transparency and trustworthiness of the diagnostic process but also fosters a collaborative relationship between AI systems and human experts, leading to improved patient care and outcomes.

VII. CONCLUSION

This work presents a review of techniques using PCG signals to detect heart abnormalities, demonstrating the significant potential for PCG analysis techniques to help identify various heart diseases. The studies discussed in this review have employed traditional signal processing methods, advanced ML and DL techniques. Despite significant progress, several challenges still hinder the widespread adoption of these automatic PCG-based diagnostic systems in clinical settings. To overcome these challenges, future research should focus on improving signal enhancement and noise reduction techniques. Additionally, new DL methods should be developed to accurately identify complex time-based patterns and subtle differences in PCG signals. It is also crucial to make these models more interpretable and explainable to increase trust and facilitate their integration into healthcare settings. Collaboration among researchers, healthcare professionals, and industry, coupled with advancements in hardware and signal processing techniques, can transform the analysis of heart sounds. This approach could enable accurate, non-invasive, and affordable screening and diagnosis of heart conditions in the future.

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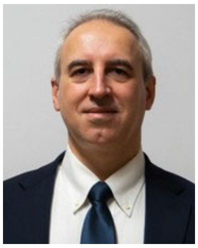

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