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Research Article

PCG Frame Classification by Classical Machine Learning Methods Using Spectral Features and MFCC Based Features

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Abstract

Cardiovascular diseases are some of the most common diseases today. Congenital abnormalities, diseases caused by impaired heart rhythm, vascular occlusion, post-operation arrhythmias, heart attacks and irregularities in heart valves are some of the various cardiovascular diseases. Early recognition of them is very important for obtaining positive results in treatment. For this purpose, it is tried to diagnose and detect cardiovascular diseases by listening to the sounds coming from the heart. During the rhythmic work of the heart, the contraction and relaxation of the heart chambers and the filling and discharge of blood from the heart into the veins create the sounds that are identified with the heart. Among the characteristic sounds of the heart, there can be some sounds similar to rustling which are indicators of pathological conditions. These unexpected sounds, similar to rustling, are called heart murmurs. Phonocardiograph device is used to record these mechanical sounds via microphone. Heart sounds recordings captured by a phonocardiograph device are called phonocardiograms (PCGs). Expert physicians try to detect the heart murmurs by listening to the heart sounds and examining PCGs. Ambient noise, the squeak of the microphone, and the patient's breathing sounds are the factors that make this task more difficult and challenging. Computer-aided systems supported with machine learning, signal processing and artificial intelligence algorithms offer solutions to help physicians in this regard. In this study, detection of heart murmur from PCG frames was examined. PCG frames of equal length, obtained by fragmenting the PCG recordings into 1-second-long frames, were classified by widely used machine learning methods namely C4.5 decision tree, Naive Bayes, Support Vector Machines and k-nearest neighbor. To train those classifiers we used spectral features of PCG signals, averages of MFCC values and some refined features obtained from a deep learning model which was inputted MFCC values. At the end of this manuscript the accuracies of those machine learning methods were compared.

Keywords: Biomedical signal processing, machine learning, deep learning, heart murmur, PCG, classification.

Spektral Özellikler ve MFCC Tabanlı Özellikleri Kullanan Klasik Makine Öğrenmesi Metotlarıyla PCG Parça Sınıflandırması

Öz

Günümüzde en sık rastlanan hastalıklardan birisi kalp damar rahatsızlıklarıdır. Doğuştan gelen anormallikler, kalp ritminin bozulmasıyla çıkan hastalıklar, damar tıkanıklığı, ameliyat sonrası ortaya çıkan aritmiler, kalp krizleri ve kalp kapacıklarındaki düzensizlikler çeşitli kardiyovasküler hastalıklardan bazılarıdır. Bunların erken fark edilmesi tedavide olumlu sonuçlar almak için oldukça önemlidir. Bu amaçla kalpten gelen sesler dinlenerek kardiyovasküler rahatsızlıkların teşhis ve tanısı yapılmaya çalışılmaktadır. Kalbin ritmik çalışması esnasında kalp odacıklarının kasılıp gevşemesi, kanının kalpten damarlara dolup boşalması kalple özdeşleşen

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sesleri meydana çıkarır. Kalbin karakteristik seslerinin içinde ise patolojik durumların bir göstergesi olarak hışırtıya benzer sesler duyulur. Hışırtıya benzeyen beklenmedik bu sesler kalp üfürümü olarak adlandırılır. Bu mekanik sesleri mikrofon vasıtasıyla kaydetmek için Fonokardiyograf cihazı kullanılır. Kalpten gelen seslerin alındığı kayıtlarda da fonokardiyogram denilmektedir. Değişken uzunlukta olabilen bu kayıtlardan üfürümü uzman hekimler dinleyerek tespit etmektedir. Ortam gürültüsü, mikrofonun cızırtısı, hastanın nefes alış/veriş sesleri ise bu görevi zorlaştıran etmenlerdir. Makine öğrenmesi, sinyal işleme ve yapay zeka algoritmalarıyla elde edilen bilgisayar destekli sistemler bu konuda uzman hekimlere yardımcı olacak çözümler sunmaktadır. Bu çalışmada PCG kayıtlarının 1 saniye uzunluğunda kesitlere parçalanmasıyla elde edilen eşit uzunluktaki segmentlerinin makine öğrenmesi yöntemleriyle normal veya üfürüm içeren şeklinde sınıflandırılması amaçlandı. Bu amaçla yaygın olarak kullanılan ve meşhur olan C4.5 karar ağacı, Naive Bayes, Destek Vektör Makinaları ve k-en yakın komşu sınıflayıcıları kullanıldı. Özellik olarak da PCG sinyallerinin spektral değerleri, MFCC değerlerinin ortalamaları ve MFCC değerlerinden derin öğrenme ile elde edilen özellikler kullanıldı. Farklı makine öğrenmesi yöntemlerinin performansları doğruluk değerlerine göre karşılaştırıldı.

Anahtar Kelimeler: Biyomedikal sinyal işleme, makine öğrenmesi, derin öğrenme, kalp üfürümü, PCG, sınıflandırma.

1. Introduction

The heart is the core organ of human body which is responsible of transporting blood to every part of the body through the veins. It acts like a pump that works continuously and regularly. Located above the diaphragm and between the two lungs, the heart is about the size of a fist. Human heart beats around 100,000 times a day, which corresponds to between 60 and 100 beats per minute [1], [2]. The process from one beat of the heart to the following beat is called as cardiac cycle. The cardiac cycle can take varying times depending on the heart rhythm. For example, in someone with a heart rate of 60, the cardiac cycle will take 1 second. With the stimulation of the heart primarily by the SA node, blood flows from the atriums to the ventricles and the heart relaxes. Then, with the contraction of the ventricles, the blood passes into the pulmonary and aortic vessels. During all this blood flow, the valves in the heart (tricuspid, pulmonary, mitral and aortic valves) open and close, and blood is transferred from one chamber to another by producing mechanical sounds.

The sounds expected to be heard in healthy people are first (S1) and second (S2) heart sounds. In addition to these, third (S3) and fourth (S4) sounds may be present in special cases (pregnant women, athletes, children). Apart from these, incomplete closure of the heart valves, backflow of blood, narrow valves, and deformations in the veins can make the blood utter a rustling sound. These abnormal sounds are called heart murmurs. Detecting and grading murmurs by listening and distinguishing them from ambient sounds and noises is a challenging job that requires expertise.

There are many tools used to examine the functioning of the cardiovascular system. Phonocardiography is one of them. It is a non-invasive, practical, inexpensive and common approach. The sounds heard during the beating of the heart are recorded electronically with a microphone held on the skin near the heart with a phonocardiograph device. These recordings are called phonocardiograms (PCGs). PCG recordings can be listened to over and over again, examined in detail, and opinions from different experts can be obtained. Although PCG examination has been the studied for a long time, it is still an important problem and attracts researchers [3], [4].

The period from one beat of the heart to the next beat is called the cardiac cycle. First (S1) and second (S2) heart sounds regularly follow each other. The consecutive S1 and S2 sounds in each cardiac cycle are heard as a loop-dup. In healthy people, there is a short silent period between these two sounds. The silent interval between S1-S2 is called systole and the silent interval between S2-S1 is called diastole. One of the most frequently used processes in PCG analysis is to segment these four phases of the heart sound signal according to the temporal start and end points. Heart murmur sounds can be heard during all four phases of the cardiac cycle. Sounds coming from the heart are rhythmic and consist of certain frequency components. First heart sound consists of components in the frequency ranges 40-200 Hz and second heart sound consists of components in the 50-250 Hz frequency range [1]. On the other hand, the frequency range of the heart murmurs is around 200-600 Hz [5].

Researchers have studied murmurs and other abnormalities in PCG recordings for decades. For this purpose, competitions were organized and data sets with various difficulties were shared. Examples of these are the PhysioNet [6] datasets (CinC2016 and CirCor2022) and the PASCAL [7] dataset. Other than these publicly shared data sets, studies have also been carried out with private data sets that are owned by institutes and hospitals.

Potes et al. [8] won the first place in the PhysioNet 2016 competition with their ensemble classifier of AdaBoost and Convolutional Neural Network (CNN) classifiers. After resampling the CinC2016 data set into 1000 Hz, they filtered out the components outside the 25-400Hz range with a band-pass filter. During the training phase of their model, they applied cross-validation by randomly dividing data set into 80%-20% train/test sets. They achieved 86% accuracy in the competition with their model.

In another study using CinC2016 dataset [9], 88.7% accuracy was obtained by using Random Forest (RF), Extreme Gradient Boosting (XGB), k nearest neighbor (kNN) and their ensemble form. In addition, Rath et al. [9] investigated the optimal k value of the kNN method for PCG classification and determined it as 50.

Noman et al. [10] used the Cinc2016 dataset as well, and they obtained 89.2% accuracy by combining two deep learning models, one of them is 1D CNN and the other one is 2D CNN. MFCC features were used in the training of the 2D CNN model.

CinC2016 data set was also used by Das et al. [11]. They first performed segmentation and then murmur detection on the cochleagram images. Those images were extracted from the PCG recordings and then classified by deep neural network (DNN). They achieved 98.3% accuracy by their model.

Arslan [12] applied 5 level Empirical Mode Decomposition (EMD), Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT) and then extracted the mean, standard deviation, energy and entropy properties from the signals. Those features were used to train kNN, Support Vector Machine (SVM), RF and Extreme Learning Machine (ELM). Chowdhury et al. [13] classified the CinC2016 dataset with 97.1% accuracy using a DNN, which was trained with MFCC features extracted from PCG signals.

Using PASCAL dataset, Ismail et al. [2] produced spectrograms from PCG signals and then used them at the training of AlexNet deep learning model. Additionally, they trained SVM classifier with features obtained from those spectrograms by using a deep learning method. Finally, classifications of AlexNet and SVM were combined to make overall classification by applying majority voting.

A necessary process in the analysis of audio signals is to divide the signal into equal-length parts. Having frames which are equal with respect to length is generally necessary for feature extraction and neural network training. Variable lengths can be experimentally chosen. For example, Langley and Murray [14] extracted features from the 5-second-long frames of PCG signals without any segmentation and classified them with a decision tree.

In traditional machine learning approaches, it is desirable to have good feature sets that represent the data as well as possible. For this purpose, many features are extracted and used. However, not all of these features are equally important in representing the data. In addition, having a large number of features can sometimes have a negative effect such as increasing the duration of classification and consuming larger resources. To avoid this, the feature space is sometimes narrowed by methods such as Principal Component Analyses (PCA). In contrast to classical machine learning models, deep learning models automatically extracts features and put away manual feature engineering. We can say that today, researchers are more interested in deep learning methods due to good performance and automatic feature extraction attribute.

In this study, we aimed to classify 1-second-long frames of PCG recordings by using traditional machine learning methods. We compared the performances of C4.5 decision tree, SVM, Naive Bayes and kNN machine learning methods at classification of abnormal (containing murmur) and normal (murmur-free) PCG recordings. As features, we used MFCC based features and spectral properties of PCG signals. Those classifiers were trained and tested by 10-fold cross validation and their accuracies were compared.

2. Material and Method

2.1. Database

We conducted our study using two datasets shared online by PhysioNet [6] in 2016 and 2022. These are respectively PhysioNet Computing in Cardiology Challenge 2016 (CinC2016) [15] and CirCor Digiscope Phonocardiogram Data Set (CirCor2022) [16]. Both datasets have PCG recordings with murmur (abnormal) and without murmur (normal). In addition to these two classes, the CirCor2022 dataset also contains a small number of samples labelled as unknown. The details of the data sets are given in the Table 1. By eliminating samples which are labelled as unknown from the CirCor2022 dataset, we obtained a database with two classes. We conducted our study using only abnormal and normal samples.

As it can be seen in Table 1, the data sets consist of records captured at different sampling frequencies. Therefore, all samples were resampled to 1000Hz to eliminate this problem in the preprocessing stage. In addition, PCG signals were normalized to the [-1, 1] range.

Table 1. Properties of the data sets used in this study. FS: Sampling frequency in Hz.

Data set	FS	Total Samples	Distribution
CinC2016	2000	3240	665 abnormal, 2575 normal
CirCor2022	4000	3118	604 abnormal, 2358 normal, 156 unknown

2.2. Method

The PCG records in our datasets are of variable size. During preprocessing, the PCG signals were resampled to 1 kHz, normalized and then split into 1-second-long frames. At the end of splitting process, the CinC2016 data set was divided into 71344 frames, of which 16687 are abnormal and 54657 are normal. On the other hand, the CirCor2022 data set was divided into 66300 parts, having 13070 abnormal and 53230 normal ones. The abnormal/normal ratios of the datasets are approximately 31% and 25%, respectively.

Unbalanced data affect negatively the training performance. Therefore, we applied sliding window with 1-second-long windows length and 50% overlap rate to augment the fewer class frames. Equal numbers of normal and abnormal PCG signal frames were obtained and used for training. The proposed method in our study is shown in Figure 1.

In the feature extraction phase, we first obtained the Mel-Frequency Cepstrum Coefficients (MFCC) which are frequently used features in speech recognition. Like human ear, MFCC tends to show more sensitivity below a certain frequency band during distinguishing sounds and in this sense, it mimics human auditory system [13], [17].

To obtain MFCC features, pre-emphasizing is the first step in which high frequencies are amplified. Then the quasi-stationary signal is divided into short frames across which the signal is assumed to be stationary. Generally consecutive frames overlap a pre-defined amount of time. Then a window (such as Hamming, Hanning or etc.) is applied on the frames to reduce edge effects and smooth the edges. Then Discrete Fourier Transform is applied on the windowed frames to compute the periodogram. Then the Fourier transformed signal is passed through Mel-filter bank (a set of bandpass filters). This phase results in non-linear frequency resolution. It is given in the Equations 1 and 2 where f is physical frequency and f_{MEL} is its Mel-frequency representation.

$$X(k) = \sum_{n=0}^{N-1} x(n)\, e^{\frac{-j2\pi nk}{N}};\ 0 \le k \le N-1 \tag{1}$$

$$f_{MEL} = 2595 \log_{10}\left(1 + \frac{f}{700}\right) \tag{2}$$

Now Mel spectrum is fit into log format in which most of the signal information is represented by the first few coefficients. M is total number of Mel weighting filters and $H_m(k)$ is the weight given to k^{th} energy spectrum bin according to Equation 3.

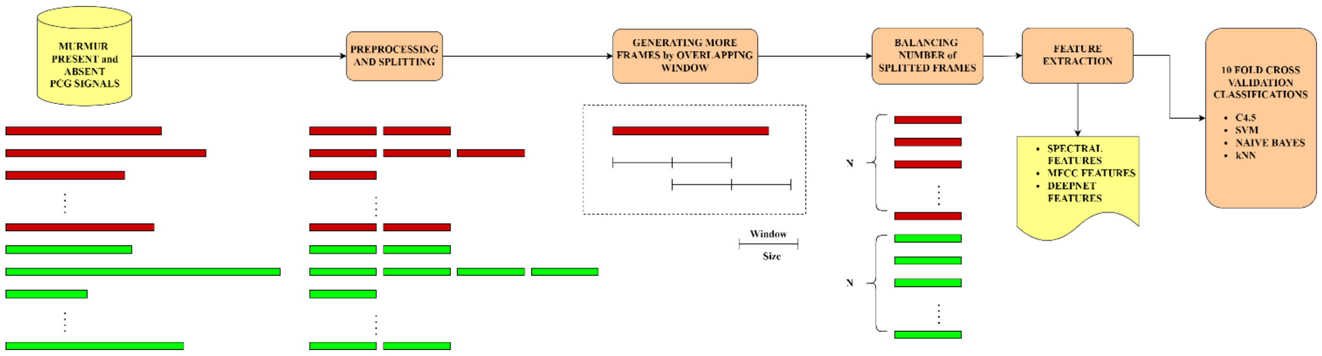

Fig. 1. Proposed method

$$P_{filt} = \sum_{k=0}^{N-1} [|X(k)|^2 H_m(k)];\ 0 \le m \le M-1 \tag{3}$$

Finally, MFCCs are obtained by taking a discrete cosine transform. This process converts the Mel spectrum to finite sequence of cosine functions oscillating at different frequencies. In Equation 4, MFCC(t,k) is k^{th} cepstral feature of t^{th} time frame and $P_{filt}(t,n)$ is filtered power at time frame t for n^{th} filter bank. The number of MFCCs for each frame is C and zeroth coefficient can be excluded since it represents the average log energy of the input signal.

$$MFCC(t,k) = \sum_{n=0}^{N-1} \log\left(P_{filt}(t,n)\right) \cos\left(\frac{k\pi}{N}(n-0.5)\right);\quad k = 0,1,2 \ldots, C-1 \tag{4}$$

We obtained 5x99 MFCC features by choosing the window size as 20 ms, the overlap rate as 10 ms and the number of coefficients as 5 from the PCG frames with a sampling frequency of 1000 Hz and a length of 1 second. During feature engineering we firstly calculated the average of 5 coefficients of each 99 parts. Then, we processed the MFCC features of 5x99 size with our DNN model shown in Figure 2, and took the activation values of the last fully-connected layer and converted them into 2 features.

Finally, we extracted 8 spectral features (spectral centroid, spectral crest, spectral entropy, spectral flux, spectral kurtosis, spectral roll off point, spectral skewness and spectral slope) from 1-second-long PCG frames. Those three feature sets were used to train classifiers.

In our study, we used the classifiers implemented in the Waikato Environment for Knowledge Analysis (WEKA) [18] workbench. WEKA includes many classification methods, clustering algorithms and data processing tools. It is free under the GNU General Public License and it is widely used for data mining. We aimed to obtain and present more general results by using the methods found in WEKA instead of our own implementation.

We used C4.5 decision tree (J48), SVM, Naïve Bayes (NB) and kNN (IBk) classifiers. For SVM, John Platt's sequential minimal optimization algorithm implementation namely weka.classifiers.functions.SMO classifier is used. Additionally, 51 is used as the k value in the kNN classifier. We applied 10-fold cross validation.

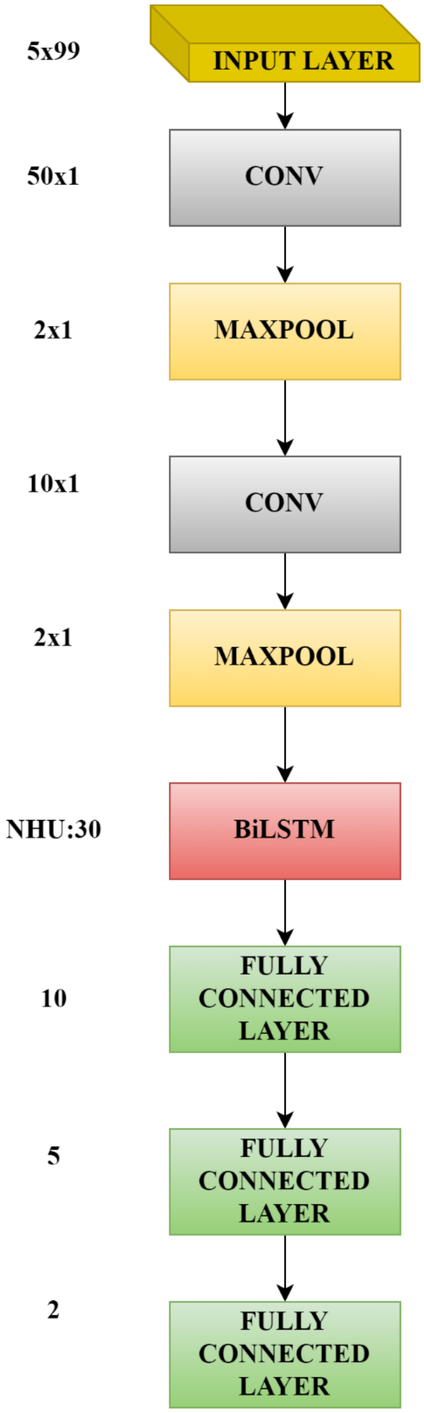

Fig.2. Layers of DNN model which is used to extract features

3. Experiment Results

Four classifiers' performances were compared according to the accuracy measure obtained at the end of 10-fold cross validation. Experimental results are given in Figures 3 and 4 for CinC2016 and CirCor2022, respectively.

In the CinC2016 dataset, the highest accuracy was obtained as 86.4% using the average MFCC features with the C4.5 decision tree classifier. In the CirCor2022 dataset, the highest accuracy was observed as 74.6% with the SVM classifier, which uses the features obtained by DNN model. Confusion matrices for the best results are given in Tables 2 and 3. According to the confusion matrix in Table 2, the weighted average of recall and precision values are 0.864 and 0.866, respectively. According to the confusion matrix in Table 3, the weighted average of recall and precision values are 0.746 and 0.752, respectively.

$$\text{Accuracy} = (TP + TN) / ALL \quad (5)$$

$$\text{Recall} = TP / (TP + FN) \quad (6)$$

$$\text{Precision} = TP / (TP + FP) \quad (7)$$

Table 2. Confusion matrix obtained as a result of training C4.5 decision tree classifier with MFCC averages using CinC2016 dataset. R. Abnormal: Real Abnormal, P. Abnormal: Predicted Abnormal, R. Normal: Real Normal and P. Normal: Predicted Normal

	P. Abnormal	P. Normal
R. Abnormal	49339	5318
R. Normal	9559	45098

Table 3. Confusion matrix obtained as a result of training SVM classifier with DeepNet Features using CirCor2022 dataset. R. Abnormal: Real Abnormal, P. Abnormal: Predicted Abnormal, R. Normal: Real Normal and P. Normal: Predicted Normal

	P. Abnormal	P. Normal
R. Abnormal	35631	17599
R. Normal	9478	43752

As seen in Figure 3 in the experiments where we used the CinC2016 data set, the classifier with the highest overall success is the C4.5 decision tree. It is followed by kNN, SVM and NB, respectively. Looking at the feature sets, the most successful classifications were obtained with C4.5 and kNN when the average MFCC was used as training set. However, this feature set gave low accuracy results when used with SVM and NB classifiers. The features produced using the deep learning model gave an accuracy of approximately 80% in all classifiers. On the contrary, other feature sets yielded variable performance results in different classifiers.

In the experiments where we used the CirCor2022 data set, as seen in Figure 4, all classifiers achieved an accuracy of approximately 74.5% with the features we produced using our deep learning model. The mean MFCC features were successful in representing the data in second place. The lowest performance was measured in experiments where SVM and NB classifiers were trained with spectral features.

When we compare the experiments using the CinC2016 and CirCor2022 datasets in general, it is seen that the CinC2016 dataset can be classified more successfully with the approaches used in our study. There is a 12% difference between the best results obtained in the experiments performed in the two different sets. It is common in the both classification experiments made by using deep learning features that all classifiers gave close results.

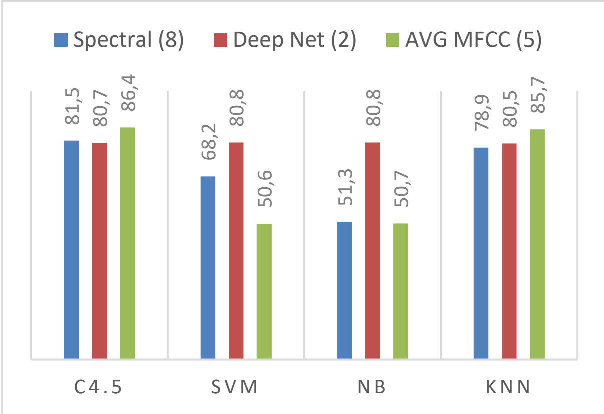

Fig. 3. CinC2016 experiment results

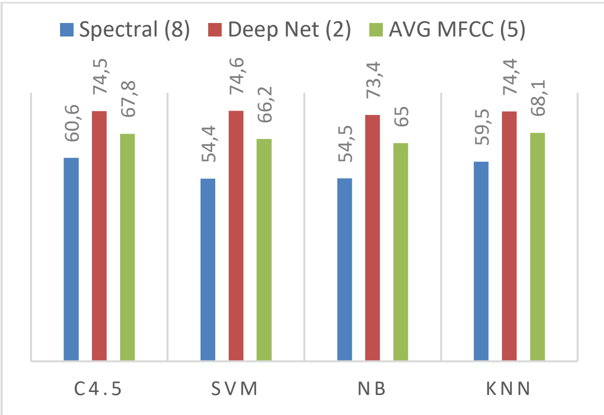

Fig. 4. CirCor2022 experiment results

4. Conclusions

In this study, we examined the classification performances of traditional machine learning methods C4.5 decision tree, SVM, NB and kNN. We used two datasets (CinC2016 and CirCor2022) shared online publicly by PhysioNet. We extracted two MFCC-based feature sets from these datasets. Firstly, we averaged the MFCC coefficients. Secondly, we produced a new feature set with our deep learning model, to which we provided the MFCC features as input. In addition to these, we extracted features based on spectral properties of the PCG signals and used them in the classification.

The worst and best results in the CinC2016 dataset are 50.6% and 86.4% respectively. The worst and best results we got in the

CirCor2022 dataset are 54.4% and 74.6% respectively. C4.5 decision tree is appeared as the best classifier when we look at the overall performance among the classifiers for solving defined problem in this study.

Sound signals derived from the heartbeat and the mechanical events of cardiovascular system triggered by the heart are recorded in PCGs. PCG carries important clues for the detection and diagnosis of various diseases. However, PCG has a non-stationary characteristic because it is a biological signal. Due to this fact, it is difficult to classify it with very high accuracy by using classical machine learning methods. As a result, deep learning-based models are needed in this area.

It is also important to note that the frame size of PCG segments affects the results. Experiments with different frame lengths can be done in the future. In addition, classifiers can be trained with all of the features which are used independently in this study. Moreover, ensembles of the classifiers can used.

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