sciendo INTERNATIONAL JOURNAL ON SMART SENSING AND INTELLIGENT SYSTEMS

Review | DOI: 10.2478/ijssis-2024-0012 Issue 1 | Vol. 17 (2024)

Recent Advances in PCG Signal Analysis using AI: A Review

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Received for publication:
xxxx xx, 2023.

Abstract

The paper reviews the milestones and various modern-day approaches in developing phonocardiogram (PCG) signal analysis. It also explains the different phases and methods of the Heart Sound signal analysis. Many physicians depend heavily on ECG experts, inviting healthcare costs and ignorance of stethoscope skills. Hence, auscultation is not a simple solution for the detection of valvular heart disease; therefore, doctors prefer clinical evaluation using Doppler Echo-cardiogram and another pathological test. However, the benefits of auscultation and other clinical evaluation can be associated with computer-aided diagnosis methods that can help considerably in measuring and analyzing various Heart Sounds. This review covers the most recent research for segmenting valvular Heart Sound during preprocessing stages, like adaptive fuzzy system, Shannon energy, time-frequency representation, and discrete wavelet distribution for analyzing and diagnosing various heart-related diseases. Different Convolutional Neural Network (CNN) based deep-learning models are discussed for valvular Heart Sound analysis, like LeNet-5, AlexNet, VGG16, VGG19, DenseNet121, Inception Net, Residual Net, Google Net, Mobile Net, Squeeze Net, and Xception Net. Among all deep-learning methods, the Xception Net claimed the highest accuracy of 99.43 + 0.03% and sensitivity of 98.58 + 0.06%. The review also provides the recent advances in the feature extraction and classification techniques of Cardiac Sound, which helps researchers and readers to a great extent.

Keywords

Auscultation, Feature Extraction, Classification, Shannon Energy, Deep Learning, Xception Network, Valvular Heart Disease, Convolutional Neural Network, Preprocessing, Segmentation

1. Introduction

The repeated sounds occurring from the heart valves are known as Heart Sound. The sounds come from the movement of the bicuspid/mitral valves, the tricuspid valves, and the aortic valves. These valves move up and down, allowing blood to flow inside the heart. They create the heartbeat sound. The study of phonocardiogram (PCG) signal is inevitable as it leads to the early detection and diagnosis of valvular heart disorder. In medical science, people suffering from valvular heart diseases, more often than not, always invite the risk of cardiac attacks or cardiac malfunction at later stages of their life. Various methods are developed, and few recent studies are going on to study these PCG signals.

1.1 PCG Signal Characteristics

In healthy young adults, a PCG signal is characterized by the periodic occurrence of S1 and S2 Heart Sounds at repeated intervals of time as shown in

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Figure 1. Sometimes, normal Heart Sounds are accompanied by S3 and S4 sounds in abnormal subjects. The systolic time period ranges from starting of S1 to starting of S2. The diastolic time period ranges from the start of S2 to the start of S1; sometimes, it may contain S3 and S4 in case of abnormal Heart Sounds. The time duration of the diastolic period is around 240 ms, whereas the systolic period is 360 ms. One complete human cardiac cycle is composed of a systolic period and a diastolic period.

1.2 PCG Signal Analysis

Feature learning [1, 27] and categorization become very handy when dealing with Heart Sound signal analysis. However, many developments are made toward Heart Sound segmentation, feature extraction, cardiac disease identification, and categorization. Nevertheless, an adaptive model for denoising, preprocessing, and filtering background noises would still significantly help further processing in this domain, especially when working with Heart Sound captured in real-time, like diagnosis centers and labs. Feature learning has been done on captured Heart Sound signals using transformation methods and to analyze Heart Sounds with computing features such as the following:

- Acoustic features: MFCCs, Mel, Chroma, Contrast, and Tonnetz
- Time-domain features: RMS, Signal Energy, Signal Power, ZCR, and THD
- Frequency domain features
- State Amplitude domain features
- Entropy domain features
- Cyclostationary features
- Statistical features: Skewness, Kurtosis, Standard Deviation, Variance, and Mean.

The Figures 1(a) and 1(b) show various steps involved in PCG signal analysis. The features of human Heart Sounds are extracted through computation, and after that, the categorization is done depending on various deep-learning methods.

1.3 Motivation

The study was designed to keep the analysis and diagnosis part of the valvular Heart Sound. There exist different Heart Sound analysis methods but screening time, portability, and cost are the important parameters when selecting the proper one.

The study carrying part is carried out on selected volunteers of different age groups and genders. Formal consent was taken from the volunteers followed by the application of the real-time developed analysis method.

In the data analysis part, artificial intelligence-based intelligent systems have been used. Different Python based developed deep-learning algorithms are chosen and implemented for the analysis.

The motivation behind this study of PCG signal and its analysis is mainly divided into two parts:

- Challenges in PCG signal analysis.
- The commercialization of the PCG signal analysis in detecting and screening valvular diseases.

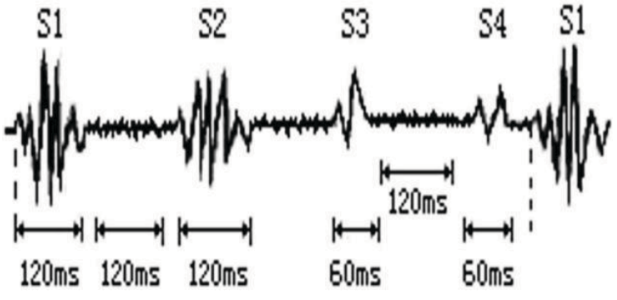


Figure 1: A typical recorded PCG signal [1]. PCG, phonocardiogram.



Figure 1(a): Various phases engaged in PCG analysis [2]. PCG, phonocardiogram.

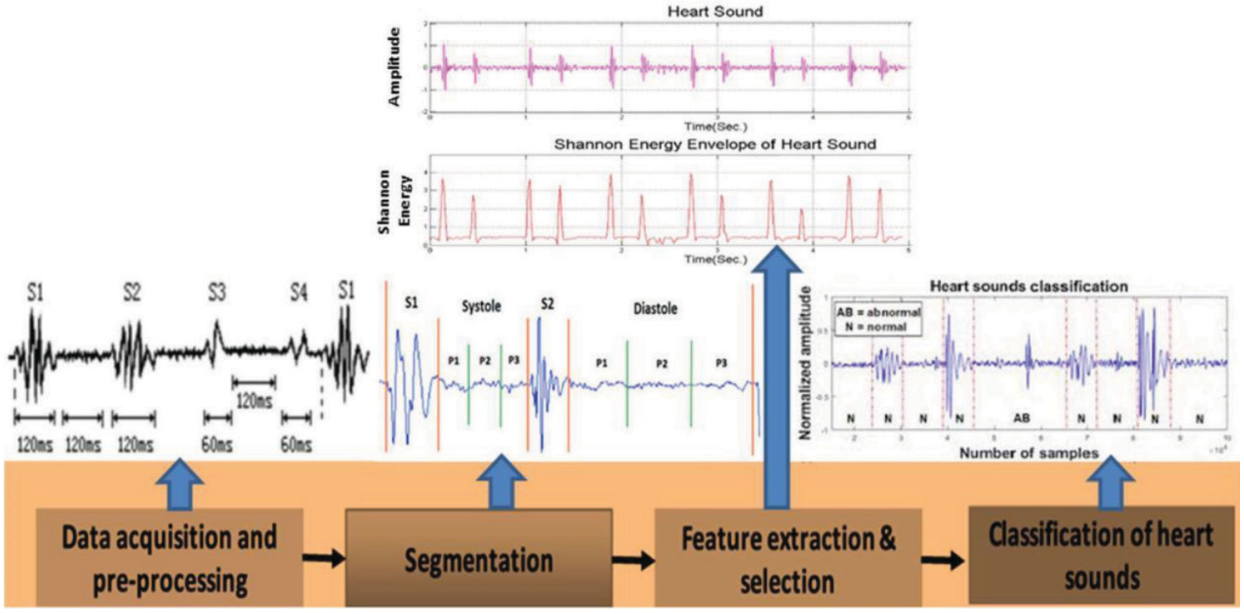


Figure 1(b): Graphical representation of various steps involved in PCG signal classification [2, 14]. PCG, phonocardiogram.

1.3.1 Challenges in PCG Signal Analysis

The significant challenges lie in PCG signal analysis are:

Filter design for noise handling while recording real-time Heart Sound: The filter design part lies with the design of a proper signal conditioning unit for the captured Heart Sound to be processed. The ambient noise and the cable of the microphone chest piece movement noise are the two important noises that need to be dealt with. Over the years, different researchers have designed different pre-amplifiers circuits, filter circuits, etc., but still, none were able to find any solutions related to the microphone chest piece movement noise.

Separating Lung sound with Heart Sound: Another major challenge is the separation of Heart Sound from lung sound. While collecting the Heart Sound in a real-time environment, lung sound gets superimposed into it, which can invite classification errors during analysis of Heart Sound only. As Heart Sounds and lung sounds lie in different frequency ranges, separation can be done using a proper selection of filters. In order to filter out the lung sound, different filters are designed that can separate the lung sound from the Heart Sound quite easily.

Development of efficient artificial intelligence-based PCG signal analysis method: An efficient classification-based method is equally important for Heart Sound analysis. Several deep-learning and machine-learning methods have been developed and discussed in this paper over the years. Classification of Heart Sound is done with the help of an efficient deep-learning method. The developed deep-learning method should be efficient in terms of evaluation parameters like accuracy, precision, recall, and F1 Score.

Design of low-cost hardware circuit for collecting shallow amplitude-based real-time Heart Sound: The design of a low-cost hardware circuit for picking up low-amplitude Heart Sound is another challenging task in PCG signal analysis. Low-amplitude Heart Sounds are captured through the chest piece of the stethoscope fitted with a microphone followed by a pre-amplifier circuit. The use of a proper pre-amplifier circuit plays a key role in collecting low-amplitude real-time Heart Sound.

1.3.2 Commercialization of PCG Signal Analysis

Earlier, the financial cost attached to the Heart Sound signal analysis of patients suffering from various heart diseases was higher. Nowadays, various low-cost PCG signal analysis methods are being developed and coming into the markets. Apart from their lower cost, the accuracy and feasibility of these devices are

equally important at the same time. Thus, low-cost PCG signal analysis is the need of the hour.

1.4 Related Work

The study would like to highlight a few recent significant works done by different researchers. The research focuses on identifying Heart Sound and their analysis. In this work, the signal categorization of the PCG signal is essential.

As per the literature study, many workers are researching in this field. Many researchers have described different algorithms and categorization methods for cardiac sounds. Randhawa and Singh [1] surveyed methods for automatically analyzing and classifying cardiac sounds. Gupta et al. [2] worked on identifying S1 & S2 Heart Sounds using a Stacked Auto Encoder with the combinatory feature for categorizing fundamental Heart Sounds. Then, the CNN approach is also used. This method has restrictions on analyzing and detecting S3 Heart Sounds. Lecun et al. [3] proposed an innovative algorithm to detect heart and lung sounds (HLS) based on the variational mode decomposition (VMD) of PCG signal. It is helpful to detect the third Heart Sound. However, this algorithm has limitations in real-time environment applications. Roy and Roy [4] proposed a new method of extracting PCG signals from noise through sparse recovery analysis. Barma et al. [5] did focus on the detection of second Heart Sound, which engages with computing the time duration and the energy of normalized instantaneous frequencies of A2s (Aortic valve) and P2s (Pulmonary valve), but it could not categorize cardiac sounds.

Tavel [6] and Muduli et al. [7] did work on Heart Sound analysis using the discrete wavelet transform (DWT) algorithm. It has specific restrictions in real-time analysis. Roy et al. [8] made PCG signal analysis using Shannon Energy Envelop and DWT method, but it cannot classify the Heart Sounds efficiently. Mishra et al. [9] made heart defect analysis and classification using Pattern Recognition Technique, but the method is based on echo imaging. Mishra et al. [10] made PCG signal analysis using classification by feature extraction but not in the real-time analytical process. El-Segaier et al. [11] made Heart Sound analysis and its categorization using a fuzzy classifier-based soft computing method. The laboratory study was done on a readily available online Heart Sound repository. It was an offline study and not validated with human volunteers. Nygaard et al. [12] studied the classification of PCG signals. Anju and Sanjay Kumar [13] did a segmentation and categorization of PCG signals for Heart Sound analysis. There is no significant work on developing real-time screening of valvular diseases. Buchanna et al. [152] studied the classification of EEG signals using fractal analysis and support vector regression. Ye et al. [151] analyzed multimodal medical images using semantic segmentation maps generated through deep learning. Many researchers studied PCG signal analysis; some of the corresponding algorithms are given below in Table 1.

1.5 Paper Organization

The full review paper is structured as mentioned. Section 2 provides a background of different types of Heart Sound and their characteristics. Section 3 provides details of real-time PCG signal analysis. Section 4 explains the other methods used in Heart Sound analysis. Section 5 describes the deep-learning and machine-learning methods adopted in Heart Sound analysis. Finally, Section 6 summarizes the conclusions and future scope.

2. Heart Sounds and Their Characteristics

Table 2 shows frequency ranges for different types of PCG signals that are used in the Heart Sound analysis [37]. Typically, Heart Sound lies in the frequency range of 45–450 Hz, including stenosis and regurgitation condition of the heart. The maximum and minimum frequency range of each PCG signal is also shown in Table 2.

Figure 2 highlights the characteristics and features of different PCG signals. Generally, s1 and s2 sounds can be heard in regular Heart Sounds, comprising short duration and high pitch. Under abnormal Heart Sounds, s3 and s4 sounds can be heard with short duration and low pitch. Common disorders occurring due to abnormal Heart Sounds are mitral stenosis (MS), aortic stenosis (AS), ventricular septal defect (VSD), etc. Apart from these disorders, some other disorders may happen due to the murmur Heart Sound. The aortic regurgitation (AR), mitral regurgitation (MR), mitral valve prolapse (MVP), and patent ductus arteriosus (PDA) are a few examples of murmur Heart Sounds.

Sitting, standing, and supine are postures for capturing Heart Sounds. Typically stethoscope sensors are placed on different locations of the body. Some of the positions are Cardiac Apex, Upper Left Sternal Border (ULSB), Upper Right Sternal Border (URSB), Lower Left Sternal Border (LLSB), etc.

Table 1. A study of PCG signal and their gap analysis reported in the literature

Ref.	Author	Year	Methodological problem and research gap analysis	Features
[15]	Dewangan et al.	2018	Basic features used in the time domain only	Heart Sound analysis using the DWT method
[16]	Thomas Schanze	2017	Biomedical heart signal analysis not using latest machine-learning and deep-learning methods	Singular value decomposition
[17]	Othman and Khaleel	2017	Only time-domain analysis has been made	PCG signal analysis using Shannon Energy Envelop and DWT method
[18]	Martinek et al.	2017	PCG signal analysis applicable to fetal heart only, not real-time human subjects	Adaptive filtering based fetal heart rate monitoring
[19]	Abhijay Rao	2017	It is a survey paper only, not a research paper	Biomedical signal processing
[20]	Sh-Hussain et al.	2016	Frequency domain and statistical domain features need to be analyzed	Heart Sound monitoring system using wavelet transformation
[21]	Prasad and Kumar	2015	Real-time PCG signal analysis was not applied	Analysis of various DWT methods for feature extracted PCG signals
[22]	Pan et al.	2015	Real-time analysis not done	Categorization of PCG signals using multimodal features
[23]	Lubaib and Muneer	2015	More features need to be considered for this analysis	Using pattern recognition techniques
[24]	Roy et al.	2014	No proper experimentation has been done	A survey on classification of PCG signals
[25]	Mishra et al.	2013	It deals with PCG signal noise removal only, not classification	Denoising of Heart Sound signal using DWT
[26]	Zhao et al.	2013	PCG signal/Heart Sound biometric	Marginal Spectrum Analysis
[27]	Singh and Cheema	2013	Limited application of deep-learning algorithms has been used	Classification using Feature Extraction
[28]	Safara et al.	2013	Only time-domain analysis has been made	Multi-level basis selection of wavelet
[29]	Salleh et al.	2012	PCG signal analysis using Kalman filter, not using any standard deep-learning method	Heart Sound analysis: a Kalman filter-based approach
[30]	Misal and Sinha	2012	It deals with PCG signal noise removal only, not classification	Denoising of PCG signal using DWT
[31]	Kasturiwale	2012	Biomedical signal analysis, limited features.	Analysis using component extraction
[32]	McNames and Aboy	2008	It deals with the modeling part of PCG signals, not the classification and analysis	Techniques, statistical modeling of PCG signals
[33]	Ahmad et al.	2009	More feature extraction needs to be done for the PCG signal analysis	Classification of PCG signal using an Adaptive Fuzzy Inference System.
[34]	Debbal and Bereksi-Reguig	2006	Time-domain analysis in time domain only	PCG signal analysis using the CWT
[35]	Gupta et al.	2005	A real-time PCG signal analysis was not done	Segmentation and categorization of Heart Sound for analysis purpose.
[36]	Muthuswamy	2004	It is a survey paper only, not a research paper	Biomedical signal analysis

DWT, discrete wavelet transform; PCG, phonocardiogram.

Table 2. Heart Sound frequencies found in various abnormal Heart Sounds.

Heart Sound	Lowest frequency (Hz)	Highest frequency (Hz)
First Heart Sound	100	200
Second Heart Sound	50	250
AR	60	380
PR	90	150
AS	100	450
PS	150	400
ASD	60	200
VSD	50	180
MR	60	400
TR	90	400
MS	45	90
TS	90	400
MVP	45	90
PDA	90	140
Flow murmur	85	300

AR, aortic regurgitation; AS, aortic stenosis; ASD, atrial septal defect; MR, mitral regurgitation; MS, mitral stenosis; MVP, mitral valve prolapse; PDA, patent ductus arteriosus; PR, pulmonary regurgitation; PS, pulmonary stenosis; TR, tricuspid regurgitation; VSD, ventricular septal defect.

Table 2 provides the characteristics of frequencies in different types of abnormal Heart Sounds. The minimum and maximum frequency range of every kind of Heart Sound is mentioned in Table 2. Generally, Heart Sound frequency ranges from 45 Hz to 450 Hz. Thus, valuable information lies only in this range, and the rest needs to be filtered out using various processing methods.

2.1 Different Valvular Heart Sound Disorders

Different types of valvular Heart Sound disorders are explained below:

AS – Aortic valve could not open properly.
AR – Aortic valve could not close completely.
PR – Pulmonary valve could not close completely.
PS – Pulmonary valve could not open completely.
ASD – A hole by birth between the heart's upper chambers.
VSD – A hole by birth between the heart's lower chambers.
MR – Mitral valve could not close completely.
TR – Tricuspid valve could not close completely.
MS – Mitral valve could not open properly.
TS – Tricuspid valve could not open completely.
MVP – Mitral valve accelerates into the left atrium and stops abruptly.
PDA – An opening between two major blood vessels leads from the heart.
Flow murmur – It is an unusual sound heard when blood is through the heart chambers.
Normal Heart Sound – It is caused due to the combination of S1 (first Heart Sound) and S2 (second Heart Sound) Heart Sounds only.

3. Real-Time PCG Signal Analysis

3.1 Use of Sensors, Denoising Filters, and Pre-amplifiers in Real-Time Heart Sound Analysis

Figure 3 (a) depicts the block diagram of sensors used in the Heart Sound signal analysis. It also gives us an idea about how filters play a pivotal role in PCG signal analysis. Generally, low-pass, high-pass, and bandpass filters are used in the said process. New technologies like adaptive noise cancellers (ANCs) and adaptive line enhancers (ALEs) are used in the modern-day era to meet the requirements in a better-enhanced manner in terms of efficiency and stability.

PCG signal in the chest generates pressure waves that the stethoscope diaphragm has picked up. The electret microphone fitted inside the chest piece and the stethoscope tube convert Heart Sound signal to electrical signal. This electrical signal is boosted by an audio amplifier based on a MAX 9812 IC chip of gain 20 and fed to the notch filter to remove electrical interferences. The processed signal is fed to an analog tunable bandpass filter with a 35–470 Hz spectrum. The Heart Sound signal typically belongs to 35–470 Hz for normal and abnormal sounds. Finally, the processed signal is converted to digital form in a USB sound card connected to a Raspberry Pi 4B computer. The Heart Sound samples are picked up in real-time by a stethoscope sensor and saved in WAV. format for further processing through Raspberry Pi

4B with developed deep-learning models, as illustrated in Figure 3 (b).

Figures 4 and 5 illustrate the denoising methods used in the Heart Sound analysis and diagnosis. Table 3 highlights the various sensors used in the denoising algorithms adopted for the Heart Sound classification.

ANC is composed of two input signals from two separate sources. The first signal is noisy, and another contains ambient noise only. These two signals

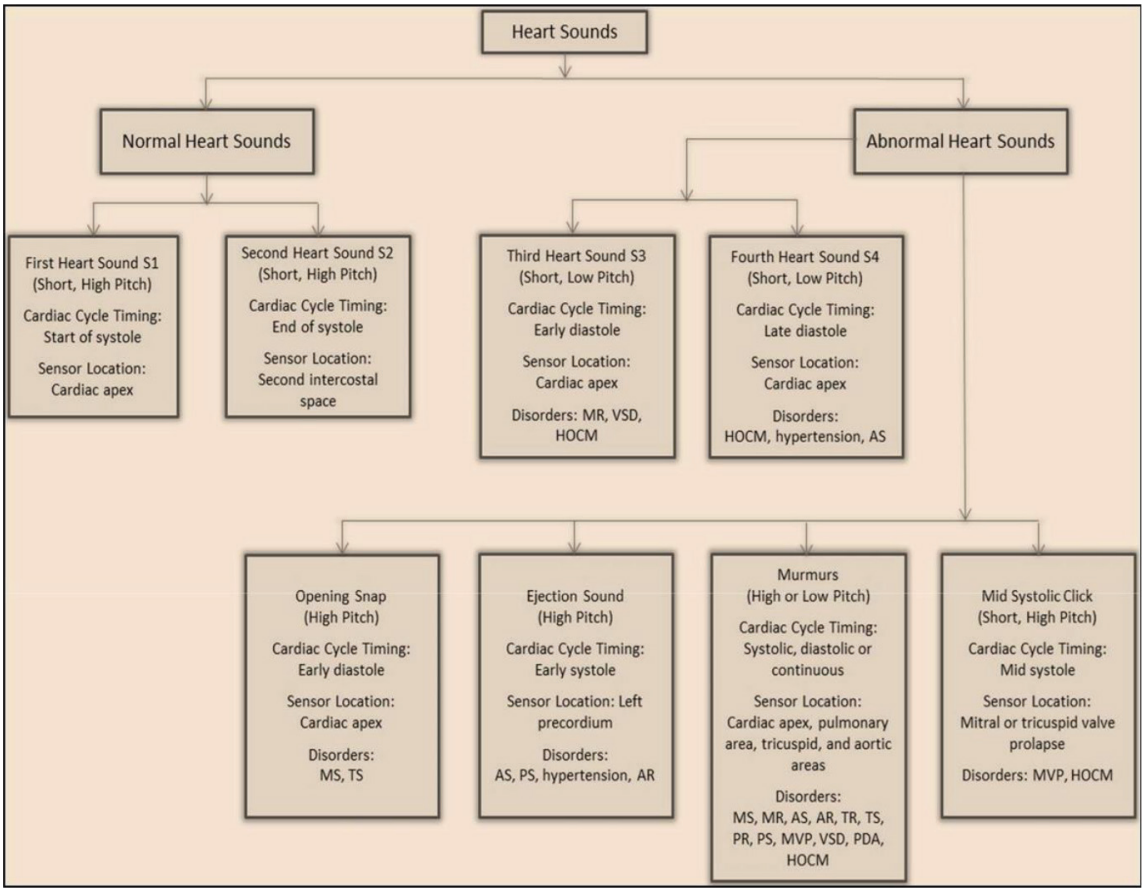


Figure 2: Characteristics of various kinds of Heart Sounds. AR, aortic regurgitation; AS, aortic stenosis; MR, mitral regurgitation; MS, mitral stenosis; MVP, mitral valve prolapse; PDA, patent ductus arteriosus; PR, pulmonary regurgitation; PS, pulmonary stenosis; TR, tricuspid regurgitation; TS, tricuspid stenosis; VSD, ventricular septal defect.

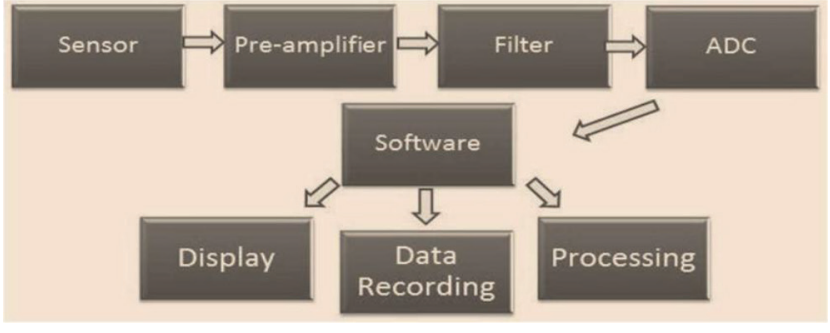


Figure 3(a): Schematic diagram of sensors, pre-amplifier, and filters used in PCG signal analysis. PCG, phonocardiogram.

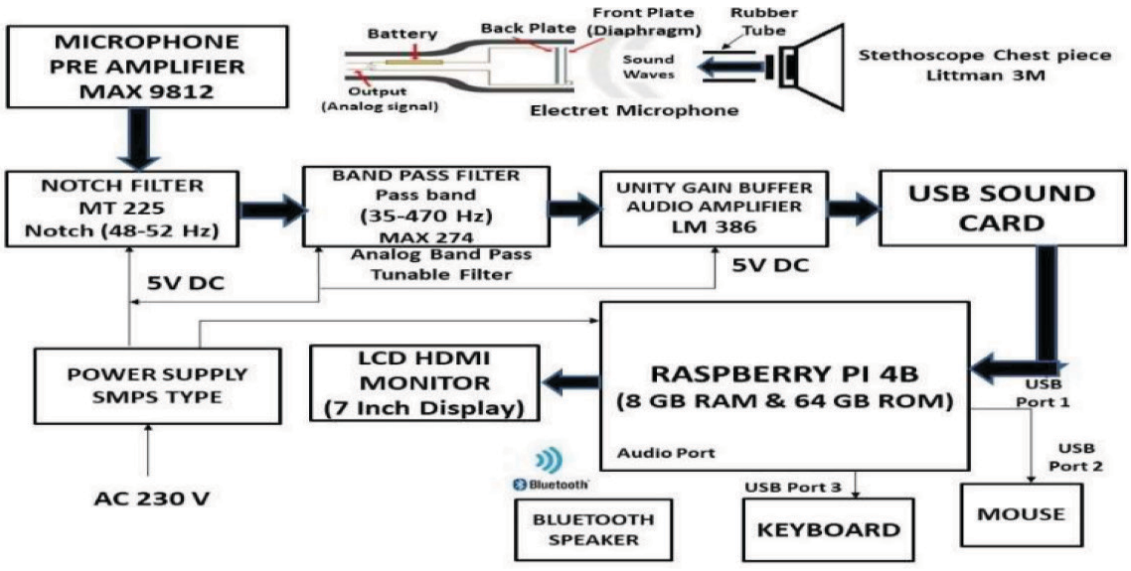


Figure 3(b): Schematic diagram of PCG signal acquisition system. PCG, phonocardiogram.

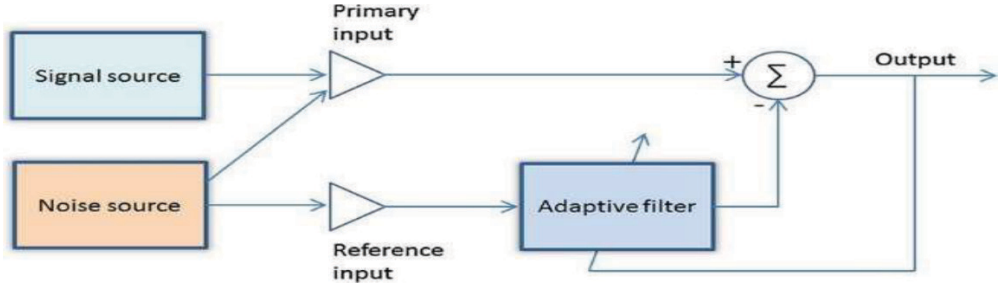


Figure 4: Block diagram of ANC. ANC, adaptive noise canceller.

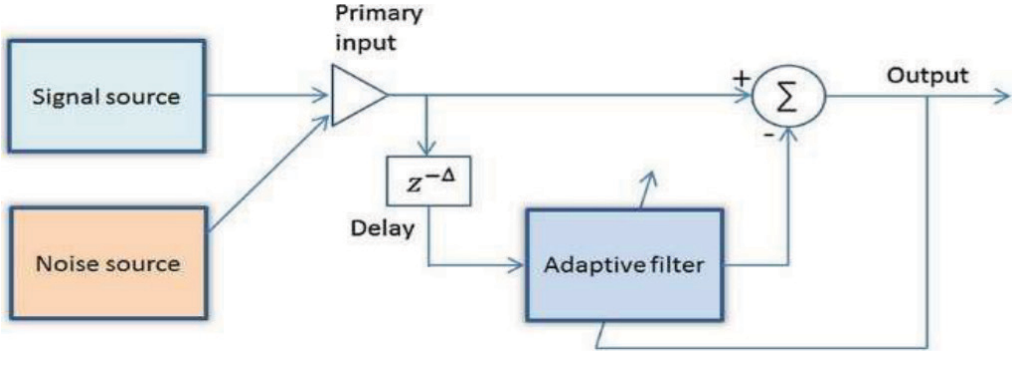


Figure 5: Block diagram of ALE. ALE, adaptive line enhancer.

are subtracted at the subtractor circuit, producing a noise-free desired signal.

In ALEs, digital adaptive filters can change their characteristics depending on the input signal change. Adaptive filters generally use the least mean square (LMS) algorithm to work. It can be considered one of the better tools for the Heart Sound denoising process. Figure 5 shows an ALE where a delay block

Table 3. Different sensors used in real-time Heart Sound analysis methods.

Denoising domain	Type of sensors used	Number of sensors	Algorithm adopted
Time	Electret condenser microphone	1	LMS-ANC
Time	Electronic stethoscope	1	Single input ANC
Time	Microphone	1	LMS-ALE, RLS-ALE
Frequency	Electronic stethoscope with an electret microphone	1	DWT, Hilbert transform
Frequency	Microphone	1	DWT, LMS-ALE, RLS-ALE
Frequency	NM	NM	EMD

ALE, adaptive line enhancer; ANC, adaptive noise canceller; DWT, discrete wavelet transform; EMD, empirical mode decomposition; LMS, least mean square; RLS, recursive least square.

is also appended with the adaptive filter to obtain a noise-free Heart Sound signal.

3.2 Description of Available Heart Sound Repositories

Generally, Heart Sound banks are used in real-time valvular Heart Sound analysis. The following are the Heart Sound bank repositories:

(a) 2016 PhysioNet/Computing in Cardiology (CinC) Challenge – Normal and Abnormal Heart Sound [76]
(b) Classification of Heart Sounds into three types – namely, normal (N), murmur (M), and extrasystole (EXT) in PASCAL Classifying Heart Sound Challenge [75]
(c) Classification of five types of Heart Sounds – normal, AS, MR, MS, and MVP; available in public databases in Yaseen et al. [https://github.com/yaseen21khan/Classification-of-Heart-Sound-Signal-Using-Multiple-Features] [74]
(d) Kaggle Dataset for Normal and Abnormal Heart Sound [77].

4 Various Methods used in Heart Sound Analysis

Cardiac sounds are captured with an electronic stethoscope with a sampling frequency of about 4.7 KHz. The collected Heart Sounds are saved as a WAV. file. The auscultation recordings [129, 130] are done in postures such as sitting, standing, supine, etc.; all other essential information pieces are stored for further processing.

4.1 Computerized Heart Sound Analysis using Wavelet Transforms

General preprocessing methods used for Heart Sound analysis are:

1. Normalization.
2. Filtering.
3. Feature extraction.

4.1.1 Preprocessing of Signal [40, 83]

The cardiac sounds are preprocessed first to generate the required Heart Sound data, as shown in Figure 6. Under the preprocessing stage, Heart Sound normalization occurs, followed by filtering and feature extraction. A typical normalization process is shown in Figure 7.

Normalization is expressed as shown in Eq. (1):

$$x(n) = xr(n) - xr(min) / xr(max) - xr(min) \quad (1)$$

where xr(n) denotes the recorded PCG signal, and x(n) symbolizes the normalized Heart Sound signal [47, 51, 87]. At the same time, xr(min) and xr(max) are the lowest and highest values of the Heart Sound, respectively.

In filtering operation, second-order high-pass and low-pass Butterworth filters with 15 Hz and 700 Hz cut-off frequencies are used to filter the normalized PCG signal and remove unwanted background noise. Feature learning is used for the filtered signal

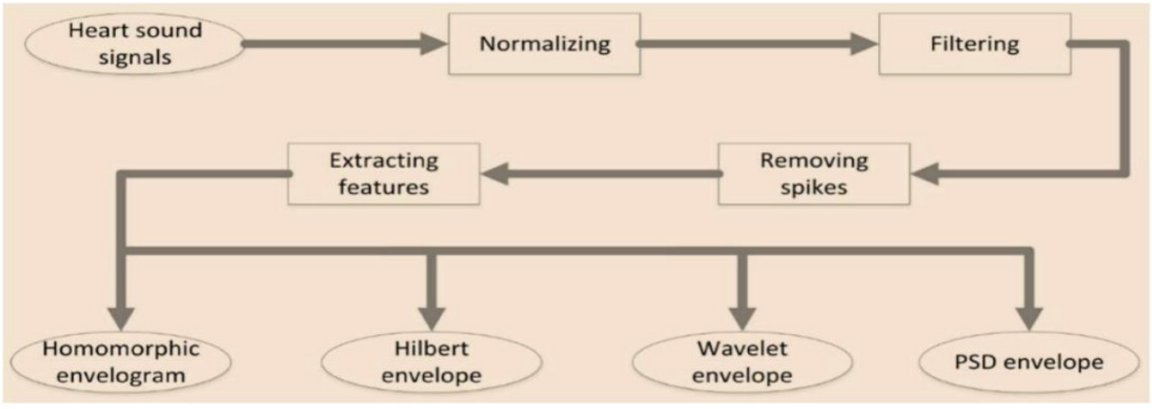


Figure 6: Block diagram of Heart Sound preprocessing.

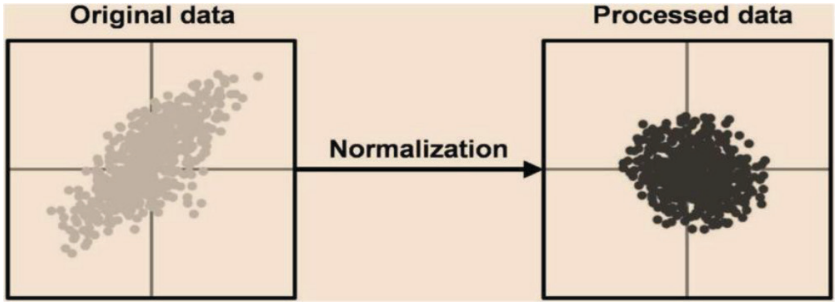


Figure 7: Normalization process.

as expressed in the literature [41, 45, 88]. The four commonly used envelop-energy-based algorithms employed in the production of features are: (1) Hilbert envelope, (2) Homomorphic environment map, (3) Wavelet envelope, and (4) Power spectral density envelope.

4.1.2 Heart Sound Segmentation

The Heart Sound segmentation is the split-up of the Heart Sounds into four sections: the first Heart Sounds (S1), systole, second Heart Sounds (S2), and diastole. Each section [42, 49, 82] comprises essential features that discriminate the various types of cardiac sounds. The common segmentation methods that researchers used over the recent years are mainly:

1. Envelope-based methods
2. Shannon energy-based method
3. Hilbert envelope method
4. Squared envelope method
5. Hidden Markov model methods
6. Feature-based method.

4.1.3 Feature Extraction

The segmented Heart Sound [89, 95, 97] goes to the feature extraction block where new features are extracted, which results in a reduced Heart Sound data size and eventually classifications based on these extracted features using CNN-based deep-learning [90, 96] methods. Figure 8 describes the reduction in data size of the PCG signal by the feature learning method.

4.1.4 Signal Segmentation using Shannon Energy

The method based on the Shannon energy of the Heart Sound [125, 126] is considered for extracting the Heart Sound signals as shown in Figure 9. Shannon energy fetches the medium-intensity cardiac sound and removes the noise effect. It is the best way to

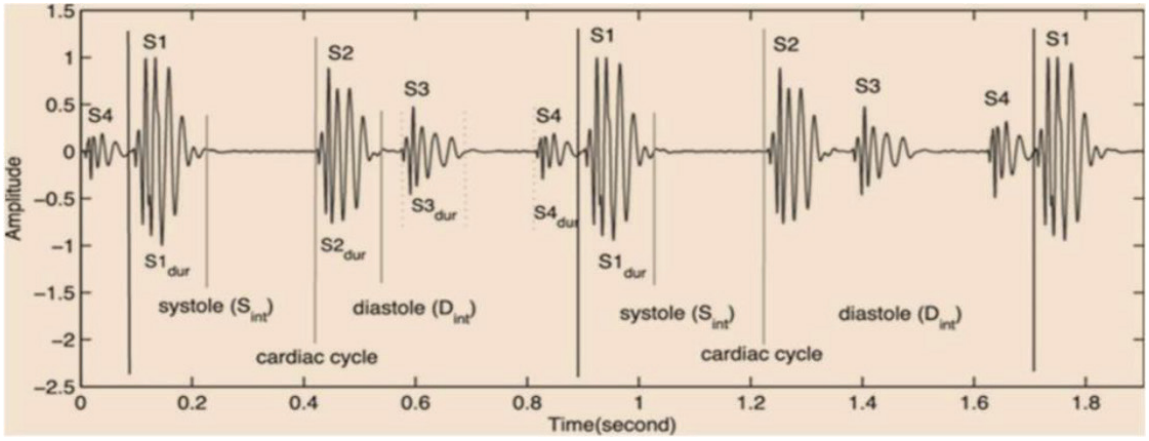


Figure 8: Different segments in Heart Sound.

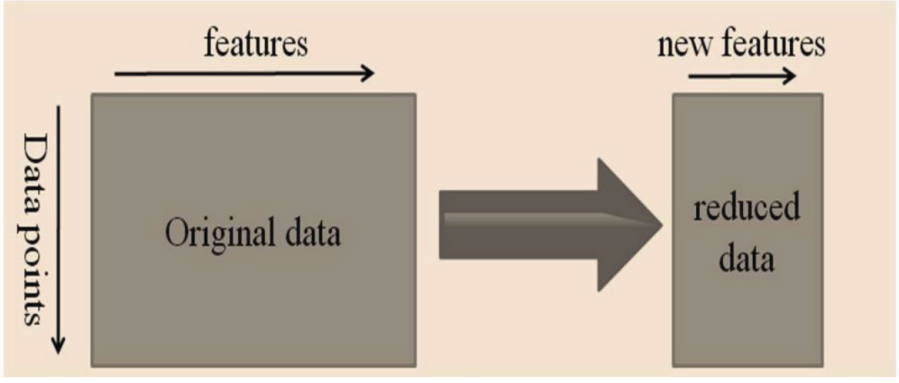


Figure 9: Reduction in data size due to feature extraction.

extract the envelope of any cardiac sound signal compared to other methods, and the following terminologies are used to compute the different parameters:

(a) Shannon Energy: It is the average of the spectrum energy in the Heart Sound signal.
(b) Shannon Entropy: It is the amount of information in the Heart Sound signal.
(c) Absolute Value: The positive values of Heart Sound signal.
(d) Energy (square) value: It is related to the square of the amplitude of the PCG signal.

4.1.5 Feature Extraction and Classification

To differentiate between various kinds of cardiac sounds [127, 128] as normal or abnormal and then identify the abnormal sound as an MR or MS case, the following stages are considered in this method:

(i) Averaging energy envelop
(ii) Finding averaged envelop peaks
(iii) Fixing threshold (S1 and S2 duration computation)
(iv) Murmurs detection and analysis

Figure 10 (a) illustrates the PCG of a typical cardiac sound, and Figure 10 (b) denotes the Shannon energy envelope of a typical cardiac sound. Figure 11 depicts the flowchart of the said algorithm used.

The Shannon energy method can be a handful tool for identifying different types of Heart Sounds. Figure 10 gives a description of the feature extraction technique using the Shannon energy envelop method. In the flowchart, the preprocessed Heart

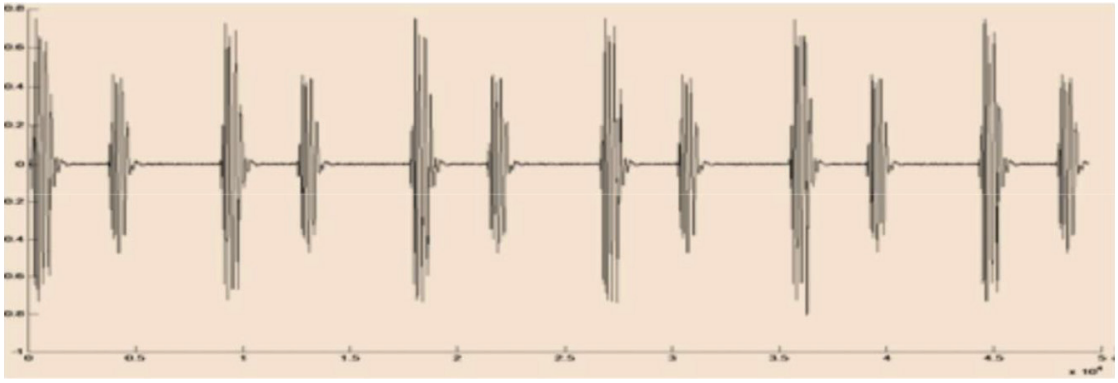


Figure 10(a): PCG of a normal cardiac Heart Sound. PCG, phonocardiogram.

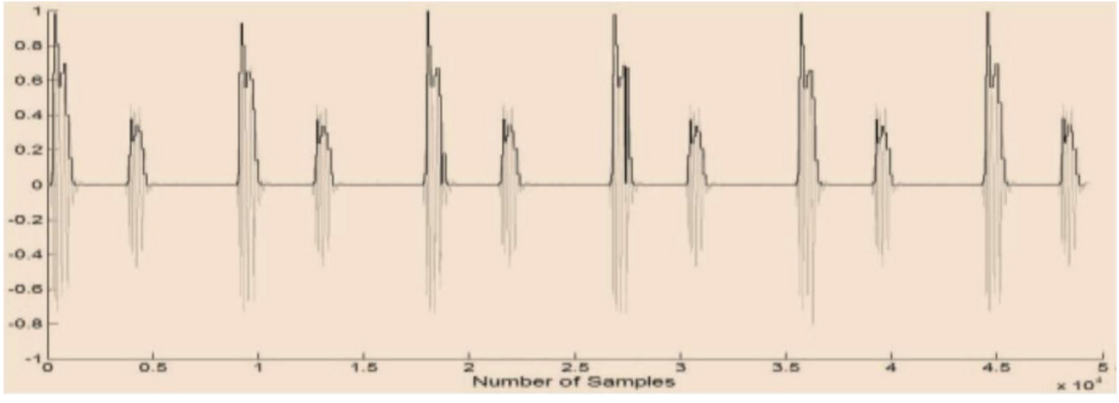


Figure 10(b): Shannon energy envelogram of the PCG of a normal Heart Sound. PCG, phonocardiogram.

Sound is checked for the threshold amplitude value (set by the user) and a cycle duration of less than 0.9 s. If it satisfies the condition, then it is a normal sound. Otherwise, the algorithm proceeds to the ascertainment of the S1 and S2 peak locations and the extraction of murmur. The murmur sound undergoes DWT. The 5th level of DWT is selected in the frequency domain using a Fast Fourier transform. If the center frequency is lying at 200–250 Hz, it is an MR; otherwise, it is an MS.

4.2 PCG Signal Analysis using DWT

In this method [40, 15, 25], Heart Sound signals are decomposed to a desired number of levels (n). The variance of detail coefficients is produced at the required levels. The computation has been made separately to normal, AS, AR, MS, and MR types of PCG signals. The schematic diagram of PCG signal analysis has been described in Figure 12.

Different abnormal Heart Sounds are considered and analyzed. All Heart Sounds are taken from a standard cardiac repository available online. Figure 13 illustrates the time-domain representation of normal PCG signal, AS, AR, MS, and MR in the time domain.

Figure 14 (a) illustrates a generalized block diagram of the DWT. In this Transform, the input signal initially passes through two types of filters: high-pass and low-pass. The high-pass filter output is known as the detail coefficient, and the low-pass filter output is represented as the approximation coefficient. The low-pass filter output is further passed through two filters, thus generating another set of detail and approximation coefficients. This process continues up to the required level n.

Figure 14 (b) describes the flowchart of DWT where a signal S is at first divided into CA1 (approximation coefficient at level 1) and CD1 (detail coefficient at level 1). CA1 is further divided into CA2 and CD2, and this process continues until the desired

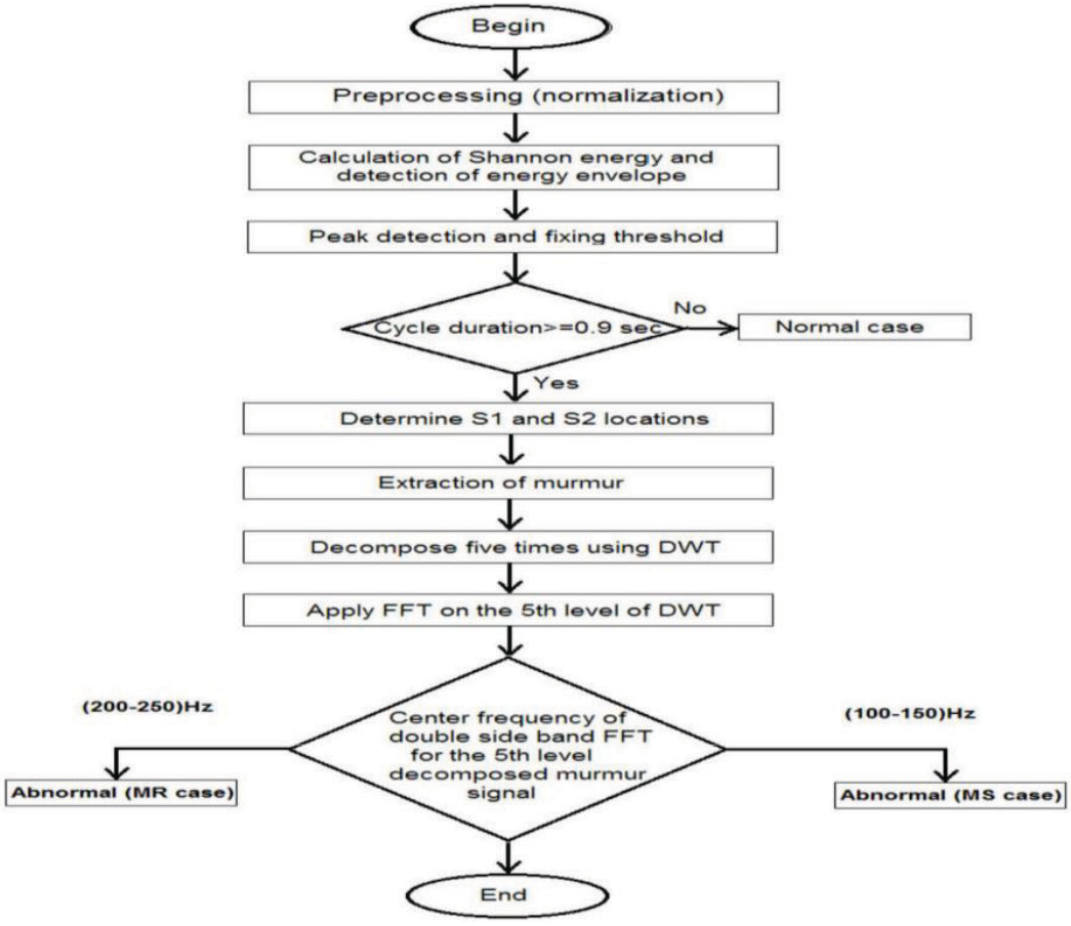


Figure 11: Flowchart of the method used.

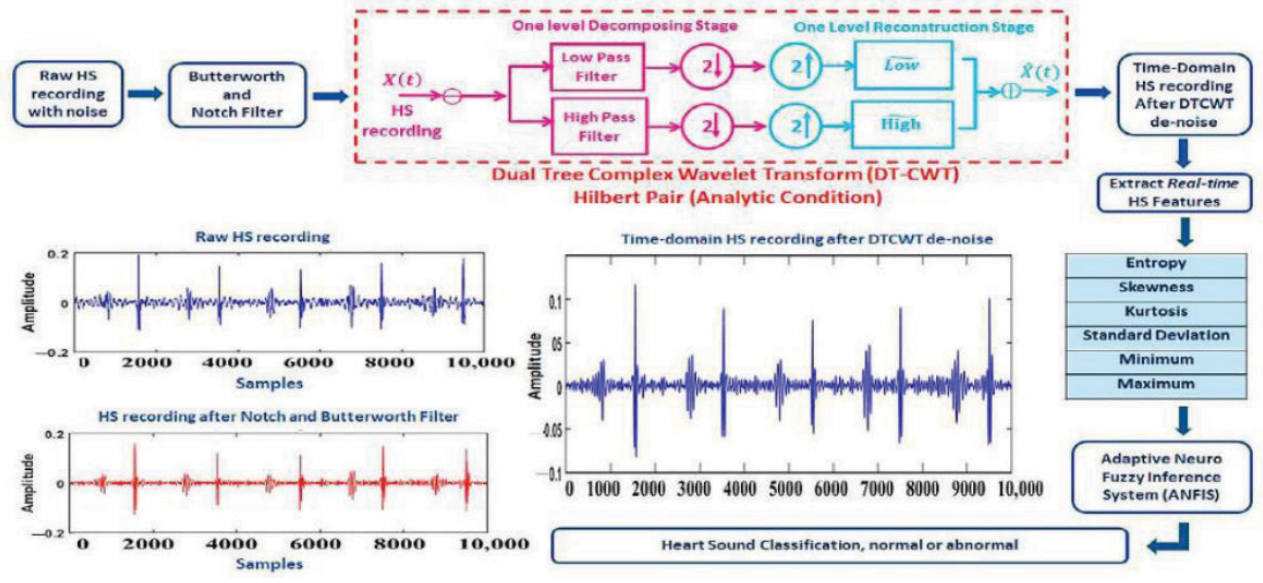


Figure 12: Schematic diagram of Heart Sound analysis using DWT. ANFIS, adaptive neuro fuzzy inference system; DWT, discrete wavelet transform; DT-CWT, dual tree complex wavelet transform.

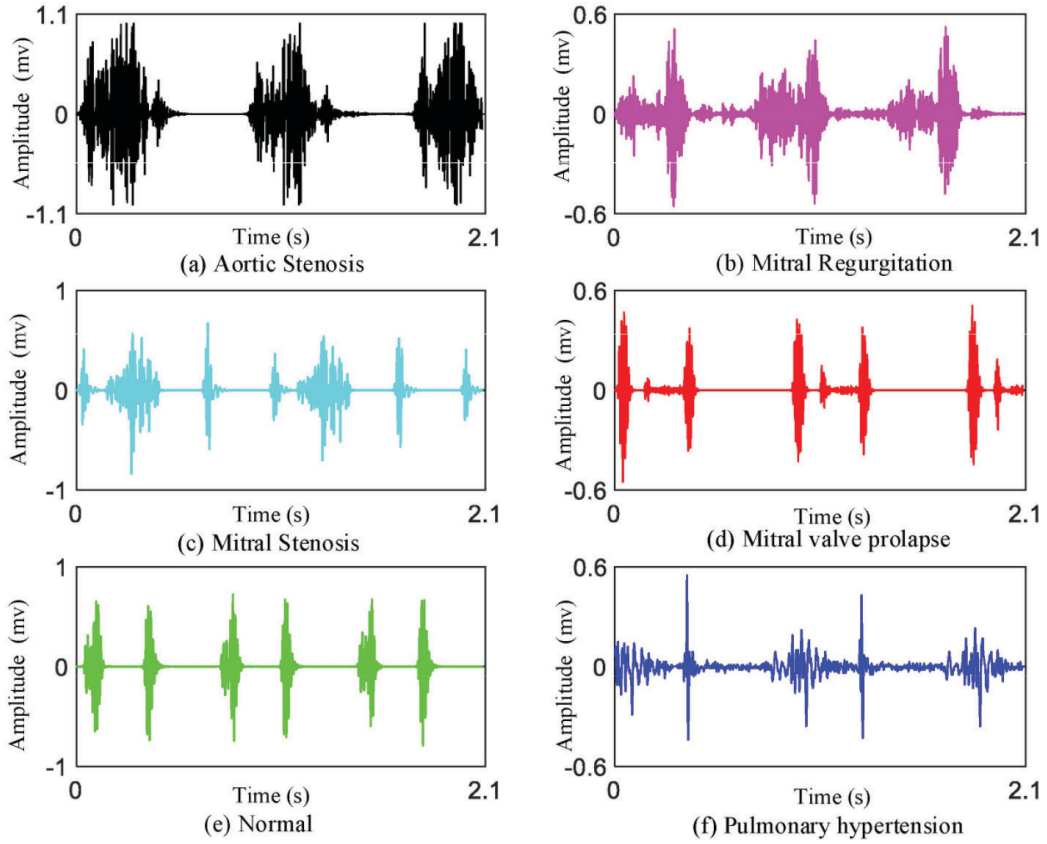


Figure 13: PCG analysis of different types of Heart Sounds [41, 39, 49]. PCG, phonocardiogram.

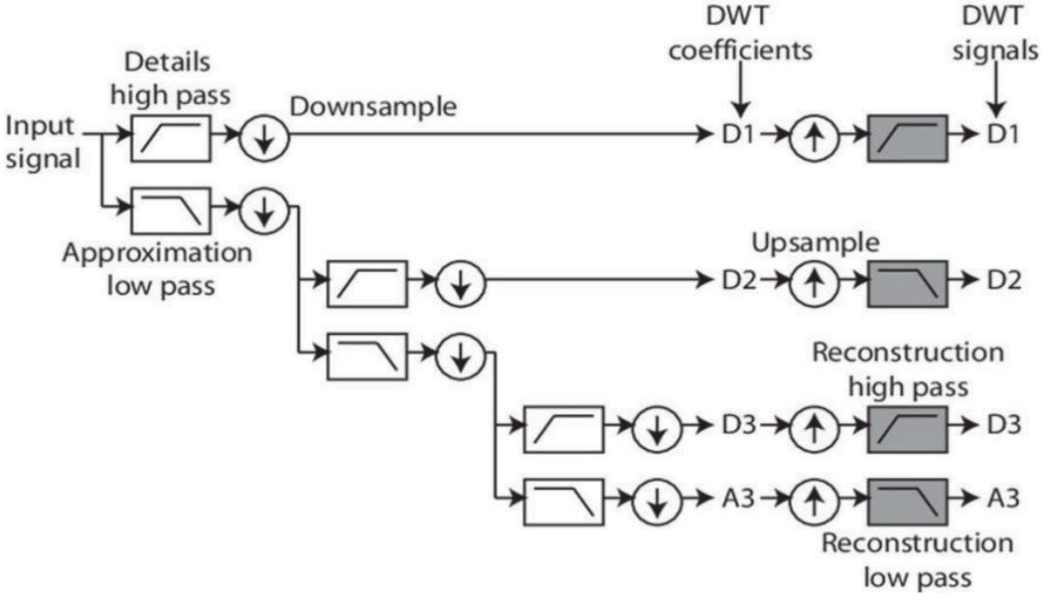


Figure 14(a): Different coefficients in DWT [121, 122]. DWT, discrete wavelet transform.

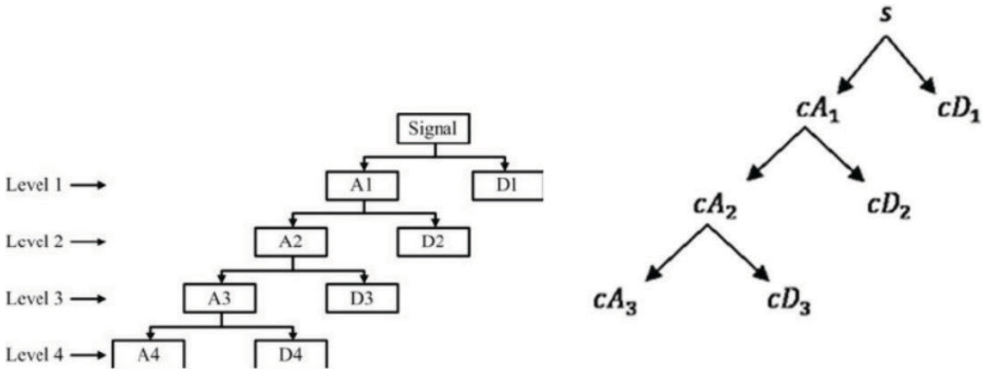


Figure 14(b): Flow chart of DWT [121, 122]. DWT, discrete wavelet transform.

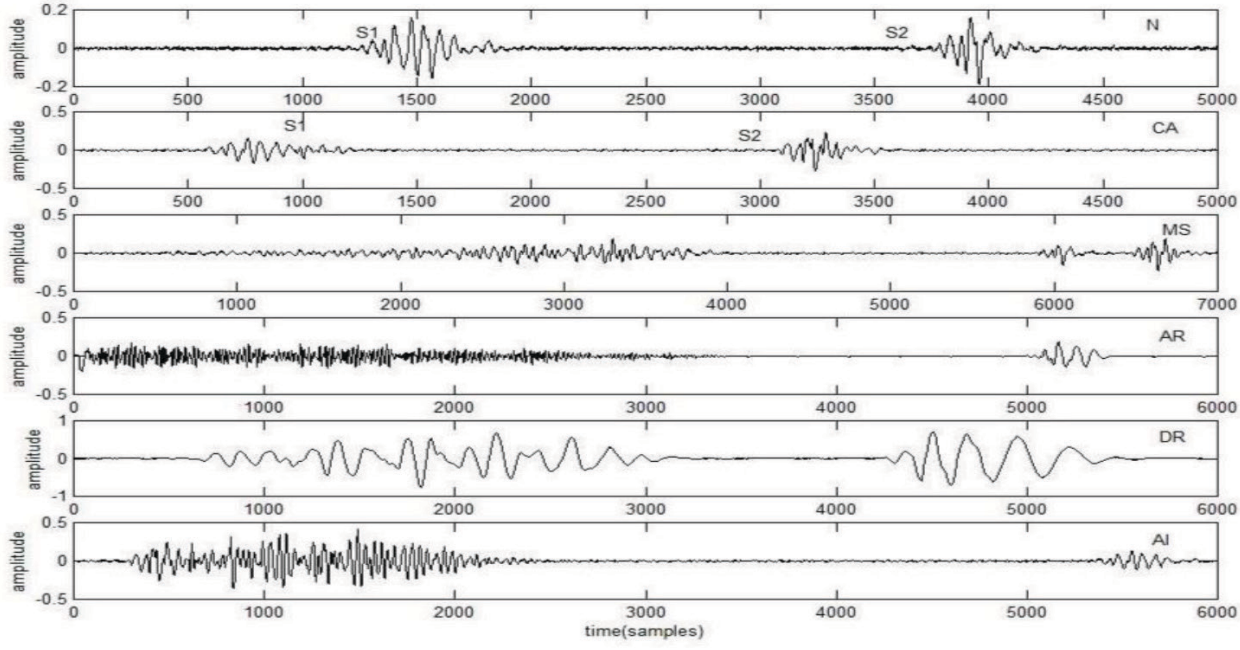


Figure 15: Time-domain analysis of different Heart Sounds using wavelet transform [121, 122]. AR, aortic regurgitation; MS, mitral stenosis.

level is reached. In this way, different PCG signals can be classified using DWT, as illustrated in Figure 15.

Various types of PCG signals are analyzed and plotted in Figure 15 using DWT. The Heart Sounds are plotted against the amplitude vs. time domain of the Heart Sound samples. Systolic murmurs and diastolic murmurs can be easily observed from the said characteristics plot.

The DWT [8, 24, 40] is a conversion method to analyze the temporal and spectral features of non-stationary signals like sound. The PCG signals are convenient for identifying the different types of valvular heart diseases. ECG readings are not good enough to find information related to the heart valves. This paper uses DWT to categorize normal and various abnormal Heart Sounds without getting into the hectic segmentation method. The proposed method is quickly adopted using a stethoscope without the help of ECG readings. In this paper, Heart Sounds are acquired through data acquisition and decomposed into n number of levels using DWT. Then variance of detail coefficients is calculated. The variance of detail coefficients at the required number of levels will form a feature set to classify normal Heart Sound, abnormal Heart Sound, and cardiac murmurs. Using DWT, any Heart Sound is represented in terms of Detailed Coefficients and Approximate Coefficients. Figures 16 (a) and (b) highlight the description of

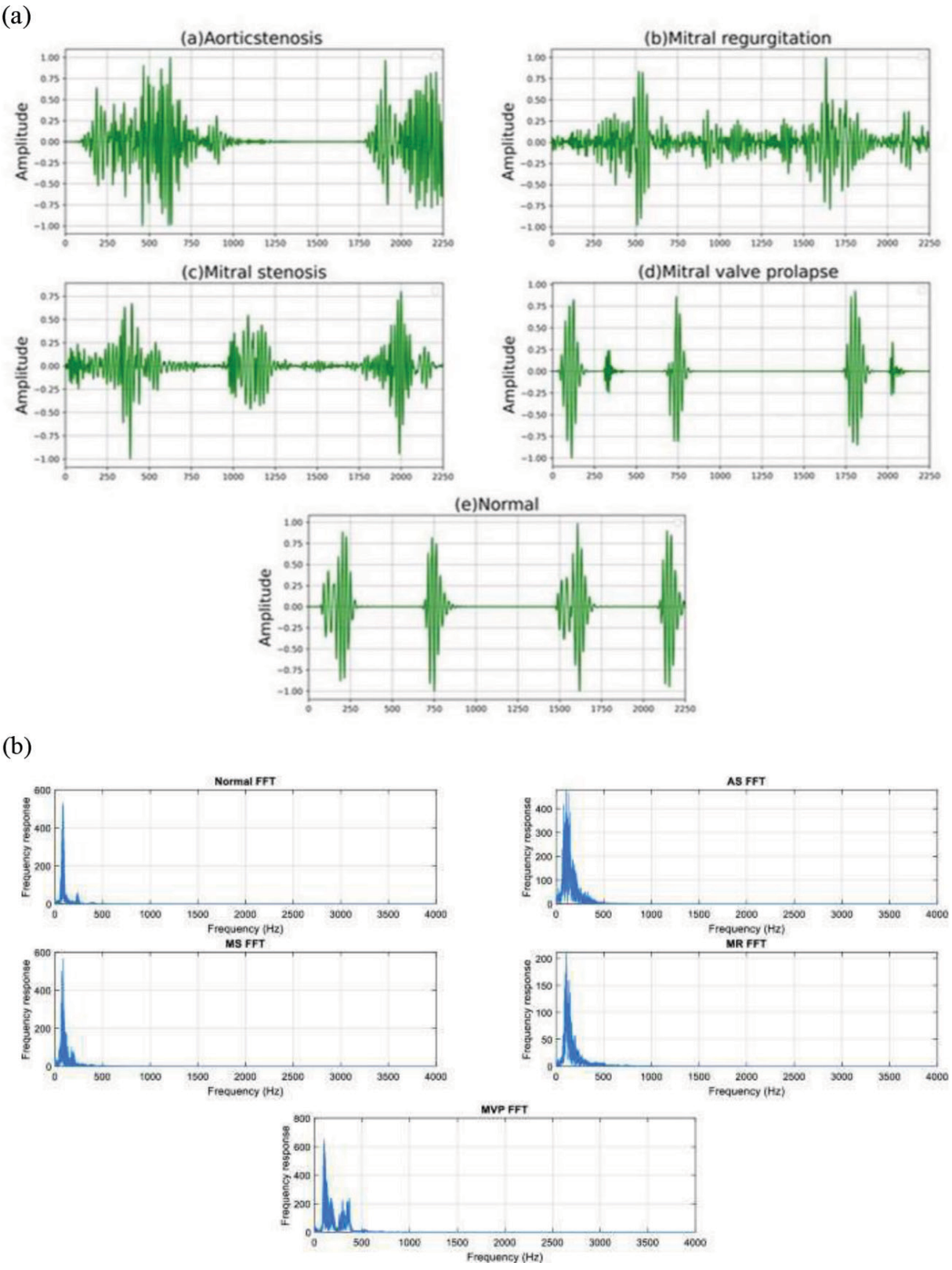


Figure 16: Time (a) and frequency (b)-domain analysis of different PCG signals using DWT. AS, aortic stenosis; DWT, discrete wavelet transform; MR, mitral regurgitation; MS, mitral stenosis; MVP, mitral valve prolapse; PCG, phonocardiogram.

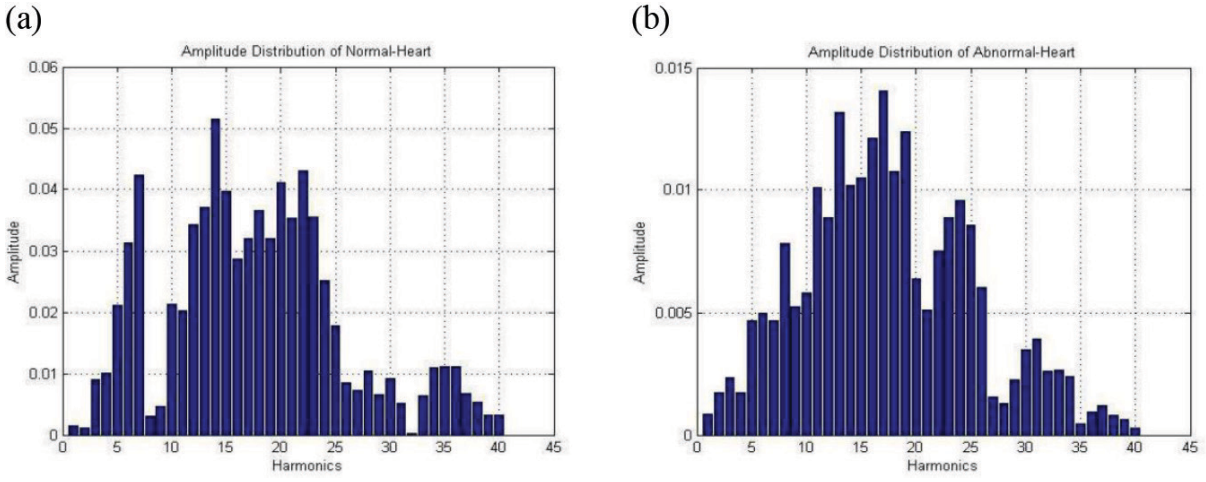


Figure 17(a,b): (a). Amplitude distribution of Normal Heart. (b). Amplitude distribution of Abnormal Heart.

various Heart Sounds [123, 124] using time-domain and frequency-domain analysis that uses DWT.

4.3 Harmonic-Distribution Method for PCG Signal Analysis

In Harmonic-Distribution [43, 44, 1], the amplitude and phase may be ignored due to negligible values. Harmonic-Distribution is produced initially by transforming the time-domain Heart Sound into the frequency domain and then by taking out the real and imaginary components separately.

Stages for computing the Harmonic-Distribution of a recorded cardiac sound signal:

1. Load the cardiac sound using Python in the time domain.
2. Compute the Fourier transform of a cardiac sound [117, 118] in frequency-domain spectrum analysis.
3. Compute the real and imaginary parts of the frequency domain cardiac sound signal.
4. Calculate the amplitude and phase of every harmonic frequency component.
5. Plot the Harmonic vs. Amplitude and Harmonic vs. Phase value of the cardiac sound signal.

For understanding, a harmonics order of up to 40 is selected. The following distributions provide the Harmonic-Distribution of Amplitude for normal and abnormal Heart Sound as well as for Cardiac Murmurs [119, 120].

Figures 17 (a–c) highlight various Harmonic-Distributions of normal, abnormal, and murmur Heart Sound.

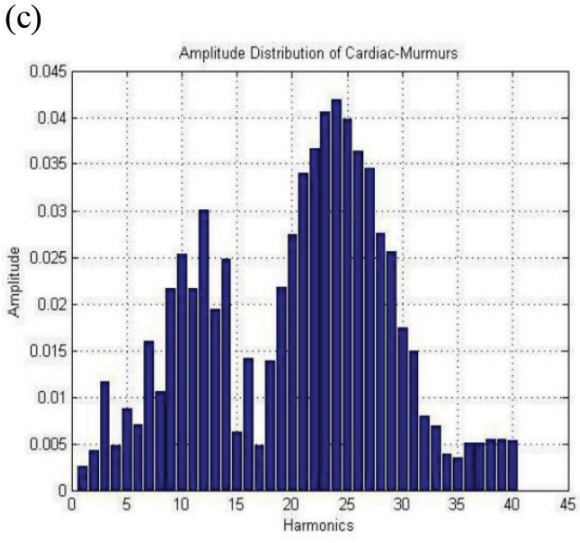


Figure 17(c): Amplitude distribution of Murmurs.

Figure 18 illustrates the classification of various types of cardiac sounds. Murmurs have a smaller amplitude in distribution, while abnormal sounds have a higher amplitude in distribution. This method can identify and classify multiple types of Heart Sounds accurately.

5. Deep-Learning-Based Heart Sound Analysis

Figure 19 highlights the earlier studies of deep-learning-based PCG signal analysis and classification methods published in the last 5–7 years.

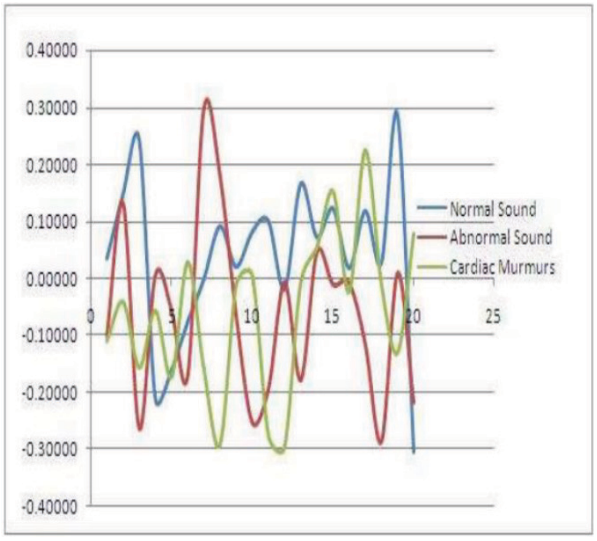


Figure 18: Comparison of different Heart Sounds.

The Convolution operation is the concatenation of scalar multiplications between the elements of two matrices. A typical convolution operation is highlighted in Figure 20, having an input square matrix and a kernel size of 2. The convolution operation occurs between a part of the input matrix and the kernel, as shown in the figure. Every time the kernel slides over the input matrix, it results in one output value, and this process is continued until the entire matrix is not covered.

Figure 21 highlights a block diagram of machine-learning and deep-learning methods adapted to categorize a set of entities. It basically depicts a comparison study between the two algorithms. In machine learning, preprocessing, feature extraction, and feature selection [115, 116] exist, followed by classification. However, no such blocks exist in the deep-learning model; only the deep model, followed by the classification part, is there. Deep-learning models can work with a

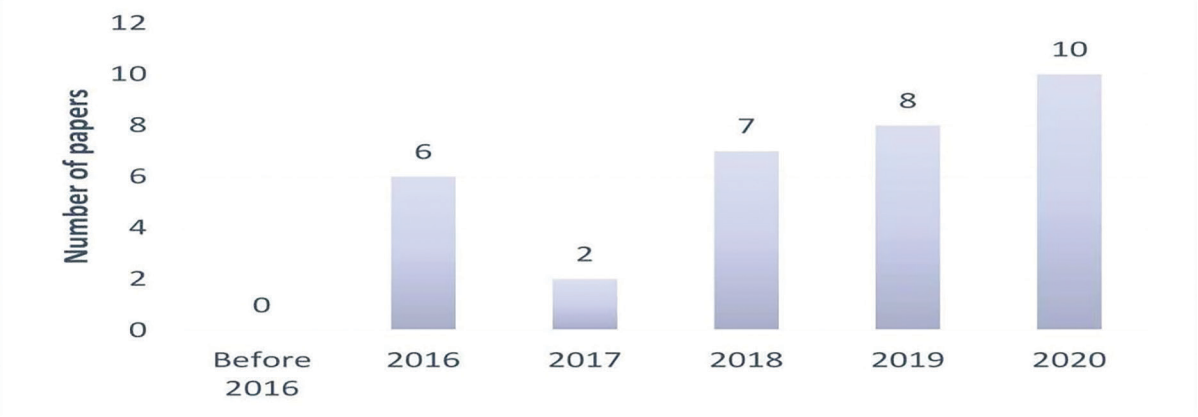


Figure 19: Earlier studies on deep-learning-based methods for cardiac sound classification.

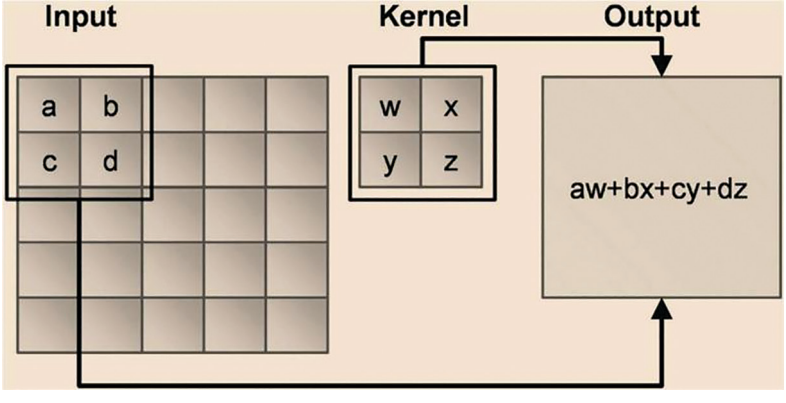


Figure 20: Convolution operation [131, 132].

large number of data as they can be developed by having a large number of layers that can go very deep compared to a machine-learning model that cannot work with a large number of data, and their models cannot go very deep. Figure 22 shows the architecture of a generalized deep-learning based [113, 114] convolutional neural network model.

Various methods have been used over the years for PCG signal analysis [38, 53] (Figure 23). However,

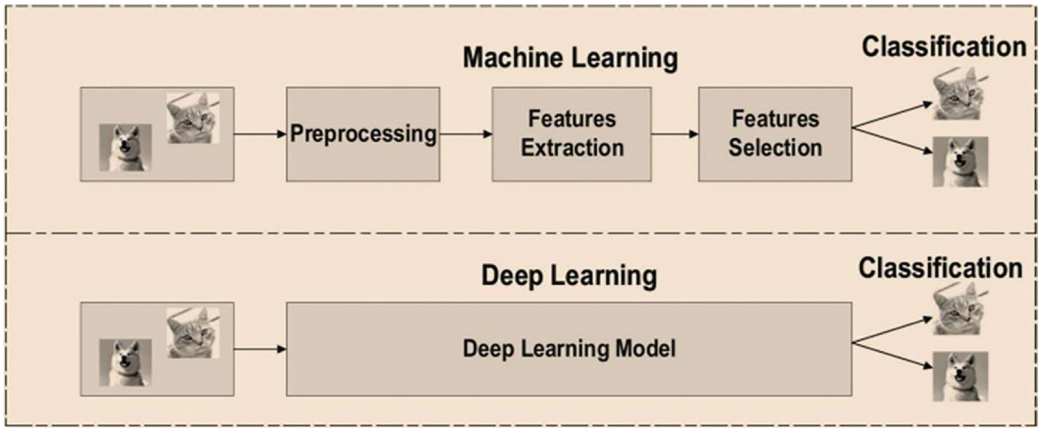


Figure 21: Comparison of machine-learning and deep-learning architectures.

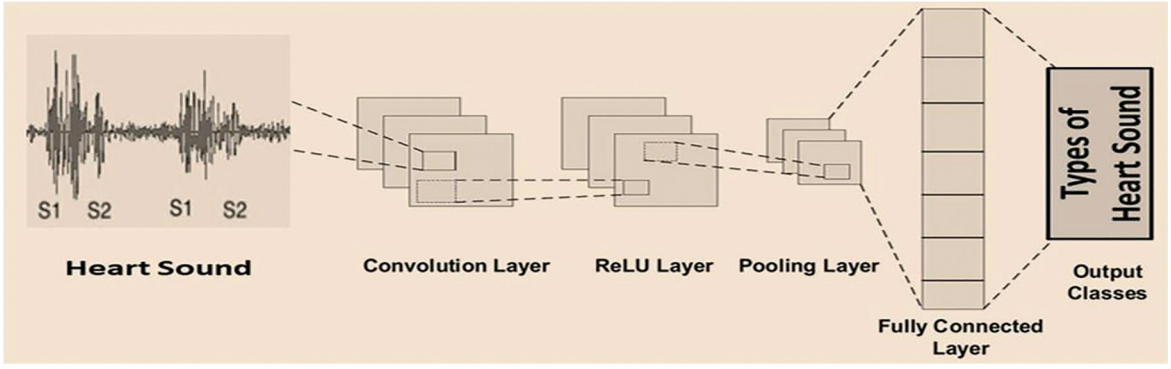


Figure 22: Architecture of CNN model [137] for Heart Sound classification.

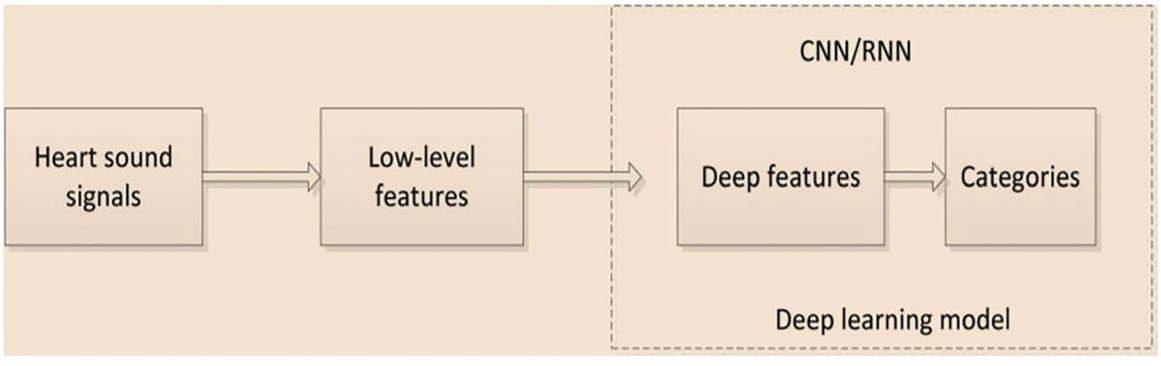


Figure 23: PCG signal classification based on deep-learning models [138, 139]. PCG, phonocardiogram.

Table 4. A summary of CNN and RNN based methods used in PCG signal analysis [108, 109].

S. No.	References	Methods	Features used	Segmentation optimizer		Types of PCG signal
1	Maknickas and Maknickas 2017 [55]	2D-CNN	MFSC	No	RMSprop	N, A
2	Alafif et al. 2020 [56]	2D-CNN + transfer learning	MFCC	No	SGD	N, A
3	Deng et al. 2020 [54]	CNN + RNN	Improved MFCC	No	Adam	N, A
4	Abduh et al. 2019 [57]	2D-DNN	MFSC	No	Adam	N, A
5	Chen et al. 2018 [58]	2D-CNN	Wavelet transform + Hilbert–Huang features	No	Adam	N, M, EXT
6	Rubin et al. 2016 [59]	2D-CNN	MFCC	Yes	Adam	N, A
7	Nilanon et al. 2016 [60]	2D-CNN	Spectrograms	No	SGD	N, A
8	Dominguez-Morales et al. 2018 [61]	2D-CNN	Spectrograms	No	Adam	N, A
9	Bozkurt et al. 2018 [62]	2D-CNN	MFCC + MFSC	Yes	Adam	N, A
10	Chen et al. 2019 [63]	2D-CNN	MFSC	No	Adam	N, A
11	Cheng et al. 2019 [64]	2D-CNN	Spectrograms	No	Adam	N, A
12	Demir et al. 2019 [65]	2D-CNN	Spectrograms	No	Adam	N, M, EXT
13	Ryu et al. 2016 [66]	1D-CNN	1D time-series signals	No	SGD	N, A
14	Xu et al. 2018 [67]	1D-CNN	1D time-series signals	No	SGD	N, A
15	Xiao et al. 2020 [68]	1D-CNN	1D time-series signals	No	SGD	N, A
16	Oh et al. 2020 [69]	1D-CNN WaveNet	1D time-series signals	NO	Adam	N, AS, MS, MR, MVP
17	Khan et al. 2020 [70]	LSTM	MFCC	No	Adam	N, A
18	Yang et al. 2016 [71]	RNN.	1D time-series signals	No	Adam	N, A
19	Raza et al. 2018 [72]	LSTM	1D time-series signals	No	Adam	N, A
20	Tschannen et al. 2016 [73]	2D-CNN + SVM	Deep features	Yes	Adam	N, A

AS, aortic stenosis; EXT, extra systole Heart Sounds; M, murmur Heart Sounds; MR, mitral regurgitation; MS, mitral stenosis; MVP, mitral valve prolapse; N, normal Heart Sounds; PCG, phonocardiogram.

because of their accuracy, Precision, Recall, and F1 Score, only deep-learning-based CNN methods [84, 98, 99], in comparison with the other methods, have found popularity.

Table 4 summarizes recently developed CNN [111, 112] and RNN models for valvular Heart Sound analysis and diagnosis. It deals with the methods, optimizer, features used, types of Heart Sound, and algorithms involved in deep-learning models [100. 110].

Figure 24 depicts a clinical PCG signal analysis method a medical practitioner uses.

Figure 24 depicts the application of a stethoscope [135, 136] in a Heart Sound analysis problem. Heart Sound is acquired from the patient and goes to the preprocessing block for further preprocessing, like filtering, normalization, and segmentation. Eventually, deep-learning techniques are applied to classify the cardiac sound. Finally, this classified cardiac sound

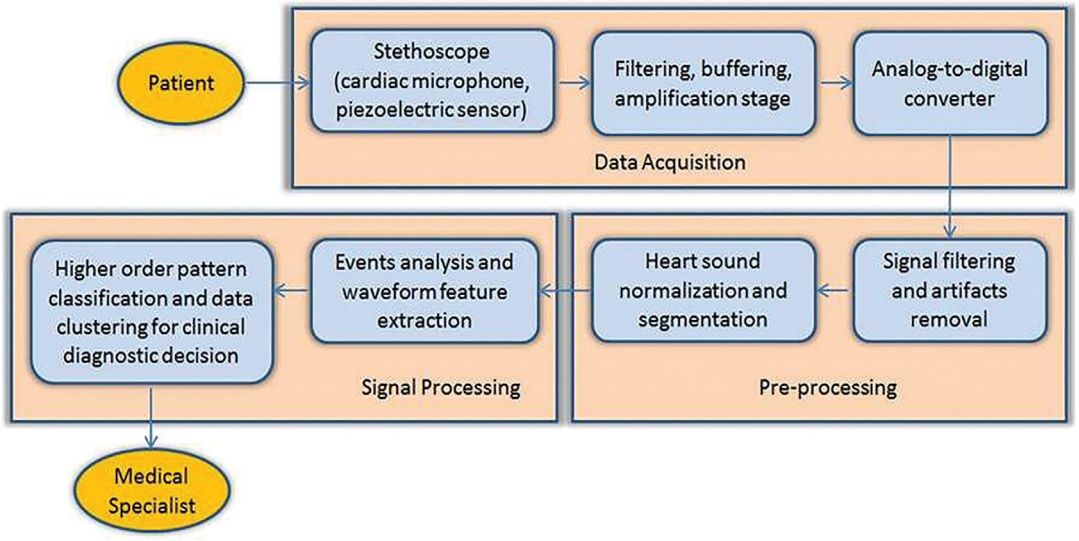


Figure 24: Application of Heart Sound classification method adopted by a medical practitioner [140, 141].

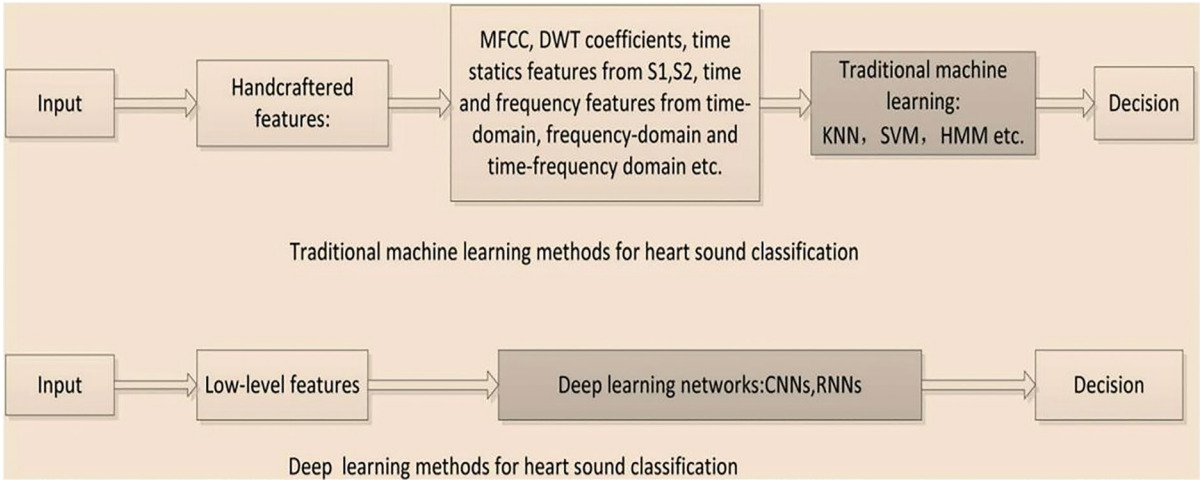


Figure 25: Study of machine-learning vs. deep-learning methods for cardiac sound classification [148, 149, 150].

is sent to the medical practitioner to examine the patient's Heart Sound [133, 134].

5.1 Comparison of Deep-Learning Methods with Conventional Machine-Learning Algorithms

Figure 25 compares the deep-learning-based classification [39, 50] method used for valvular Heart Sound analysis with the traditional machine-learning methods. It highlights low-level features used for deep learning and handcrafted high-level features used for conventional machine learning [85, 86].

5.2 Le Net Model

It is the first Convolutional Neural Network model developed in deep learning. It has five layers comprising three convolutions and two fully connected layers. This network also includes two max-pooling layers and one Softmax layer, as illustrated in Figure 26.

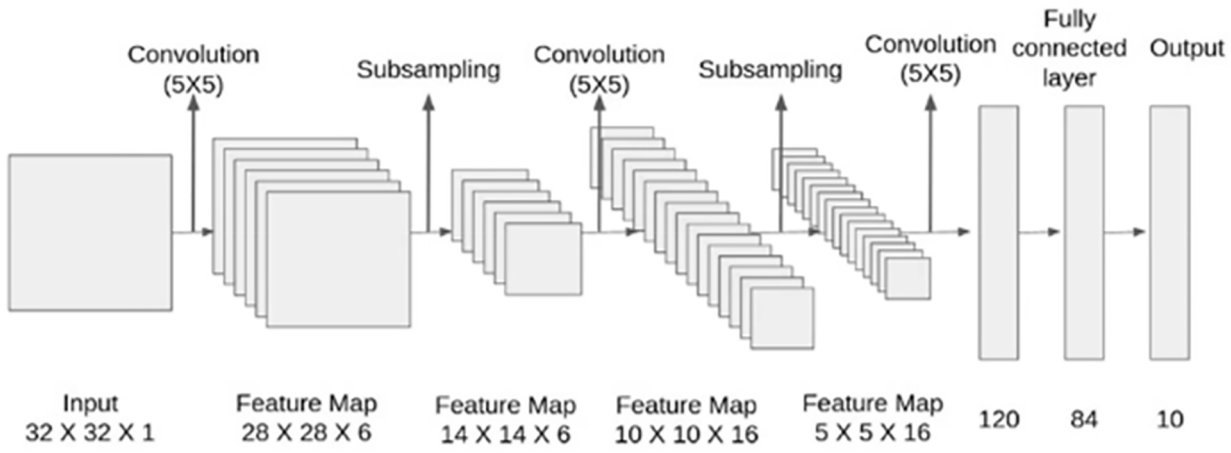


Figure 26: Schematic block diagram of Le Net.

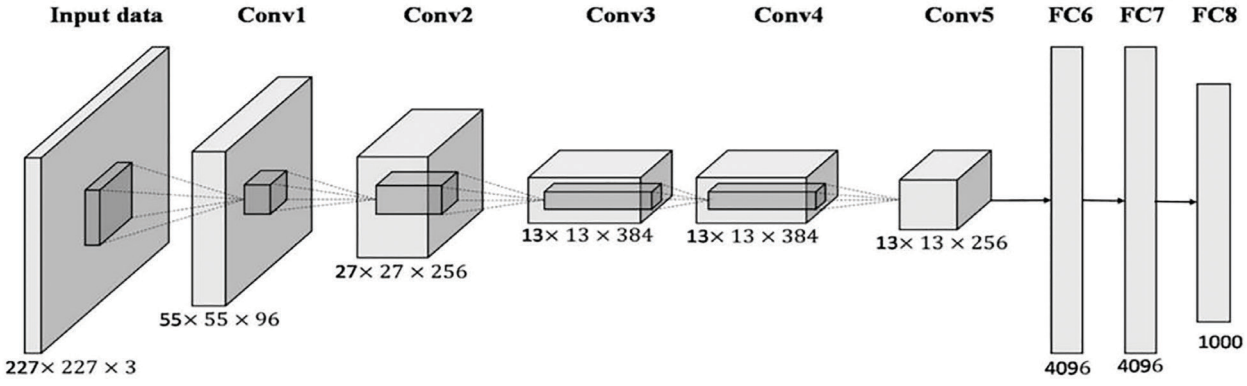


Figure 27: Schematic block diagram of Alex Network.

5.3 Alex Net Model

It is the second Convolutional Neural Network model developed in deep learning. It has eight layers comprising five convolution layers and three fully connected layers. This network also contains three max-pooling layers and one Softmax layer, as depicted in Figure 27.

5.4 VGG 16 Model

It is the third Convolutional Neural Network model developed in deep learning. It contains 16 layers comprising 13 convolution layers, and 3 fully connected layers, as illustrated in Figure 28.

5.5 VGG 19 Model

It is the fourth Convolutional Neural Network model developed in the field of deep learning. It has 19 layers comprising 16 convolution layers, and 3 fully connected layers, as illustrated in Figure 29.

5.6 Dense Net 121 Model

It is the fifth Convolutional Neural Network model developed in the field of deep learning. It has 121 layers comprising 120 convolution layers and 1 fully connected layer, as illustrated in Figure 30.

5.7 Squeeze Net Model

It is the seventh Convolutional Neural Network model developed in deep learning. It is named after squeeze and expand layers. Generally, it is 18 layers deep, containing fire blocks. Fire blocks comprise the desired number of squeeze and expand filters, as illustrated in Figure 31. Squeeze layers have 1×1 filters, whereas the expanded layer combines 1×1 and 3×3 filters.

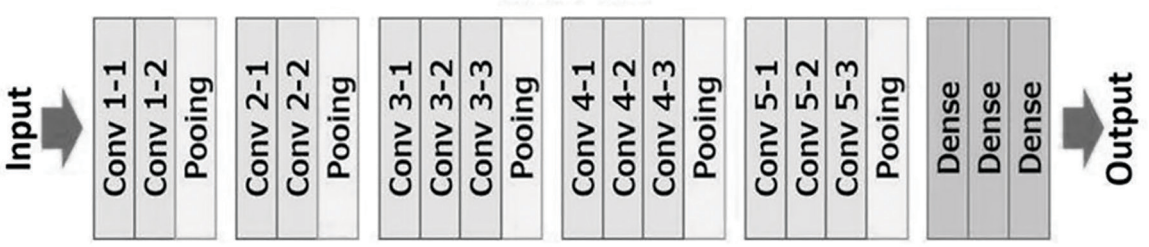


Figure 28: Schematic block diagram of VGG 16.

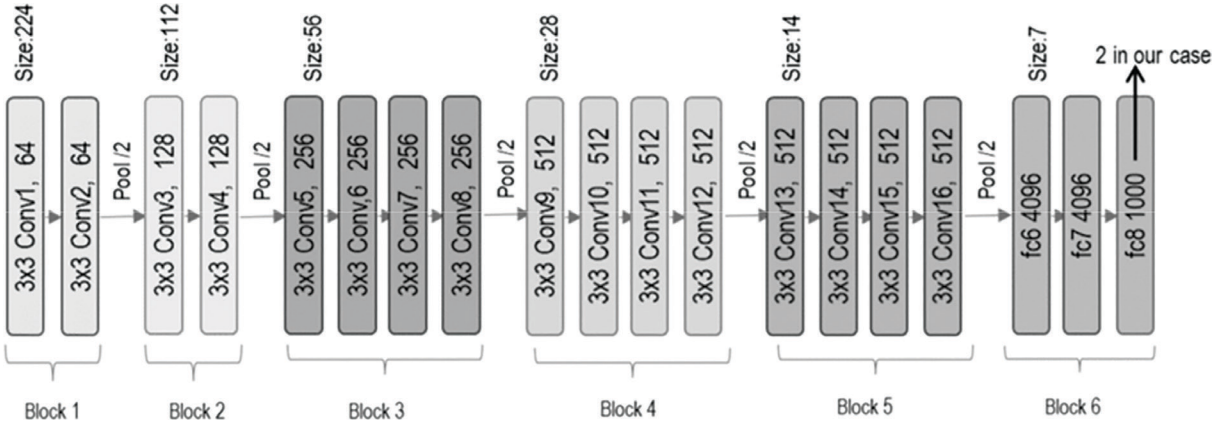


Figure 29: Schematic block diagram of VGG 19.

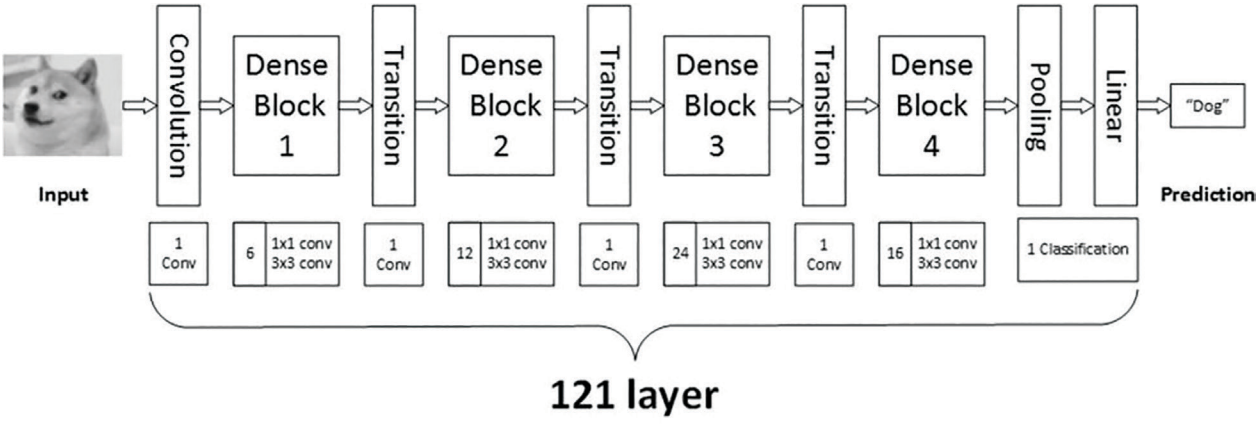


Figure 30: Schematic block diagram of Dense Net 121.

5.8 Mobile Net Model

The mobile net is compatible with mobile operating systems and can be embedded in mobile devices. The modified CNN-based mobile network [6, 15] is used in this research. It is based on the idea of depth-wise separable convolution, where convolution takes place in two steps, namely those of depth-wise and point-wise convolutions. Depth-wise separable convolution takes less complexity of the model as the computations become lower in the mobile network. Figure 32 shows a modified mobile network model module, where depth-wise convolution uses a 3×3 kernel, batch normalization, and ReLU activation function,

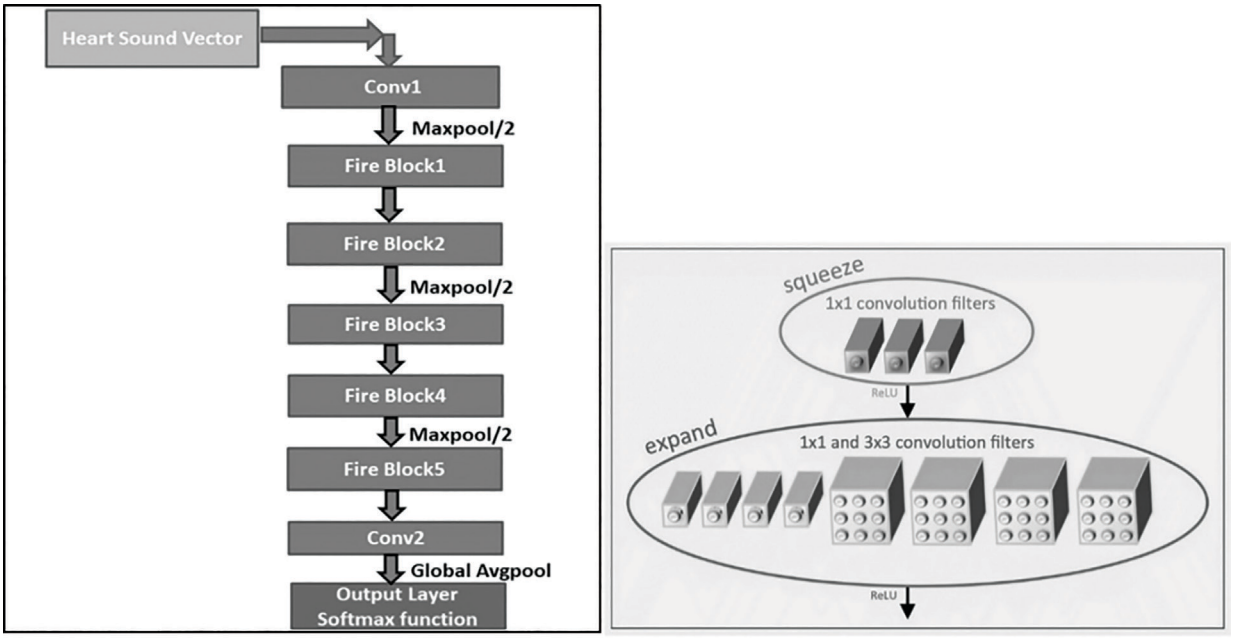


Figure 31: Schematic block diagram of Squeeze Net.

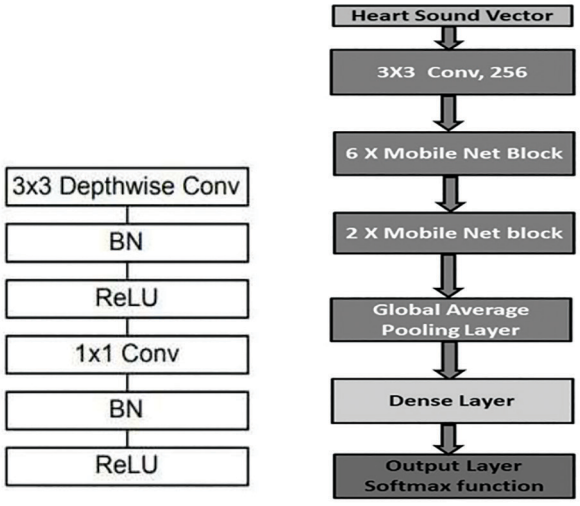


Figure 32: Schematic block diagram of Mobile Net 5.9 Inception Net Model.

followed by a 1 × 1 normal convolution [9, 18], batch normalization, and ReLU activation function.

It is a sparsely connected network that runs deep. It contains multiple numbers of inception modules connected in series. The inception module comprises the max pool and various filter sizes of 1, 3, and 5 at the same layer. Thus, multiple convolutions occur at the same layer, followed by a concatenation operation, as shown in Figure 33.

It is an intense network that uses skip connections. As the number of layers increases, an issue called a vanishing gradient occurs. This problem can be resolved by residual blocks used in the residual network, as illustrated in Figure 34.

6. Results and Discussions

There are different means to compute the effectiveness of any deep learning [106, 107] algorithm. These are Accuracy, Precision, Recall, and F-Measure. To calculate these parameters, the numbers of true-positive (TP), false-positive (FP), true-negative (TN), and false-negative (FN) counts are needed, as given below.

$$\text{Accuracy} = TP + TN/TP + FP + FN + TN \quad (2)$$

$$\text{Precision} = TP/TP + FP \quad (3)$$

$$\text{Recall} = TP/TP + FN \quad (4)$$

$$\text{F1 Score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision}) \quad (5)$$

Figure 35 compares all CNN-based deep-learning models [43, 80, 93] used for different datasets. It is observed that, in comparison with other models, complex deep-learning models like inception networks, residual networks, and Xception networks

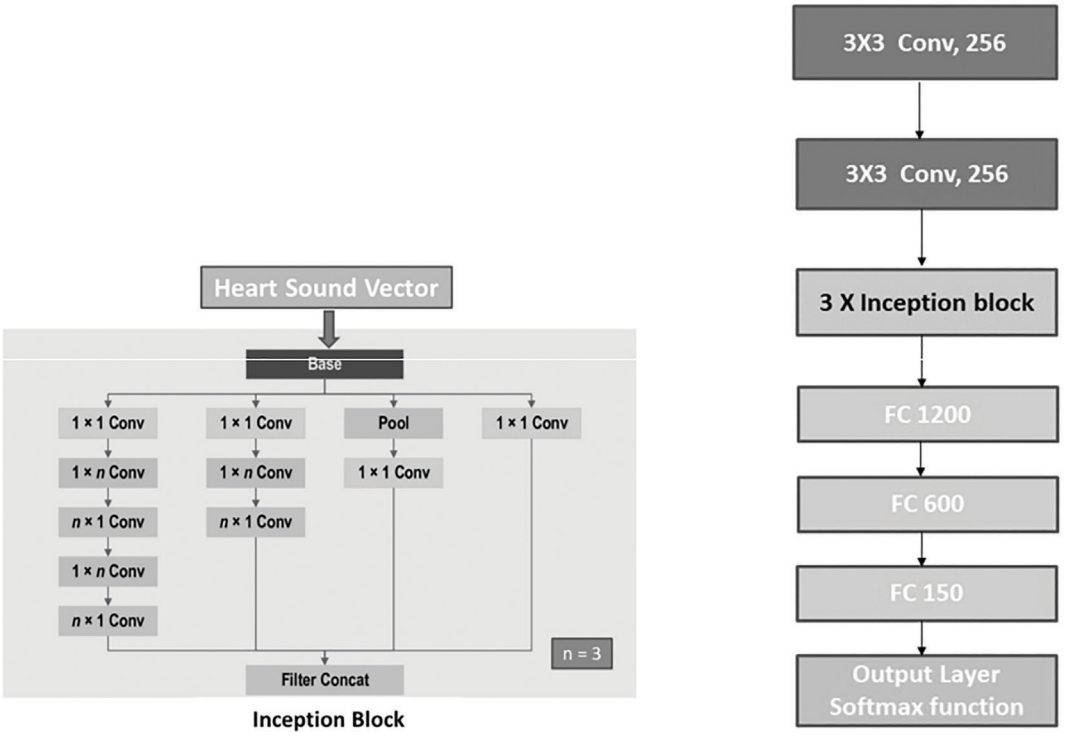


Figure 33: Schematic block diagram of Inception Net 5.10 Residual Net Model.

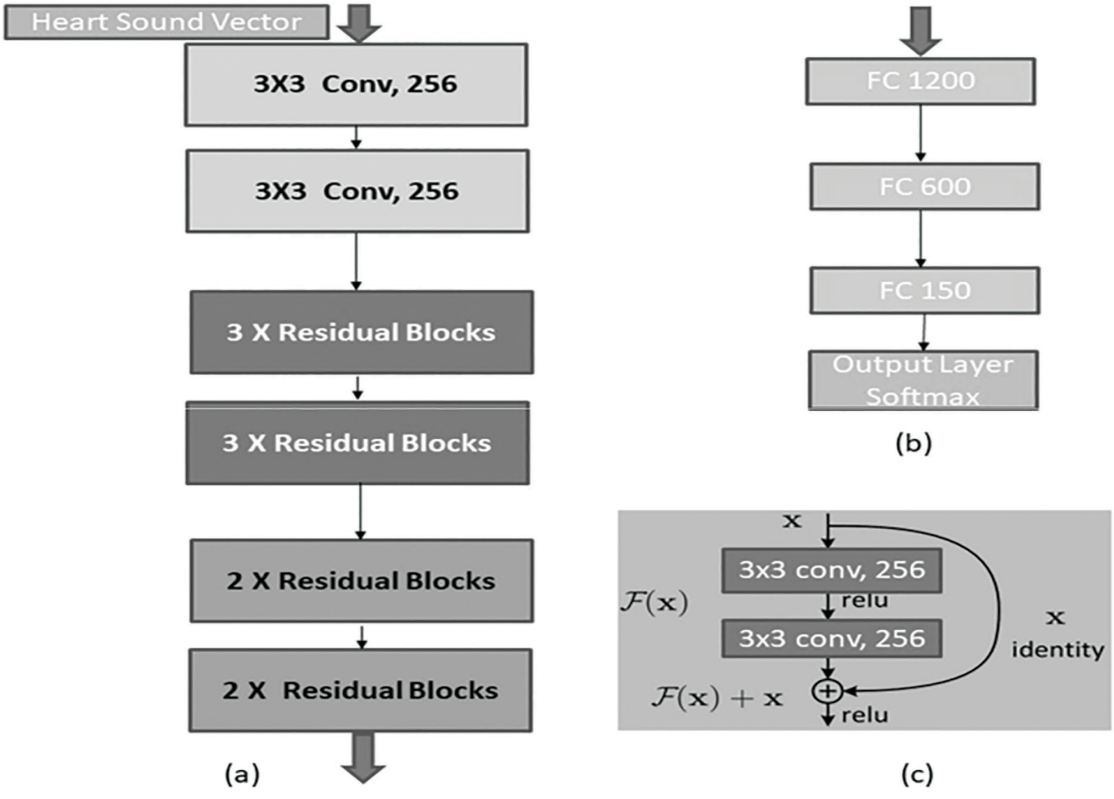


Figure 34: Schematic block diagram of Residual Net.

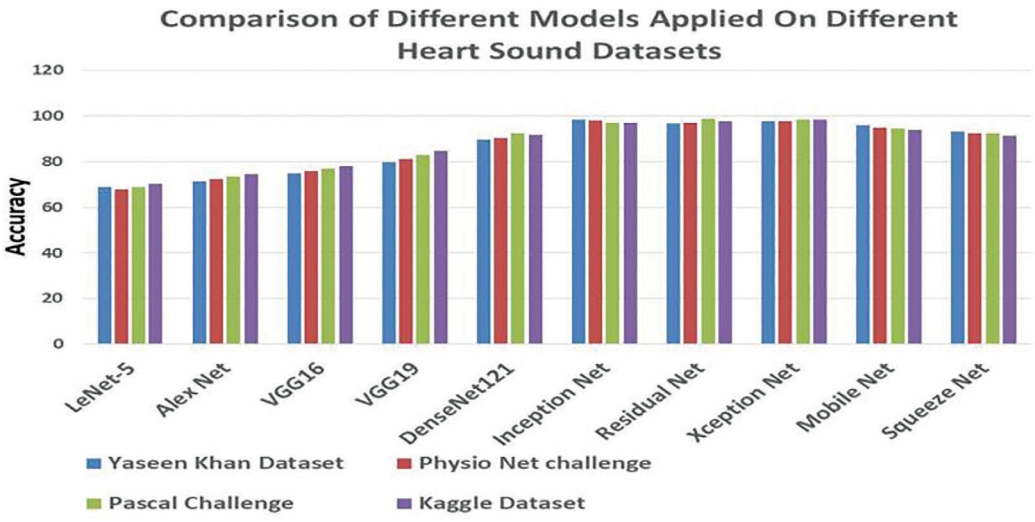


Figure 35: Study of all CNN-based deep-learning models [142, 143].

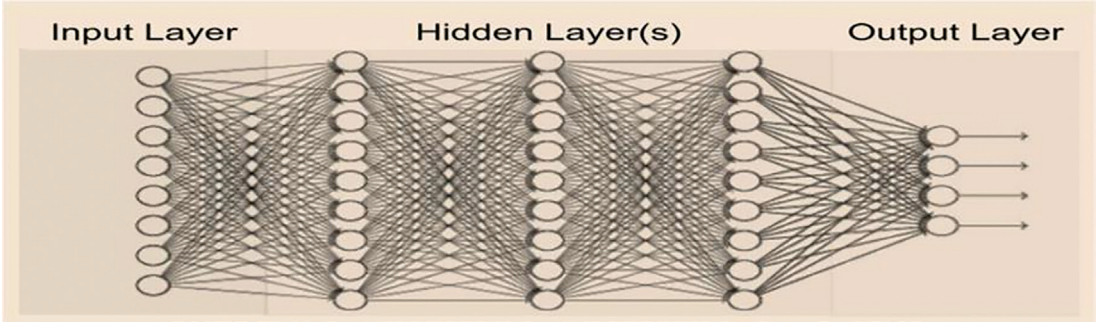


Figure 36: Deep neural network based model architecture [144, 145].

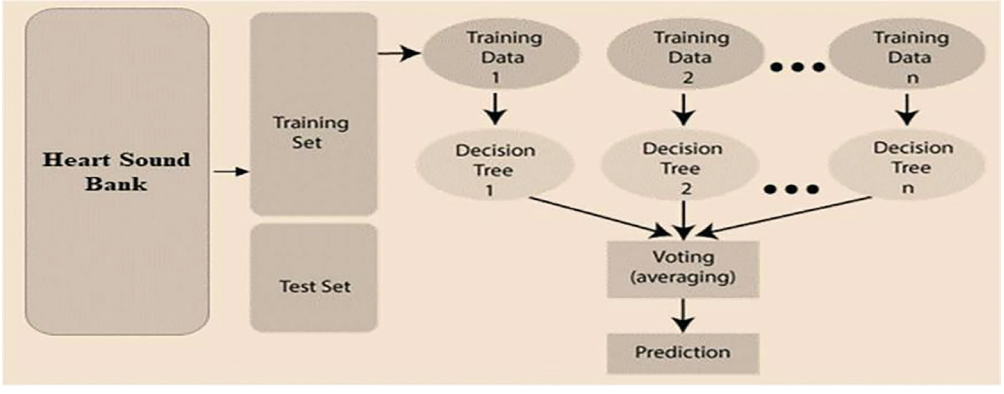


Figure 37: Architecture of a machine-learning algorithm like Random Forest [146, 147].

work the best [81, 91, 92]. Figure 36 illustrates a deep neural network based model architecture containing multiple hidden layers comprising several thousand nodes.

Figure 37 illustrates a block diagram of a machine-learning algorithm like Random Forest that can be applied to smaller datasets and has a decent accuracy in the case of classification [104, 105] of PCG

signals. It is an ensemble method that works on the supervised machine-learning concept principle. The following table is based on the various research works on Heart Sound analysis using different deep-learning models.

Table 5 compares different CNN-based models during the training and validation phase used over the last 3–5 years for valvular Heart Sound analysis [44, 78, 94]. The analysis showed that training and validation loss decreases drastically as we move towards more complex models like inception, residual, and Xception networks. At the same time, training and validation accuracy increases effectively to a more considerable extent for a large number of heart data samples [79, 101]. In this paper, different deep-learning methods are used for cardiac sound analysis. The following study explains in Table 5 how efficient network B3 works best for PCG signal categorization in terms of evaluation metrics. Table 6 depicts the study [45, 102, 103] of performance

Table 5. Comparison of training and validation performance metrics of CNN-based deep-learning models.

System	Training loss	Training accuracy	Validation loss	Validation accuracy
LENET-5	0.4352	0.7089	0.4757	0.6799
Alex Net	0.3476	0.7379	0.3837	0.7199
VGG16	0.2979	0.8102	0.3134	0.7978
VGG19	0.2692	0.8709	0.2899	0.8469
DENSENET121	0.2476	0.9087	0.2665	0.8876
Squeeze Network	0.2097	0.9265	0.2098	0.8906
Mobile Network	0.1576	0.9435	0.1376	0.9073
Inception Network	0.0472	0.9843	0.0654	0.9863
Residual Network	0.0432	0.9856	0.0533	0.9892
Xception Network	0.0320	0.9951	0.0325	0.9926

Table 6. Comparison of performance metrics in various CNN-based deep-learning models.

System	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Train time (s)	Test time (s)
LeNet-5	68.97	69.75	67.44	66.68	1086	1135
Alex Net	72.34	70.74	73.88	71.24	1233	1337
VGG16	74.08	75.29	75.08	75.13	1352	1011
VGG19	82.17	83.33	82.19	84.21	1343	947
DenseNet121	92.47	93.55	93.47	94.48	1201	937
Squeeze Network	93.57	92.65	94.79	93.56	1098	1012
Mobile Network	95.09	94.35	95.68	93.46	890	987
Inception Network	96.96	98.17	98.96	97.02	710	974
Residual Network	97.32	98.42	98.32	98.35	783	1056
Xception Network	99.13	98.18	98.43	99.19	750	865
Efficient Network-B3	99.49	98.62	98.72	99.37	786	854

metrics in different CNN-based deep-learning methods applied for cardiac sound analysis. The following table is based on the research carried out over the last 3–5 years on Heart Sound analysis using various deep-learning models.

7. Conclusion

Recently, Heart Sound analysis has been a trending domain of research. Researchers are developing different deep-learning models for PCG signal analysis and classification that can produce more accurate computations for the user and, simultaneously, be handy in the early detection of valvular heart diseases.

In this review paper, the authors have touched upon different points of feature extraction techniques, preprocessing methods, segmentation methods, and CNN-based classification methods using deep learning. The preliminary concept of Heart Sound signal analysis is mentioned, and along with the basic idea, different signal processing algorithms adopted in Heart Sound signal analysis are discussed. Finally, the performance metrics of various deep-learning methods applied to various Heart Sound datasets are addressed. The other applications of Heart Sound signal analysis in various fields are summarized in this paper. The entire analysis has been done by comparing different research works done in this field. The conventional acoustic stethoscopes used during auscultation are inadequate for the detection and diagnosis of heart anomalies in human subjects. Conventional stethoscopes are characterized by a lack of efficiency when it comes to use in the classification of various Heart Sounds for early prediction of heart diseases. The need of the hour is to work with electronic stethoscopes having Raspberry Pi to ensure an intelligent way of overcoming the deficiency faced in the use of acoustic stethoscopes. The electronic stethoscope not only is efficient but also can, at the same time, address the issue of ambient noise while collecting the real-time Heart Sound. It is also a portable, low-cost option, and features a low screening time for the diagnosis and analysis of Heart Sound.

Author Contributions

All the authors contributed to the study of algorithms and review work, as well as to the formation and recording of the experimental evaluations. All authors have read and approved the final version of the manuscript submitted for publication.

Funding

The authors provided the total funding for this research work.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Not applicable.

Conflicts of Interest

The authors confirm that no conflicts of interest exist.

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