International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:12, No:8, 2018

Automated Heart Sound Classification from Unsegmented Phonocardiogram Signals Using Time Frequency Features

Nadia Masood Khan, Muhammad Salman Khan, Gul Muhammad Khan

Abstract**—**Cardiologists perform cardiac auscultation to detect abnormalities in heart sounds. Since accurate auscultation is a crucial first step in screening patients with heart diseases, there is a need to develop computer-aided detection/diagnosis (CAD) systems to assist cardiologists in interpreting heart sounds and provide second opinions. In this paper different algorithms are implemented for automated heart sound classification using unsegmented phonocardiogram (PCG) signals. Support vector machine (SVM), artificial neural network (ANN) and cartesian genetic programming evolved artificial neural network (CGPANN) without the application of any segmentation algorithm has been explored in this study. The signals are first pre-processed to remove any unwanted frequencies. Both time and frequency domain features are then extracted for training the different models. The different algorithms are tested in multiple scenarios and their strengths and weaknesses are discussed. Results indicate that SVM outperforms the rest with an accuracy of 73.64%.

Keywords**—**Pattern recognition, machine learning,computer aided diagnosis, heart sound classification, and feature extraction.

I. Introduction

VALVULAR heart disease is categorized by damage in one of four heart valves namely mitral, aortic, tricuspid or pulmonary. The main symptom of heart valve disease is an unusual heart sound called murmurs. Listening to the heart sound is called auscultation. It is one of the most widely used technique to detect heart abnormality. However, physicians and expert cardiologist might make an error during auscultating by sending normal heart patients for echo-cardiogram (ECG) and abnormal heart patients to home. Researchers have proposed different approaches to classify healthy people and pathological patients.

As shown in Fig. 1 the de-oxygenated blood comes from right atrium to right ventricle (Tricuspid valve) and goes form right ventricle into the lungs (Pulmonary valve). Oxygenated clean blood comes back in the left atrium and enters left ventricle through Mitral valve, and further supplied to the whole body (Aortic valve). Blood is moving constantly and two chambers open at same time, de-oxygenated blood moves from right atrium to right ventricle at the same time when oxygenated blood comes from left atrium to left ventricle.

Nadia Masood Khan is with the Department of Electrical Engineering, University of Engineering and Technology Peshawar, Pakistan (e-mail: nadiakhan@uetpeshawar.edu.pk).

Muhammad Salman Khan is with the Department of Electrical Engineering Jalozai Campus, University of Engineering and Technology Peshawar, Pakistan (e-mail: salmankhan@uetpeshawar.edu.pk).

Gul Muhammad Khan is with the Department of Electrical Engineering, University of Engineering and Technology Peshawar, Pakistan (e-mail: gk502@uetpeshawar.edu.pk).

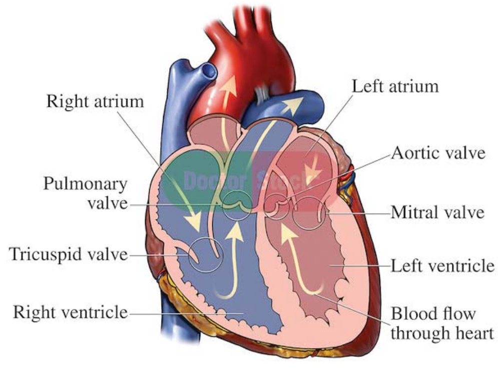

Fig. 1 Heart Valves

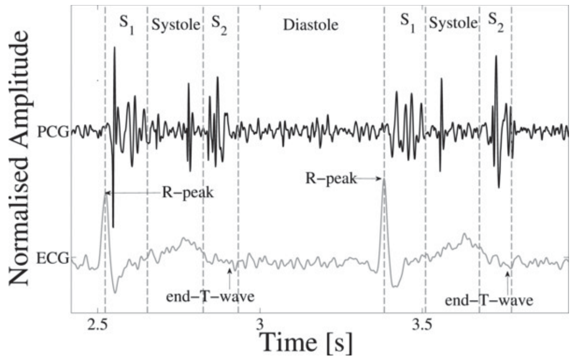

Fig. 2 PCG Signal Representation

When the ventricles are full of blood, then right ventricle sends blood to lungs by opening P valve but at the same time tricuspid valve must be closed. Similarly, left ventricle sends blood to rest of the body through aortic valve and to prevent back flow from left atrium to left ventricle, Mitral valve are snap shut. The closing of tricuspid and Mitral valve produces a noise ”lub” called first heart sound and labeled as S1. The sound produced when blood is squeezed from left ventricle to whole body is called systole. The ”dub” sound labelled as S2 is produced on the closing of pulmonary and aortic valves to prevent back-flow when the blood moves form arteries to ventricles. The movement of blood from arteries to ventricles is called diastole, Fig. 2 depicts a labeled PCG signal. When the heart valves do not open and close properly, the fundamental heart sounds (FHSS) produced are different and thus identified as abnormal heart sounds.

Bradley et al. [1] conducted their experiments on PCG audio data obtained from the 2016 PhysioNet/CinC Challenge and used sparse coding as a feature extraction tool. The preprocessed PCG audio data was decomposed into a dictionary matrix and a sparse coefficient matrix. The important features of PCG audio segments were represented in dictionary matrix and the mapping between these features were given in sparse coefficient matrix. They used Support Vector Machine (SVM) for classification. Before extracting features, the heart sound data was segmented using Springers segmentation algorithm [2] and converted the data into frequency domain. High score of 0.812 was obtained on the testing dataset.

ANN together with short-time Fourier transform and wavelet entropy has been used for heart valve disease detection in [3] to identify important features of heart signal. Detection accuracy of 94% obtained for normal heart sounds, and 95.9% for abnormal heart sounds.

The primary goal of this research is to classify normal and abnormal heart sounds that can be achieved without segmentation. In this study, training is performed on full cardiac cycle instead of sound segments (S1, systole, S2, diastole). The possibility of detecting abnormal heart signals without application of additional data pre-processing, feature extraction and segmentation algorithm has been explored in this work.

II. Literature Survey

Classifiers classify new unlabeled data using observation feature vectors from previously categorized data. Algorithms commonly used for classification are: k-nearest neighbor (KNN) [4], support vector machines (SVMs) [5] and probabilistic neural networks (PNNs) [6]. Heart murmurs are the first step in the identification of abnormal heart sounds when a patient visits the physician for auscultation. The most common cause of heart murmur is mitral or aortic stenosis and mitral or aortic regurgitation. The stenosis is a condition when the heart valve is narrowed and does not allow normal flow of blood to the main pumping chamber of the heart. And the regurgitation occurs when there is a leak in the heart valve which causes blood flow in the opposite direction. Both of these conditions can be dangerous and patient should be immediately prescribed for further tests and medication. A reliable cheap diagnostic tool with high accuracy is needed to differentiate between normal and abnormal heart sound.

Ortiz et al. [7] explored temporal alignment technique i.e. dynamic time warping (DTW) together with the Mel-Frequency Cepstral Coefficients (MFCCs) spectral features as input to linear SVM and obtained score of 82.4%. Gangulyn et al. [8] proposed an economical heart diagnosis methodology to classify heart sound signals having murmurs without the need of complex pre-processing techniques e.g. segmentation. They have identified pathological heart sounds by using a large set of features extracted in time, frequency and statistical domain.

Potes et al. [9] obtained the highest score of 0.8602 (overall sensitivity) from experimentation performed on 2016 PhysioNet/CinC challenge data openly available. They have proposed an ensemble of time frequency features and deep learning based classifier to obtain an extraordinary classification accuracy. They have extracted 124 features from the PCG recording, out of which 36 features were time domain and the remaining 88 frequency features. Mean and standard deviation (SD) of PCG intervals and peaks were computed for time domain features. Hamming window and the discrete-time Fourier transform (DFT) is used for finding the power spectrum of each heart sound state i.e. S1, systole, S2, and diastole. The band pass filtered heart sound signals having frequency in the range 25-40 hz were divided into 9 frequency bands corresponding to states of each cardiac cycle was calculated. Then, the mean and median power of theses frequency bands was used as frequency domain feature (9x4 states=36). Furthermore, 13 mel-frequency cepstral coefficient (MFCC) were calculated from each state of each cardiac and used as frequency domain feature (13x4 states=52). AdaBoost-abstain classifier and convolutional neural network were combined for the classification of normal/abnormal heart sound which helped in improving the overall challenge score.

The second best score in the PhysioNet/CinC challenge achieved by Zabihi et al. [10] used ensemble of neural networks without segmentation for categorizing normal and abnormal heart sounds. A subset containing 18 out of 40 features were selected as useful features using wrapper-based feature selection scheme. They have divided selected features into five classes: Linear Predictive Coefficient (LPC), Entropy based features, Mel Frequency Cepstral Coefficients (MFCCs), Wavelet transform based features and Features extracted over power spectral density. They have achieved overall score of 85.90% on unseen test dataset which highlights the importance of proper feature extraction algorithm and classifier.

Features that are highly correlated in two classes must be removed as they can reduce the accuracy of a classifier. Neural network with two hidden layers trained with error back propagation and regularized with DropConnect is proposed in [11]. They have used openly available hidden Markov model for the segmentation and a wavelet transform, inter-beat properties, mel-frequency cepstral coefficients, signal complexity for feature extraction. Feature normalization is performed by subtracting from mean and dividing by standard deviation across the whole dataset. Accuracy of 85.2% has been reported by Kay et al. [11] for which they obtained third prize in PhysioNet/CinC challenge. Redlarski et al. [12] have used combination of feature extraction (Linear Predictive Coding coefficients) and classifier built upon combining Support Vector Machine and Modified Cuckoo Search algorithm for developing medical diagnostic system. Accuracy of 93% for heart sound classification is recorded. Wu et al. [13] have used wavelet transform for extraction of the envelope of PCG signals and then applied SVM for heart sounds identification reporting accuracy of 95%.

Physionet challenge 2016 contains datasets which are from noisy real world problems due to which some cardiac cycles are wrongly segmented and contains noise. Cycle quality assessment (CQA) proposed by Abdollahpur et al. [14] for detecting wrongly segmented and noisy heart sounds.

III. Methodology

A. Pre-Processing and Filtering

Heart sound signal downloaded from training database is first down sampled to 2 kHz sampling frequency. Presence of noise in heart sound signal makes the classification inaccurate. A high-pass butterworth filter with cut-off frequency fc = 25Hz and order N = 3 is applied which effectively reduced noise without affecting the core morphology of clean signals.

Before extracting the features, the filtered signal is normalized to have zero mean and unit variance for machine learning application.

$$NormalizedSignal = \frac{OriginalSignal - Mean}{StandardDeviation} \tag{1}$$

The filtered and normalized signals are used for extracting the features. The features are given as it is for ANN and SVM but for CGPANN zero-one min-max scaling is performed to the features in order to reduce bias towards any one dimension.

IV. Feature Extraction

Feature vectors consist of ten features having both time and frequency domain features used for identification of normal/abnormal heart sounds.

A. Time Domain Features

The first three features in the feature vector are time domain features that are extracted from preprocessed and normalized heart cycle.

1) Energy Entropy: A hypothesis that defines relationship between entropy and signal processing is as follows:
”A noise (white noise) is a projection of a system in thermodynamic equilibrium into a signal. As a result the noise is supposed to have the highest entropy value while the speech has significantly lower entropy value as it is more organized and required an extra energy to be produced in such an organized form” [15]. Mathematical, energy entropy is represented as follows:

$$Entropy = \sum_{n=1}^{N} -x_(n) * log2x_(n) \tag{2}$$

2) Short Time Energy: Short time energy of a signal is calculated to find the variation of energy with time specially for the short term region of signal. It can be defined in terms of total energy relationship already defined in signal processing and is given in (3).

$$STE = \frac{1}{N}\sum_{n=1}^{N}[x_(n) * w(m-n)]^2 \tag{3}$$

x(n) represents discrete time sound signal, time index of the short-time energy is given by n, and w(m) is used for window.

3) Zero Crossing Rate: Zero crossing rate (ZCR) is a measure of how frequently a signal changes from positive to negative or vice versa and is given in (4)

$$ZCR = \frac{1}{N}\sum_{n=1}^{N}|(sign(x(n)) - sign(x(n-1))| \tag{4}$$

4) Temporal Crest Factor: Temporal crest factor is the measure of peak values to the effective values in a waveform. Mathematically, represented as follows:

$$Crestfactor = \frac{|xpeak|}{xrms} \tag{5}$$

B. Frequency Domain Features

Time domain analysis is not enough due to non-stationary and time varying nature of heart sounds. The frequency domain features are also extracted for better discrimination between the two classes.

1) Spectral Roll Off: The spectrum which contains some percentage of signal’s total energy is called roll-off frequency. It is used to distinguish between harmonics and noisy sounds.

$$SpectralFlux = 0.9 * \sum_{n=1}^{N}|x(n)|^2 \tag{6}$$

2) Spectral Centroid: Spectral centroid quantifies of brightness of sound and locates the center of mass in the spectrum. It is given by weighted mean of frequencies in the signal with their magnitudes as weight.

$$SpectralCentroid = \frac{\sum_{n=1}^{N} n.f(x(n))}{\sum_{n=1}^{N} f(x(n))} \tag{7}$$

3) Spectral Flux: Spectral flux is determined by changes in the power spectrum of a signal which can be calculated by comparison of power spectrum for present frame with the previous frame as shown in (8).

$$SpectralFlux = \sum_{n=1}^{N}(f[x(n)] - f[x(n-1)]^2) \tag{8}$$

4) Fast Fourier Transform: FFT coefficients are extracted from each signal using discrete Fourier transform (DFT) obtained through (9) to provide spectrum of the signals.

$$F(w) = \sum_{n=1}^{N}(f(n).e^-j2\pi wn/N) \tag{9}$$

where w=1,2,.....,k.

Average of fft coefficients is calculated and used as a signal feature for the discrimination between normal and pathological heart sound.

5) Linear Predictive Coding: Linear Predictive coding (LPC) has been used extensively in audio signal and speech signal processing for the representation of spectral envelope using the information from a linear predictive model. Heart sounds have large variation in time and frequency domains and hence are characterized as non stationary. There is difference between dynamics of speech and heart sound. Redundancy in signal is removed by predicating next value as a linear combination of previous values as shown in (10).

$$s(n) = \sum_{k=1}^{p} a_k.s(n-k) + e(n)) \tag{10}$$

The pth-order linear predication of a signal s(n) is given by a_k, n represents the time index, the LPC coefficient index (k), and e(n) is the residual prediction error. The residual error is reduced by LPC coefficients . In this work, LPC analysis has been carried out on five co-efficient set and average of these coefficients is used a feature to the machine learning algorithms.

V. Experimental Setup

Experiments are performed on publicly available heart sound recordings training data in the PhysioNet/CinC challenge 2016. The training dataset consists of 3181 heart sounds from 764 patients.

The training dataset has been observed keenly and separated into normal and abnormal heart sound recordings. 663 audio files are categorized as abnormal and the remaining 2518 are labeled as normal. SVM, ANN and CGPANN is applied for the classification of heart sound signals.

Identifying abnormal heart sound is quite challenging because of its low number of occurrence. Pattern recognition tool of MATLAB has been used for the implementation of ANN. Different sets of training is created to evaluate the performance of algorithm. For the implementation of support vector machine, MATLAB functions svmtrain and svmclassify are used for the training and testing of heart sound signals.

Following ten features has been extracted from heart sound signal:
1. Energy entropy
2. Short time energy
3. Zero Crossing Rate (ZCR)
4. Spectral roll off
5. Spectral centroid
6. Spectral flux
7. FFT coefficients (Average value of FFT coefficients is used)
8. LPC coefficients (Average value of LPC coefficients is used)
9. Temporal crest factor

A. Support Vector Machine

Support vector machine has been employed to identify abnormal heart sounds. SVM is used in pattern recognition problems when the data cannot be separated linearly but is separable nonlinearly. Support vectors finds the coordinates of individual observation. SVM performs linear separation of data by constructing a separating hyperplane between the data of two classes. SVM uses nonlinear kernel functions e.g. sigmoid, polynomial, Gaussian, or a radial basis function (RBF) for linear separation of data.

During the designing of SVM model, selecting the type of kernel function and setting the parameters of selected kernel is challenging as there is no good method on how to choose the kernel function till now. We have applied different kernel functions and results are shown in Tables IV and V. The kernel function computation is done in input space rather than in the feature space. In our experiments, linear, radial basis function (RBF) and multi layer perceptron (MLP) kernel function performance has been tested. The standard kernel function parameters defined in MATLAB is used.

SVM has been used in [16] for classification of abnormal and normal heart sounds and have reported accuracy of 92.29%. They have used new mother wavelet for extracting discrete wavelet transform (DWT) of the signal and then statistical components are calculated to get the features of heart sounds. SVM performs well when combined with suitable feature extraction method. In our future work, we will extract features using principal component analysis PCA using different classifiers such as linear discriminant analysis LDA and neural networks (NNs) which will give better results.

B. Artificial Neural Network

ANN experiments were performed on different number of neurons and different training/testing data division. Class 1 depicts normal heart sounds and class 2 are abnormal heart sounds. The testing dataset for (70,15,15) contains total of 477 signals and 15% of normal and abnormal heart sound is taken in the testing phase. Similarly (50,25,25) dataset contains 795 signals in the testing dataset. 25% of normal/abnormal each is given to network during testing. The data points is picked randomly and number of normal/abnormal instances may slightly vary in different neural network architecture.

C. Cartesian Genetic Programming Evolved Artificial Neural Network

The selection of optimal network architecture requires tuning of network parameters and reasonable amount of computational time. The tuning method for ANN used in this work is Cartesian genetic programming (CGP) [17]. CGP consists of phenotype showing system connectivity and genotype showing the number and function of genes. The idea of CGPANN was initially proposed by Khan et al. [18] as it evolves artificial neural network architecture based on Cartesian genetic programming parameters. CGPANN has been used successfully to classify seismic signals in [19] reporting accuracy of 80%. CGPANN applies log-sigmoid as the activation function on each neurons given by (11).

$$f(x) = \frac{1}{1+e^{(int_v)}}, \qquad int_v = \sum_{i=1}^{N} [W_i].[I_i] \tag{11}$$

In this work, the input data to CGPANN was normalized in the range 0 to 1. Equal number of instances of normal and abnormal were taken for experimentation. 50% data used for training and 50% used for testing. The CGPANN performance is evaluated on different network architecture by varying number of nodes.

TABLE I
ANN RESULTS (70, 15, 15)

Number of Neurons	Test Instances	Accurate Class 1	Inaccurate Class 1	Accurate Class 2	Inaccurate Class 2	Percentage
5	477	256	132	24	65	58.7%
10	477	163	229	53	32	45.3%
20	477	299	100	20	58	66.9%
25	477	399	0	0	78	83.6%
30	477	176	224	40	37	45.3%

TABLE II
ANN RESULTS (50, 25, 25)

Number of Neurons	Test Instances	Accurate Class 1	Inaccurate Class 1	Accurate Class 2	Inaccurate Class 2	Percentage
5	795	418	227	47	103	58.5%
10	795	259	392	89	55	43.8%
20	795	487	169	29	110	64.9%
25	795	653	3	0	139	82.1%
30	795	292	362	77	64	46.4%

TABLE III
CGPANN RESULTS

Number of Neurons	50	100	150	200	250	Average
Percent Accuracy	60	61.7	61.1	60.3	60.6	60.74%

TABLE IV
SVM RESULTS (70/30)

Kernel Function	Test Instances	Accurate Class 1	Inaccurate Class 1	Accurate Class 2	Inaccurate Class 2	Percentage
Linear	602	83	151	325	43	67.77%
RBF	602	86	128	348	40	72.09%
MLP	602	66	258	218	60	47.18%

VI. Performance Evaluation

An artificial neural network was designed and trained for classifying abnormal and normal heart sound. MATLAB neural network pattern recognition tool (NPRTOOL) with different data setting and number of neurons has been used to evaluate the performance of neural network for pattern recognition problem. Class 1 represents normal instances and class 2 represents abnormal instances. Table I shows the testing results obtained on using 75% of data for training, 15% for validation and 15% for testing. The main problem is to correctly identify the pathological heart sounds. ANN fails in accurate classification when number of neurons is equal to 25, the 83.6% accuracy achieved is only for correctly identifying the normal heart sounds. Number of neurons equal to 10 is able to correctly locate the maximum number of abnormal files i.e. 53.

Table II shows results obtained on using 50% for training, 25% for validation and 25% for training. Number of neurons=10 have shown better discrimination separating total of 89 pathological heart sounds. A 25 neuron network does not provide satisfactory performance because of its misclassification of abnormal heart sound and only classifying normal heart sounds.

CGPANN gives accuracy of around 60.74% in Table IV for accurate classification of heart sounds.

Table IV depicts the results (70/30) obtained using SVM for the classification. Using Radial basis function(RBF) as a kernel function have shown good results in this particular problem and accuracy of 72.09% is reported. Similar results were obtained for 50/50 data division shown in Table V, RBF performing well as a whole and multi layer perceptron does not discriminate efficiently.

Heart sounds have complex and highly non-stationary nature. Noise cancellation can be achieved by using suitable pre-processing algorithms. Wavelet decomposition [20] has provided satisfactory results for data pre-processing. H. Salman et al. [21] proposed empirical mode decomposition (EMD) for de-nosing of heart sound signal and compared its results with other algorithms in terms of signal-to-noise (SNR) improvement.

VII. Conclusion and Future Work

In this paper three different heart sound classification techniques with unsegmented PCG signals for detecting heart abnormality were investigated. Simulations were performed in multiple scenarios. Results show that SVM performs the best with an accuracy of 73.64%. CGPANN performs better than ANN with an accuracy of 60.74% The usefulness of the proposed research is that it highlights the importance of proper feature extraction and the need of segmentation of heart sound signal for accurate classification of normal and pathological heart sounds. Signal de-noising techniques must be incorporated in the heart sound classification model. Future work will focus on better feature extraction algorithm and segmentation algorithm.

TABLE V
SVM RESULTS (50/50)

Kernel Function	Test Instances	Accurate Class 1	Inaccurate Class 1	Accurate Class 2	Inaccurate Class 2	Percentage
Linear	918	129	217	506	66	69.17%
RBF	918	125	172	551	70	73.64%
MLP	918	102	389	334	93	47.49%

REFERENCES

[1] B. M. Whitaker, P. B. Suresha, C. Liu, G. D. Clifford, and D. V. Anderson, "Combining sparse coding and time-domain features for heart sound classification," *Physiological measurement*, vol. 38, no. 8, p. 1701, 2017.

[2] D. B. Springer, L. Tarassenko, and G. D. Clifford, "Logistic regression-hsmm-based heart sound segmentation," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 4, pp. 822–832, 2016.

[3] I. Turkoglu, A. Arslan, and E. Ilkay, "An expert system for diagnosis of the heart valve diseases," *Expert systems with applications*, vol. 23, no. 3, pp. 229–236, 2002.

[4] T. J. Hirschauer, H. Adeli, and J. A. Buford, "Computer-aided diagnosis of parkinsons disease using enhanced probabilistic neural network," *Journal of medical systems*, vol. 39, no. 11, p. 179, 2015.

[5] J.-S. Chou and A.-D. Pham, "Smart artificial firefly colony algorithm-based support vector regression for enhanced forecasting in civil engineering," *Computer-Aided Civil and Infrastructure Engineering*, vol. 30, no. 9, pp. 715–732, 2015.

[6] Z. Sankari and H. Adeli, "Probabilistic neural networks for diagnosis of alzheimer's disease using conventional and wavelet coherence," *Journal of neuroscience methods*, vol. 197, no. 1, pp. 165–170, 2011.

[7] J. J. G. Ortiz, C. P. Phoo, and J. Wiens, "Heart sound classification based on temporal alignment techniques," in *Computing in Cardiology Conference (CinC), 2016*. IEEE, 2016, pp. 589–592.

[8] A. Ganguly and M. Sharma, "Detection of pathological heart murmurs by feature extraction of phonocardiogram signals," *Journal of Applied and Advanced Research*, vol. 2, no. 4, pp. 200–205, 2017.

[9] C. Potes, S. Parvaneh, A. Rahman, and B. Conroy, "Ensemble of feature-based and deep learning-based classifiers for detection of abnormal heart sounds," in *Computing in Cardiology Conference (CinC), 2016*. IEEE, 2016, pp. 621–624.

[10] M. Zabihi, A. B. Rad, S. Kiranyaz, M. Gabbouj, and A. K. Katsaggelos, "Heart sound anomaly and quality detection using ensemble of neural networks without segmentation," in *Computing in Cardiology Conference (CinC), 2016*. IEEE, 2016, pp. 613–616.

[11] E. Kay and A. Agarwal, "Dropconnected neural network trained with diverse features for classifying heart sounds," in *Computing in Cardiology Conference (CinC), 2016*. IEEE, 2016, pp. 617–620.

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

[13] J.-b. Wu, S. Zhou, Z. Wu, and X.-m. Wu, "Research on the method of characteristic extraction and classification of phonocardiogram," in *Systems and Informatics (ICSAI), 2012 International Conference on*. IEEE, 2012, pp. 1732–1735.

[14] M. Abdollahpur, A. Ghaffari, S. Ghiasi, and M. J. Mollakazemi, "Detection of pathological heart sounds," *Physiological measurement*, vol. 38, no. 8, p. 1616, 2017.

[15] K. Ekštein and T. Pavelka, "Entropy and entropy-based features in signal processing."

[16] M. M. Azmy, "Classification of normal and abnormal heart sounds using new mother wavelet and support vector machines," in *Electrical Engineering (ICEE), 2015 4th International Conference on*. IEEE, 2015, pp. 1–3.

[17] J. F. Miller and P. Thomson, "Cartesian genetic programming," in *European Conference on Genetic Programming*. Springer, 2000, pp. 121–132.

[18] M. M. Khan, A. M. Ahmad, G. M. Khan, and J. F. Miller, "Fast learning neural networks using cartesian genetic programming," *Neurocomputing*, vol. 121, pp. 274–289, 2013.

[19] G. Khattak, M. Khan, G. Khan, F. Huenupan, and M. Curilem, "Automatic classification of seismic signals of the chilean llaima volcano using cartesian genetic programming based artificial neural network," 2017.

[20] Z. Jiang and H. Wang, "A new approach on heart murmurs classification with svm technique," in *Information Technology Convergence, 2007. ISITC 2007. International Symposium on*. IEEE, 2007, pp. 240–244.

[21] A. H. Salman, N. Ahmadi, R. Mengko, A. Z. Langi, and T. L. Mengko, "Empirical mode decomposition (emd) based denoising method for heart sound signal and its performance analysis," *International Journal of Electrical and Computer Engineering*, vol. 6, no. 5, p. 2197, 2016.