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Heart Abnormality Classification Using PCG and ECG Recordings

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Abstract. Both PCG (Phonocardiogram) and Electrocardiogram (ECG) carry helpful features that aid in the fundamental analysis of heart-related disorders. Although they contain varying physical characteristics, some characteristics may predict some parameters better than the other. The research of such electrical and mechanical signals reveals a beneficial topic for any researcher. Hence, the study for automated detection and prediction of an anomaly of the heart using PCG and ECG signal is essential. The proposed method introduced modified preprocessing techniques along with features extraction techniques using both ECG and PCG datasets in tandem based on a different classification approach. The preprocessing of ECG signals comprises of the delineation and elimination of noise and artifacts whereas, the preprocessing of PCG signals includes the removal of unwanted noise and murmurs by applying a band-pass filter. The time-frequency features using PCG signals were extracted based on wavelet decomposition, Homomorphic filtering, Hilbert transforms, and Power spectral density. Using the ECG signals, the QRS based feature extraction method based on the Pan-Tompkins algorithm was performed. The extracted features from PCG and ECG signals were independently trained and tested using different classifiers (SVM, KNN, and Ensemble). Finally, the merged features of both the PCG and ECG signals were again trained and tested. The proposed model was validated using publicly available data-sets 'A' of PhysioNet 2016/ CinC challenges that comprise of both ECG and PCG data-sets. The results show that ECG and PCG signals can efficiently be employed for predicting cardiovascular disorders.

Keywords. Phonocardiogram, electrocardiogram, QRS complex, wavelet decomposition, Hilbert transform, homomorphic envelope, K nearest neighbors, power spectral density, support vector machine, ensemble of classifiers.

1 Introduction

In 1965, medical diagnostic based on artificial intelligence became revolutionized [1]. Hence, many researchers became familiarized with analyzing the medical images [2-4]. During this era, many researchers believed that computer-aided diagnosis could replace humans due to the efficient performance of the predicting model [4].

But, due to the lack of technical methodologies; such as insufficient processing power, absence of advanced image-processing methods and challenges in realizing a digital image, the above the approach was unfit. These methods evolved in the 1980s; then many researchers reported that computer-aided diagnostic could be utilized by the Physicians but not to fully substitute them [5].

Any type of disorder related to the heart can be termed as cardiac abnormalities or cardiac diseases. These comprise arrhythmias, coronary artery disease, prolapsed mitral and congenital heart disease, etc. The heart is a muscular hollow organ in humans and other living being located in the thoracic cavity. It is divided into four chambers. Its principal role is to deliver oxygen to our tissues.

Electrocardiogram (ECG) signals and Phonocardiogram (PCG) signals are two events in which ECG is the electrical signal of the cardiac movements and PCG is the visual representation on a chart of a cardiac sound [6]. A traditional means of expressing heart activities is by its energy, frequency, and time duration.

The World Health Organization reported that 31% of the world's mortality rate is due to cardiovascular abnormalities. Hence, heart analysis is one of the preliminary steps in evaluating any cardiovascular system [7]. The traditional techniques for the classification of heart abnormalities provide low classification performance and are expensive as well. Therefore, novel techniques with low cost and less implementation time are desirable.

Heart abnormality classification has been studied based on different approaches. An approach based on the non-invasive method has been popularly employed for cardiac monitoring. A recent study reports that only a limited researcher employed Electrocardiogram signal as a reference for detecting the fundamental heart sound (FHS) by segmenting the PCG signals; after detection of R peaks from the electrocardiogram signal followed by predicting the FHS of the cardiac cycle from the heart sound signals employing detected peaks as reference.

Many analysts have conducted various research for heart abnormality classification using PCG recording based on PhysioNet 2016 datasets. But only a limited study was performed by using both the PCG and ECG signals. The PCG and ECG signals provide significant characteristics that assist in predicting the heart anomaly, but failed to predict all the cases of the heart-related ailment if analyzing individually. For example, an electrical signal or the ECG signal of the heart solely can distinguish the various physiological and unusual function of the heart.

But the ECG signal alone failed to detect the signs produced due to the defective heart valve. Because of the above limitation, few researchers have used both ECG and PCGs signals for predicting the heart abnormality that results in generating high classification performance [8–11].

The database presented by the PhysioNet 2015 challenge provides a platform for many researchers in predicting heart anomaly detection using ECG signals. But only a few researchers focus on analyzing the cardiac abnormality based on both the PCG and ECG signals. The author in [11] employed both the PCG and ECG signals for arrhythmia classification and further conclude that cardiovascular abnormality analysis using both the PCG and ECG signals can yield a high classification performance.

Phanphaisarn *et al.* [10] used both the electrical and mechanical signals of the heart for analyzing the cardiac abnormality. They further report that the performance of the model based on heart anomaly detection can be enhanced by employing both the ECG and PCG signals. The authors in [12, 13] employed the electrical activities of the heart for segmenting the fundamental heart sound of the PCG signals for cardiovascular abnormality analysis.

The proposed study highlights the relationship between industrial and innovative partners collectively to encourage the practice of both the PCG and ECG signals for effective cardiac monitoring. The proposed study includes preprocessing followed by the feature extraction based on different transform methods utilizing both the PCG and ECG signals. The features were trained and tested using three machine learning classifiers for predicting the classification performance. The complete discussion about the proposed classification model has explained in the subsequent sections.

2 Theory

2.1 Wavelets

A wavelet transform is a mathematical approach for computing the data based on time and frequency characteristics. This type of analysis can be used in real-time applications like biomedical signal processing, signal compression, and seismic analysis. Since the 1990s, the use of wavelet analysis had become popular in the field of signal processing as it was in reflected the importance of various researchers. The mathematical criteria for wavelet function are as follows:

1. Finite energy:

$$\text{Energy}= \int_{-\infty}^{\infty} |\theta(t)|^2 dt < \infty. \tag{1}$$

2. Frequency component cannot be null:

$$\theta'(f) = \int_{-\infty}^{\infty} \theta(t) e^{-i(2\pi f t)} dt = 0, \tag{2}$$

where $\theta'(f)$ is the Fourier transform of $\theta(t)$.

3. The following condition should hold:

$$Admissibility\ constant(C)= \int_{0}^{\infty} \frac{|\theta(f)|^2}{2} df < \infty, \tag{3}$$

where admissibility constant depends on the wavelet.

2.2 Wavelet Transform

The wavelet transform is analyzed in two ways: change in location and change in scale. For various locations and scales, different researchers have utilized wavelet transform for computing in a continuous process using the continuous wavelet transform (CWT) and or in a discrete process using the discrete wavelet transform (DWT). Wavelet transform helps in rendering the information based on time and frequency characteristics.

2.2.1. Discrete Wavelet Transform

The process of decomposing the signal from time series into a mutually orthogonal time-frequency representation is called a discrete wavelet transform (DWT). Seshadri et al. [14] analyze the heart sound signal by comparing DWT and Fast Fourier Transform (FFT). Their study reported that DWT had outperformed FFT as DWT provides both time and frequency information. The equation representing discretized wavelet $\theta(p.q)$ after translation p and expansion q of wavelet $\theta(t)$ is shown in Eq. (4):

$$\theta(p.q) = \frac{1}{\sqrt{p}} \int_{-\infty}^{\infty} x(t) \theta' \left(\frac{t-q}{p}\right) dt. \tag{4}$$

2.2.2. Continuous Wavelet Transform

A recent study reveals that researchers have classified the heart signal after deriving the features using a continuous wavelet transform. Due to the oscillatory response and measurable time interval, CWT has been applied for estimating the time-frequency characteristics of the heart signals. The equation representing CWT is shown below:

$$W_{\lambda}^{x} = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} \theta^* \left(\frac{t-\lambda}{s}\right) dt, \tag{5}$$

where s and λ denotes scaling parameter and location parameter respectively for the mother wavelet $\theta(t)$. Based on the application, the mother wavelet has been chosen for analyzing the signal for generating the required coefficient. Some researchers have reported that morlet wavelet helps in improving the overall performance of the model while analyzing the ECG signal [15–17]. The morlet wavelet equation is shown below:

$$\theta(t) = \frac{1}{\sqrt{c\pi}} \int_{-\infty}^{\infty} e^{-(\frac{t}{c})} e^{j2\pi f_c t} dt. \tag{6}$$

2.3 Homomorphic Filtering

The homomorphic filtering technique had been implemented for computing the envelope of the PCG signal that helps in estimating the fundamental heart sounds like the first heart sound, the second heart sound, and other relevant features [19]. Various researchers used the homomorphic envelogram approach for segmentation of the heart sound [13, 18-20]. The above approach helps in computing the envelope of the heart sound and further detects the required peak. Since the principal purpose of this study is to predict the heart sound recording as either normal or abnormal by eliminating the segmentation process, hence the envelope of the heart sound has been computed using a homomorphic filtering technique for extracting the envelope-based feature. The envelope of the Phonocardiogram signal has been derived after computing the

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energy of the signal utilizing the homomorphic filtering method:

$$x[n] \approx Log\ e[n], \tag{7}$$

where e[n] represents the slowly varying component of the heart sound signal, and x[n] represents the PCG signal.

2.4 Hilbert Transform

The study of an envelope of the heart sound signal is crucial for examining the valuable characteristics that help in predicting cardiac abnormalities. For obtaining the relevant information related to the first heart sound and the second heart sound, the curve based on the Hilbert envelope has estimated. The envelope of the PCG signal has been computed after eliminating the imaginary part of the transformed signal using Hilbert transformation [21]. Since the real part holds the information correlated to S1 and S2 of the cardiac signal, the imaginary part/the instantaneous part has been overlooked. The equation representing the Hilbert transform for Phonocardiogram signal x(t) is shown below as:

$$H|x(t)| = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{x(\lambda)}{\lambda - t} dt = x(t) * \frac{1}{\pi t}. \tag{8}$$

2.5 Base Classifiers

2.5.1 K Nearest Neighbor (KNN)

K nearest neighbor is the classification technique that uses a supervised algorithm that depends on both learning samples and their respective classes. KNN classifier using the Euclidean distance approach is the commonly practiced classifier in many applications. The distances from the unknown feature vectors to all the remaining known vectors are computed using the Euclidean distance. The class/label is assigned to the anonymous feature based on the nearest k sample [7]. This type of approach is known as majority voting.

2.5.2 Support Vector Machine (SVM)

SVM is a traditional approach adopted for pattern recognition, regression, and classification. Because of its prominent performance, most scientists have used the SVM technique for analyzing the binary classes. The SVM classifier aims to generate the optimum margin between the learning sample and the targeted boundary.

The vectors of the learning sample which are nearest to the targeted boundary are set as optimum margin. SVM classifiers can classify either as a linear classifier or non-linear based on their kernel function [7].

2.5.3 Ensemble Classifier

Ensemble classifier is a supervised learning algorithm based on a combination of different machine learning approaches. This type of classifier can be broadly classified into two types: (1) Sequential approach: In this type, the relation between the two classifiers was computed by optimizing the weight of the earlier mislabeled weight. Hence, it aids in improving the overall performance of the system, (2) Parallel approach: It creates a base learner in a parallel manner that helps in diminishing the error by estimating the average value of the base classifier.

3 Methodology

The main goal of the study is to improve cardiac monitoring based on PCG and ECG signals. The layout structure of the proposed model has illustrated in figure (1). Both the signals have been preprocessed for removing unwanted noise that corrupts the signals. For ECG signals, features based on QRS complex waves have been derived from the preprocessed ECG signals. For PCG signals, features based on unsegmented heart sound have been derived from the preprocessed PCG signals. Finally, the extracted features have been trained and tested to analyze the performance of the model. The detailed analysis of the heart classification for cardiac monitoring using the PCG and ECG features have been discussed in the following subsections.

3.1 Database and Preprocessing

PhysioNet/CinC 2016 provides a platform for analyzing heart abnormality. The reason for selecting both the PCG and ECG signals is that

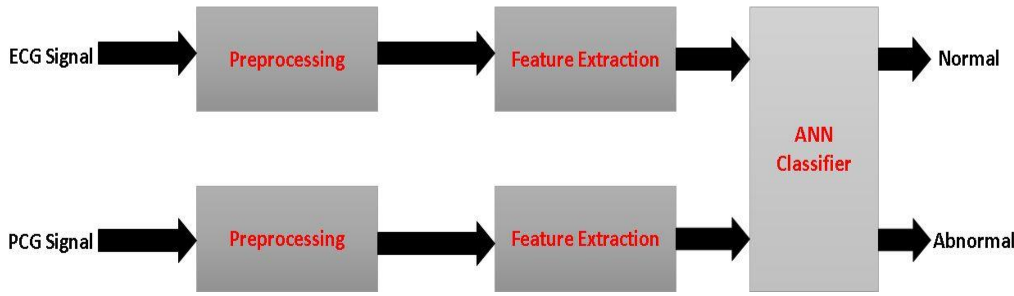


Fig. 1. The block diagram for cardiac monitoring using PCG and ECG recording

cardiovascular monitoring can be extended by improving the classification performance by using both these signals. This section illustrates the classification performance of different classification models by using the PCG and recorded signals obtained from PhysioNet/CinC 2016 [22].

The recorded heart sound signal was acquired from a different region of the body. The PCG and ECG signals are categorized as either normal or abnormal cardiac patients. PhysioNet/CinC 2016 challenge provides a pair of 409 PCG and ECG recordings for dataset A (117 normal and 292 abnormal recordings and the length of the PCG recordings vary between 5 seconds to 120 seconds and 12 seconds to 37 seconds for ECG recordings) with a sampling frequency of 2000 Hz. As the datasets were labeled as either normal or abnormal, the aim of our method is based on predicting the signal as normal or abnormal. The recordings have been collected from both cardiac patients as well as normal subjects from various health care.

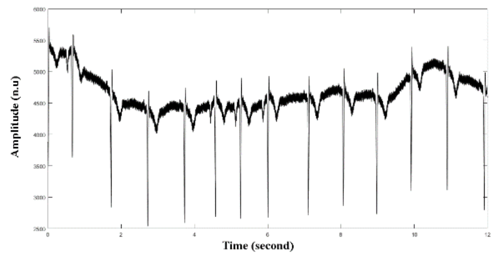
While analyzing the ECG signals manually, a few of them were corrupted by noise. We eliminate 67 ECG and corresponding PCG signals from the analysis to enhance the classification performance. Overall 342 pairs (240 abnormal and 102 normal recordings) of PCG and ECG signals have been used for analyzing the cardiac abnormality. The first 12 seconds from the ECG signals and 5 seconds from the PCG signals have been selected for uniform analysis in this study. To exclude undesired overfitting of the model, the training samples and testing samples were held mutually exclusive to each other. The heart electrical signals (ECG recording) and mechanical signals were obtained from various subjects and saved as .dat and .wav format respectively.

The detailed report about the ECG signals has not been specified precisely in the given database. In this study, the ECG signals were manually examined but observed that it was acquired from different leads at different cases. Hence, this study has been centered on extracting the features based on the QRS complex wave from the ECG signals. A recent study has reported that most researchers employed segmented-based PCG classification that increased the computational complexity of the model. Hence, for analyzing the PCG signals, the proposed method focused on extracting the features by excluding the complex segmentation process.

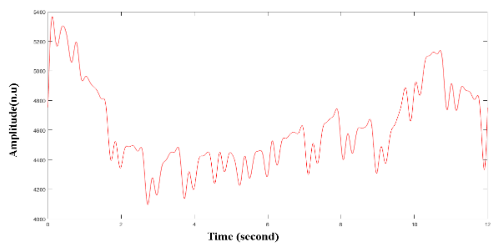
The preprocessing step has divided into two parts. The first part involves preprocessing of the ECG signals for eliminating unwanted noise and artifacts. The second part involves the preprocessing of the PCG signals for removing undesired noise and murmurs. The complete analysis of preprocessing steps involving the ECG and PCG signals has illustrated as follows:

3.1.1 ECG Preprocessing

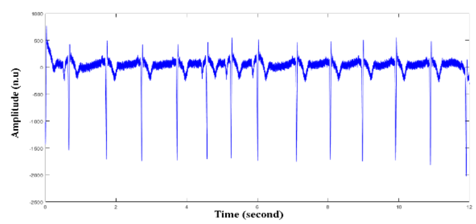
The first 12 seconds of the recorded ECG signals have been used for uniform analysis. Detrending of ECG signals is required as the ECG signals were influenced by the baseline trend developed due to breathing and ambulatory motion of the subject. Hence, a DWT method has been adopted to identify and eliminate the trend. Using the Daubechies wavelet, the raw ECG signals have been decomposed into the 10th level.



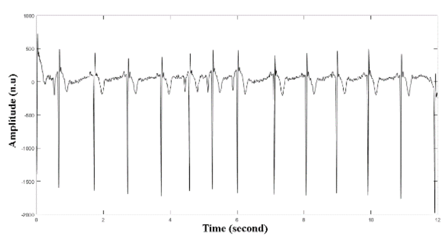
(a) Raw ECG signal



(b) Approximation coefficient at level 10



(c) Detrend ECG signal



(d) Elimination of noise and artifacts after applying passband filter

Fig. 2. Preprocessing of the ECG signal for the sample with annotation ’a0011’ from 100 samples to 24099 samples, i.e., 12 second after requisite detrending

As seen from the figure (2b), the 10th level approximation coefficient holds a trend influencing the ECG signals.

The 10th level approximation coefficient has been removed to eliminate the unwanted trend. The detrending of the raw ECG signal has been illustrated in figure (2c). Again, for removing noise and artifacts from the detrend ECG signals, a passband filter with a cut-off frequency of 5 Hz and 15 Hz were utilized. The elimination of noise and artifacts from the detrend ECG signal has represented in figure (2d).

3.1.2 PCG Preprocessing

The first 5-second of the recorded PCG signals have been analyzed for the uniform study. Most of the PCG signal has corrupted by undesired noise and murmurs. The high and low-frequency noises were reduced after applying a Butterworth low-pass and high pass filter of 4th order with a cutoff frequency of 400 Hz and 25 Hz respectively as implemented by Schmidt [13]. The elimination of noise and murmurs from the raw PCG signal has represented in figure (3).

3.2 Feature Extraction

Efficient classification of the PCG and ECG signals directly depends on the choice of features. Hence, numerous experts have been undertaking the difficulty for a decade toward predicting cardiac abnormality. The extraction of features has been separated into two parts as, ECG based feature extraction and PCG based feature extraction.

3.2.1 ECG based Feature Extraction

As discussed in section (3.1) that the detailed description of the ECG database has not mentioned clearly. The ECG signals were manually examined but observed that it was acquired from different leads at different cases.

Hence, this study has been centered on extracting the features based on the QRS complex wave from the preprocessed ECG signals. The features have been extracted by detecting the R peak using the traditional Pan and Tompkins [23] approach after normalizing the preprocessed ECG signals. Their approach is compatible with identifying the QRS complex as the ECG signals have been acquiring from different leads. Hence, four features were extracted based on the QRS complex as 1) average R-R time interval, 2) no. of

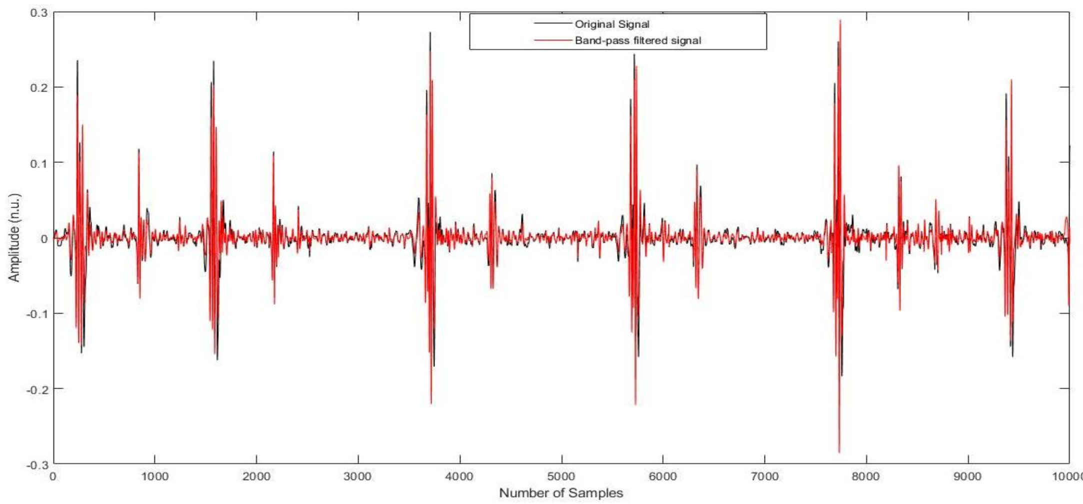


Fig. 3. PCG signal after applying band-pass filter: Raw PCG (black) and Filtered PCG (red)

R-R peak over 12 seconds, 3) maximum R peak value, and 4) average R peak value.

3.2.2 PCG based Feature Extraction

PCG-based features have been extracted based on the unsegmented approach. The preprocessed PCG signals were normalized followed by feature extraction based on wavelet transform, homomorphic envelogram, Hilbert transforms, and power spectral density. Efficient classification of the PCG signal directly depends on the choice of features. Hence, many experts have been tackling the problem for a decade toward predicting the anomaly of the heart sound. 11 features were selected based on unsegmented cardiac cycle after downsampling all the preprocessed PCG signal by downsampling to 50 samples/s using Eq. (9) before extracting the features. The decimated PCG signal reduces the complexity of the computation:

$$O[n] = x[nN] = \sum_{k=1}^{k-1} x[nN-k].\,g[k], \tag{9}$$

where $O[n]$ denotes downsampled signal with impulse response $g[k]$ over length k.

Using the wavelet decomposition method 8 features were extracted. Eight wavelet coefficients have been generated after decomposing the preprocessed PCG signal to 7 levels using 'dB10' (Daubechies 10) wavelet which comprises of 7 detail coefficients and one approximation coefficient. The equation for extracting one feature for each coefficient which was implemented by Hamidi *et al.* [24] and Singh et al. [26] have been shown in eq. (10). The author in [24] used the wavelet decomposition method for feature extraction. For each PCG signal, eight features have derived using the wavelet decomposition method after decimation:

$$C = \left|\log\left(\frac{\sum_{n=0}^{N-1} C(n)^2}{N}\right)\right|, \tag{10}$$

where $C(n)$ denotes the coefficients of wavelet.

Applying the exponential to the logarithmic term of the low pass filter given in Eq. (7) as expressed by Gupta *et al.* [18], the homomorphic envelogram has been generated. The authors in [12] used the homomorphic envelope method for feature extraction. For each PCG signal, one feature has derived using the Homomorphic envelogram method after decimation.

The envelope of the PCG signal using the Hilbert envelope method has represented as the magnitude of the above Eq. (11). As the main approach toward envelope detection is to detect S1 and S2, hence the negative frequency part has been eliminated. For each PCG signal, one feature has derived using the Hilbert envelope method after decimation.

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Table 1. Comparative study of different classifiers for heart abnormality analysis based on different signals

Signal	Classifiers	Performance		
		Sensitivity (%)	Specificity (%)	Accuracy(%)
ECG (14 features)	Ensemble	90.27	36.67	74.50
	SVM	76.38	43.30	67.00
	KNN	80.60	52.61	71.84
PCG (11 features)	Ensemble	76.39	56.67	70.59
	SVM	87.50	80.00	85.29
	KNN	88.89	56.67	79.41
PCG-ECG (15 features)	Ensemble	91.67	66.62	84.31
	SVM	**94.44**	**90.00**	**93.13**
	KNN	86.11	96.67	89.21

The magnitude response of the analytical signal based on the Hilbert transform can be expressed as:

$$B(t) = \sqrt{x(t) + H[x(t)^2]}. \tag{11}$$

Arnott *et al.* [25] approved that the energy concentration of the heart sounds (S1 and S2) was lower than 150 Hz and peak at 50Hz. After computing the mean power spectral density (PSD) between 40 Hz and 50Hz with a 50 ms width size window with 50% overlap which was analyzed based on the above frequencies.

Using a Short Time Fourier Transforms (STFT) followed by the Hamming window, PSD was computed and normalized. For each PCG signal, one feature has derived using the power spectral density method after decimation.

4 Classification and Performance

Cardiac monitoring using the PCG and ECG signals have been analyzed based on two performance parameters (sensitivity and specificity) and computed the performance of the classification model (KNN, SVM, and Ensemble classifiers). After cautiously observing and ignoring the overfitting of the model, 70% of the feature samples (70% PCG features and 70% ECG features) has randomly selected for training the neural network (KNN, SVM, and Ensemble classifiers) and remaining 30% for testing the neural network classification model. 70% of the training features consist of 168 abnormal and 72 normal recordings and the remaining 30% of the testing features consist of 72 abnormal and 30 normal recordings.

The performance of the proposed the model-based classifier was computed using the confusion matrix or error matrix after estimating sensitivity and specificity. The performance of the proposed model has predicted by computing two performance parameters. The parameters are sensitivity and specificity. The equation representing the two performance parameter has explained below as:

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% , \tag{12}$$

$$Specificity = \frac{TN}{TN+FP} \times 100\% , \tag{13}$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100\% , \tag{14}$$

where TP, TN, FP, FN denotes true positive, true negative, false positive and false negative respectively.

5 Results

The classification performance of the models has been evaluated after training 70% PCG-ECG feature samples and the remaining 30% PCG-ECG for testing the model using three different classifiers. The classification models are trained by

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bootstrapping 70% feature samples and remaining for testing the models. Three classification models have been used to analyze the performance. Firstly, the performance of the model has been analyzed by using individual feature samples (PCG or ECG features). A comparative study of different classifiers for heart abnormality analysis based on different signals is illustrated in table 1.

The proposed model based on PCG-ECG features help in enhancing the classification performance (sensitivity 94.44%, specificity 90.00%, and accuracy 93.13%) using SVM classifier. Performance of the three models (KNN, SVM, and Ensemble) has been analyzed by training and testing the individual features as illustrated in the above table. The model using PCG-ECG features achieves superior performance. SVM classifier has achieved a higher classification accuracy of 85.29% using PCG features while comparing with other classifiers (based on the feature extracted from the individual signal).

5 Discussion

The comparative results of the proposed model with state-of-the-art methods have illustrated in table (2). Most of the recent work has been centered toward improving the two parameters i.e., sensitivity, and accuracy but failed to improve the specificity of the classification model. The test performance for predicting cardiac abnormality has reduced due to an irregularity of healthy and abnormal dataset simples.

The proposed method derived the features using PCG-ECG signals based on time-frequency that helps to improve the classification of the cardiac signals. The performance of the proposed model has an accuracy of 93.13% along with sensitivity and specificity of 94.44% and 90.00% respectively. The best performance of the proposed method using an SVM classifier has obtained using the RBF kernel.

All the state-of-the-art results illustrated in table 2 have been analyzed based on the PCG features as the samples database were taken from the PhysioNet 2016 challenge and their challenge was to classify the heart abnormality using the PCG recordings. Hamidi [24] employed two of the proposed methods based on curve fitting and fractal dimension and achieved an overall accuracy of 67.00% with improved sensitivity of 77.00% based on fractal dimension. But their approach needs to improve sensitivity and specificity relatively.

Table 2. Comparative analysis of the proposed classifier model with the traditional methods

Methods	SN (%)	SP (%)	Acc (%)
Decision Fusion Method			
AlexNet-Ensemble	90.20	35.48	73.78
AlexNet-KNN	86.11	58.06	72.80
AlexNet-SVM	77.00	58.06	67.00
AlexNet-LDA	75.00	45.16	66.02
Existing Method			
Ensemble	89.00	32.00	72.55
Homomorphic	96.00	8.00	71.00
Fractal Dimension	77.00	43.00	67.00
Curve Fitting	71.00	32.00	60.00
Proposed method based on PCG-ECG			
Proposed Method	**94.00**	**90.00**	**93.13**

Using the idea implemented by Singh *et al.* [27], the decision fusion method has executed by connecting two binary classifiers that consist of a convolutional neural network for deriving high feature level and a final soft decision layer (i.,e KNN, LDA, Ensemble and SVM). The detail discussion about the decision fusion method has discussed on [27].

However, the proposed method based on an SVM classifier using PCG-ECG features can overcome the hindrances remarked in the literature with a classification accuracy of 93.13% and improved sensitivity and specificity of 94.44 % and 90.00% respectively. It has proved that the classification based on the PCG-ECG features using the proposed classifiers achieves an excellent outcome as compared with other traditional methods based on the PCG or ECG features.

Hence, the proposed classifier based on the PCG-ECG features can be employed for assisting cardiac monitoring with high classification performance.

6 Conclusion

A novel approach for classifying the heart abnormality based on the PCG and ECG signals has been presented in this study. The features of the cardiac signal vary according to the nature of abnormal heart ailments. An obstacle in cardiac movements can create turbulence in heart signals. A cheap and effective way toward monitoring the heart abnormality is by interpreting the heart signals (PCG and ECG). The proposed work was executed on a single dataset acquired from PhysioNet/CinC 2016. The result of classification utilizing the SVM classifier proves that the performance of the proposed work is excellent in comparison with the previous approaches such as curve fitting and fractal dimensions. Particularly, the efficiency of the proposed method using PCG-ECG features is much better than the traditional method using PCG or ECG features alone.

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