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A Comprehensive Survey of Analysis of Heart Sounds using Machine Learning Techniques to Detect Heart Diseases

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ABSTRACT

An estimated 32 per cent of all global deaths were due to cardiovascular diseases (CVD) in 2019 which is a leading cause of death globally. Of these, three-fourths of the deaths occur in low and middle-income nations. The CVD must be detected early for improving patient outcome. Automated heart sound analysis has been studied for more than a few decades using various Digital Signal Processing (DSP) techniques. Attempts have been made in the last decade to apply Machine Learning (ML) in the healthcare domain to make healthcare more accessible. This paper surveys the significant steps that have been taken to detect the most common heart diseases by the application of the machine learning (ML) and deep learning (DL) techniques to analyse the phonocardiograms over the last few years.

Keywords: *congenital heart disease, computer-aided auscultation, deep learning, machine learning, heart sound auscultation, cardiovascular heart disease*

INTRODUCTION

Machine learning (ML) techniques are being applied in the various fields of the healthcare domain [1]. The ML techniques have been applied to the CVD detection also as CVDs are widely prevalent in the general population. Around 17.9 million people died from cardiovascular diseases (CVDs) in 2019, representing 32 per cent of all global deaths, which is a leading cause of death globally[2]. Early detection of CVDs is crucial for improving the patient outcome.

Heart sound analysis

Auscultation is the method used to detect heart diseases for more than 200 years. The graphic plot of the audio recording of the heart sounds and murmurs is called Phonocardiogram(PCG) and the instrument used to record PCG is called the phonocardiograph[3]. Phonocardiograms have been used for research on automated heart sound analysis by using various Digital Signal Processing (DSP) techniques and AI methods to accurately detect heart diseases[4][5] during the last two decades.

Heart sounds

Normal heart sounds can be characterised by the "lub" and "dub" that occurs with a heartbeat. The first sound (lub) is called S1 and the second one is called S2 and both are called the fundamental heart sounds. The third heart sound S3, a low-pitched sound, could be found in normal people or it could even be a sign of systolic heart disease. S4 is the fourth sound and occurs just before S1 and is mostly an indication of disease[6]. The time gap between the first S1 and the next S1 is a cardiac cycle and includes one systole and one diastole phase.

Heart murmurs

Heart murmurs are the sound produced due to turbulence during the flow of blood across the heart valve. There are two types of heart murmurs - innocent murmurs and abnormal (diseased or pathological) murmurs. Abnormal heart murmurs are usually caused by congenital heart disease (CHD) and due to acquired heart valve problems. Systolic murmurs are produced during the period between S1 and S2 and can be innocent or malignant. Diastolic murmurs are always pathological[7].

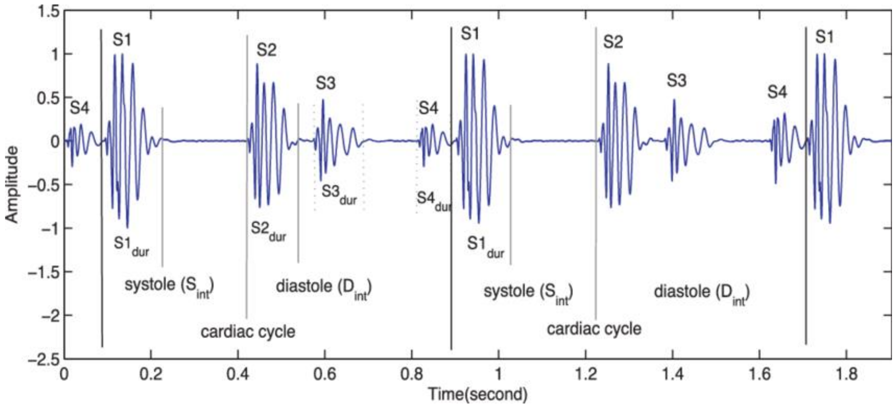

FIGURE 1: PCG signal including S1, S2, S3 and S4[8]

Methods employed for analysing heart sounds

Pre-processing

Denoising is employed to remove noise in the signal. All frequencies beyond a certain range are also eliminated. Segmentation is performed to identify S1 and S2 and then extract the cardiac cycle.

Feature extraction

The raw audio data is processed to extract features which are then fed to the ML algorithm. Feature extraction is done on the segmented signals, or the unsegmented signals, after denoising or without denoising. Various techniques are used to extract features from the audio data. Fourier Transform of the consolidated audio wave is used to convert the audio data into individual waves with their frequencies and their respective amplitudes with respect to time. Shannon energy envelop have been employed by several researchers for time-based techniques. Shannon energy is used to reduce the effect of noise and emphasize the medium intensity signals andused to extract the envelop.Discrete wavelet transforms (DWT) and continuous wavelet transforms (CWT) are used to extract spectral and temporal information from the signals.Cepstrum, Bispectrum, Wigner bispectrum and Mel Frequency Cepstrum Coefficient (MFCC) are also extracted for murmur detection. MFCCs are coefficients which together constitute the MFCs, which represent the short-term power spectrum of the audio data. The features extracted are then fed to the ML algorithms for classification. DWT is used for envelop segmentation.

FIGURE 2: Steps in the classification of heart sound signals

Several papers published on heart sound analysis over the last 5 -7 years were studied to get an understanding of the methods employed by various researchers and the level of accuracy obtained by them and to identify the research gaps in this area for further work.Several researchers have pre-processed the audio data. Most of these have also segmented the pre-processed signals to extract the cardiac cycles after identifying the S1 and S2 peaks. Some researchers using the DL techniques have bypassed the segmentation step. Figure 2 depicts the steps involved in the classification of heart sound signals.

Analysis of the existing research

Researchers implementing ML algorithms have been using segmentation as a pre-processing step as the traditional approaches require the data to be in a specific format. The traditional ML techniques that have been used for heart sounds analysis include SVMs, k-NN and RF, among others. SVMs have been a popular technique for binary classification of the heart sounds. kNN classifiers have been used to classify the heart sounds into one of the multiple classes. Random Forests that combine multiple decision trees, have also been used to classify heart sounds into normal and abnormal categories.

Some of the researchers using DL techniques have skipped the segmentation phase as the DL algorithms are designed to learn and extract features from raw data. Also, segmentation may lead to a decrease in performance in the DL algorithms as it is a time-consuming and labour-intensive process and can also introduce additional noise.

CNNs have been used for classification of heart sounds into normal or abnormal category or even a specific heart disease due to their ability to capture changes in frequency or intensity over short time intervals. This can help in identifying subtle changes in heart sounds that may be indicative of specific heart conditions. Since the heart sounds data is sequential, RNNs are well-suited for its analysis. RNNs can capture temporal dependencies between different parts of the sequence, identify patterns that could be a sign of specific heart conditions, such as pitch, intensity or duration. The subtle changes in audio data can be detected by RNNs, which could otherwise difficult to detect. Among the several variants of RNNs, LSTM and GRU are well-suited for extracting long-term dependencies in sequences.

TABLE 1: Methods used by various researchers for analysing heart sounds

Year	Author(s)	Feature extraction methods	Classification techniques / details	Results
2017	Karar et al. [9]	Segmented, DWT	Rule-based classification tree.	Acc. = 95.5%
2018	Alam et al. [10]	Spectrogram, MFCCs	Novel DNN architecture - parallel combination of BiLSTM& CNN	Se = 0.9609;Sp = 0.8549 F1 Score = 0.9801

Year	Author(s)	Feature extraction methods	Classification techniques / details	Results
2018	Hu et al.[11]	Shannon energy, spectrogram, PCA	Autoencoder; DNN.	2-class: Acc = 99.13; 7-class:Acc = 97.11
2018	Son and Kwon [12]	MFCCs and DWTs combined	SVM, DNN and kNN classifier	Acc. = 97%
2019	Esmail et. al.[13]	Important features are mean frequency, median frequency, total harmonic distortion, power correlation coefficients, covariance	Random forests classification	Acc. = 93.24%
2020	Aziz et al.[14]	1D local ternary patterns MFCCs after denoising	SVM classified the signals into normal, ASD and VSD categories	Acc. = 95.24%
2020	Gao et al. [15]	segmentation by HSMM	GRU was found to be better	Acc. = 98.82%
2020	Koike et. al.[16]	Spectrogram, log mel spectrogram	A transfer learning algorithm pre-trained on audio data	Recall=89.7%;Sp= 88.6%;Se.=96.9%
2021	J.Lv, et al.[17]	Spectrogram	Heart sounds from 1397 people were collected. Both remote auscultations by cardiologists and automatic auscultation were conducted. CNN method used.	Remote auscultation:98% Se, 91% Sp,97% Acc., and a kappa coefficient of 0.87. AI-AA :97% Se, 89% Sp, 96% Acc., and a kappa coefficient of 0.84.
2021	Yi He et al. [18]	Segmentation by U-Net framework	CNN	Overall Acc. = 0.964, Se = 0.781, Sp = 0.873
2021	Zeinali et al.[19]	PCA and LDA	The heart sounds were classified into normal, abnormal due to S3 and abnormal due to S4. PCA and LDA. gradient boosting classifier (GBC), support vector classifier (SVC), random forest classifier and genetic algorithms.	GBC: Acc = 95% two-class:Ac = 98%
2021	Kui et al.[20].	DHMM, MFSCs	CNN	2-class: Acc. = 93.89%;3-class: Acc. = 86.25%

Year	Author(s)	Feature extraction methods	Classification techniques / details	Results
2021	Soto-Murillo et al.[21]	52 features including LPC coefficients, MFCCs; statistical features	6 different ML classifiers.	Logistic regression,SVM algorithms best.
2021	Oktarina et al.[22]	CEEDMAN technique, segmented by Shannon energy; Pearson distance metric	GRU	Acc.= 87.2%;Precision = 79% for normal heart sounds; Precision = 100% for abnormal
2021	Ibrahim et al.[23]	Temporal, spectral and geometric features	Various ML algorithms used; cubic SVM performed the best.	Acc. = 0.97;F1-score = 0.98
2021	Milani et al.[24]	Time and frequency domain by LDA	ANN	Acc. = 93.33%
2021	Koike et. al.[25]	Data augmentation	Study of data augmentation by transferring cross-corpus knowledge	Improved sensitivity, specificity
2022	Wang et. al.[26]	Spectrogram using CWT	Ten transfer learning techniques were used and compared.	Acc. = 0.98
2022	Alnajjar et. al.[27]	Spectrogram, MFCCs	CNN	Acc. = 100%;F1-score = 100%
2022	Roy et. al.[28]	Time domain features	Used the CNN-based Xception model. Found to be more accurate and testing time is less	Acc. = 99.45%;Se. = 98.5%; Sp. = 98.7%
2022	Khan et. al.[29]	No pre-processing and no feature extraction	Combination of CNN and power spectrogram Cardi-Net	98.879%
2022	Abbas et. al.[30]	CWT based spectrogram (CWTS) used	A novel attention-based technique (CVT-Trans) on a convolutional vision transformer to classify into 5 classes	Acc. = 100%;Se. = 99.00%; Sp. = 99.5%;F1-score = 98%
2022	Bao et. al.[31]	MFCCs	Studied the effect of the duration of signal on the various classification techniques.	Signal duration should be at least 2 seconds
2022	Takezaki S. and Kishida K.[32]	data augmentation by window slicing with	The accuracy was found to have increased compared	Without data augmentation:Acc.

Year	Author(s)	Feature extraction methods	Classification techniques / details	Results
		spectrogram (WSS) and synthetic spectrogram based generative adversarial network (SSG)	to classification without data augmentation.	= 91.5%; With WSS (best result:Acc. = .93.7 With SSG (best result):Acc. = 92.5%
2022	Al-Sharu et al.[33]	1D CNN with FFT	CNN-kNN model achieved higher accuracy.	CNN model:Acc. = 97.66%; CNN-kNNmodel:Acc. = 100%
2022	Al-Issa et. al.[34]	FFT, data augmentation	CNN and LSTM using both augmented and non-augmented datasets	Acc. = 98.5%; F1-Score = 98.501%; AUC = 0.9978 for non-augmented dataset

A PhysioNet/Computing in Cardiology (CinC) challenge was held in 2016 which gave a boost to this field.CNN and its variations were used by several researchers and the accuracy ranges between 84% to 97%. Singh et al.used CNN, but without the segmentation phase to get better results. RNN-based Bidirectional Long Short-Term Memory (BiLSTM) and CNNs were used by Alam et al. [10] used three public heart sound datasets to build a parallel DNN by using the CNN for the spectral images and BilSTM for the MFCCs. Hence, the combined model performs better than either of the individual models.

The UNet* network, a framework developed using CNN to work with lesser training data[39], was used by He et al.[18] after segmenting the heart signals and was found to perform better than the AdaBoost classifier. A lightweight CRNN architecture called CardioXNet was proposed by [36] for the classification of heart sounds into five classes. Two learning phases, the representation learning phase by three parallel CNN pathways to extract time-invariant features and the sequence residual learning temporal features implemented by bidirectional LSTMs and skip connection, to extract temporal features were implemented.

Yaseen et al. [12] found that using both MFCCs and DWT features combined from the signals gave higher accuracy than using only MFCCs or DWT. The SVM classifier was found to perform better compared to both DNN and centroid displacement-based kNN in classifying the signal as one of the four heart disease categories and one normal category. Renna et al. [37] used CNNs in combination with HMM and a hidden semi-Markov model to segment the heart sounds and it performed better than the other segmentation techniques.

Recently, Zeinali et al.[19] classified the heart sounds into three classifiers, namely, normal, abnormal due to s1 and abnormal due to s2, after using PCA and LDA. Wei Hu et al. [11] used a two-layer autoencoder to extract features which were then used for classification using DNN to get very high accuracy. Karar et al. [9] used a rule-based classification tree to classify the signals. The largest Lyapunov exponents are calculated after pre-processing the segmented cycle with DWT to generate the dynamical features of the heart sounds in the second step.

An SVM classifier was used by Aziz et al.[14] to classify the signals into normal, ASD and VSD categories by implementing three-stage processing- denoising, feature extraction and SVM classifier. The performance of six different algorithms was compared by Suto-Murillo et al. [21] and they reported Logistic Regression and

SVM algorithms to be better. Fifty-two features were extracted from the signals including 36 statistical features, 8 MFCCs and 8 LPC coefficients and a normalised and one standardised dataset were created. Six different classifiers analysed the dataset. Milani et al. [24] used LDA to select the features and then classified the signals using ANN. Noman et al.[40] used an ensemble of deep CNNs for classification after combining time-domain and frequency domain features.

A novel framework based on the gated recurrent unit (GRU) was proposed in [15] without denoising and hand-crafted feature extraction. The logistic regression-based hidden semi-Markov model was applied to segment the signals and the normalised frames were given as input to the model to achieve an accuracy of 98.82%. Wang et. al.[26] claimed to have achieved good results when transfer learning was used for classification. Alnajjar et al.[27] claimed to have achieved 100% accuracy by using CNN method of DL with the MFCCs as the input features. An Xception network model that took time domain features as input and gave high accuracy and took less testing time was proposed by Roy et. al. [28]. No pre-processing and features extraction were done by Khan et. al.[29] as they used CNN and power spectrogram Cardi-Net to achieve a very high accuracy A novel attention-based technique (CVT-Trans) on a CWT-based spectrogram was developed by Abbas et. al.[30] and they could achieve very good results.

The effects of signal duration were studied by Bao et. al [31]l. They concluded that the optimal duration of the signals as 2 seconds for classification of the heart sounds.

Gaps in research

Active research has been going on in area of using AI techniques to analyse heart sounds to detect heart diseases. There are several gaps that could be addressed by the researchers.

Limited availability of labelled data: There are only a few large datasets available for use. The availability of labelled heart sound data of high quality is the most challenging part of this research due to the difficulty in collecting the data. The data privacy and ethical issues further limit the availability of data. Data should be collected from a diverse population to develop a model that is robust, accurate and reliable. Some of the approaches to address this issue include generating synthetic data with known labels using generative models and the use of transfer learning, where models built using labelled data from one population are adapted to new populations with a smaller set of labelled data. A few researchers have also attempted semi-supervised learning. Finally, collaboration is required to pool data from multiple sources.

Heterogeneity of heart sounds: Heart sounds vary slightly between individuals and within the same individual over time. The models need to be trained on a diverse set of heart sound recordings to be able to detect abnormalities. Heterogeneity is occurring due to individual anatomy and physiology, health conditions, and external factors including noise, body shape and size and patient positioning.

Lack of standardisation in data acquisition and processing: The lack of standardization in data acquisition and processing is a significant challenge. The quality of recordings varies depending on factors such as the recording device, the duration of recording, the sampling rate, the environment, and the positioning of the patient. The methods used to extract features from the recordings are different and there are differences in the method of segmentation. Standardised protocols are being developed for segmentation and classification, to promote consistency.

Interpretability: The AI models are difficult to be understood and interpreted due to their black box nature. Clinicians would want to understand the logic to make informed decisions. Decision trees based models and feature importance analysis may help to address the challenge of interpretability to a limited extent.

TinyML and Edge Computing: TinyML involves deploying ML algorithms on small, portable devices. Edge computing, on the other hand, is the processing of the data locally instead of the cloud. Both will reduce latency and bandwidth requirements and enable the development of devices with more accuracy and reduce the cost and size.

CONCLUSION

CVDs are one of the main causes of death worldwide. Early detection and diagnosis are required to improve the patient outcome. Auscultation, the traditional method of analysing the heart sounds is highly subjective. The AI-based approaches have reduced the subjectivity of the traditional methods. AI based approaches have shown promise in detecting heart diseases by analysing the heart sounds and accuracies have improved over the years. This approach will address the shortage of healthcare professionals.

There are some challenges that need to be addressed including the heterogeneity of heart sounds, the need for a large, diverse dataset for training and testing the AI models and the requirement of a standardised approach for data acquisition and processing. Despite all these challenges, the potential benefits are huge and interest is growing in this area among AI researchers and healthcare professionals.

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