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Diagnosis of Valvular Heart Regurgitation Using Auscultation of Heart Sounds (Pcg) Based on Deep Learning

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Abstract

Today, several methods are used to diagnose heart diseases, include invasive methods, ECG, etc. Recently, due to the expansion of signal processing and deep learning functions, an attempt has been made to diagnose some diseases based on the signal components with non-invasive and low-cost methods. Currently, PCG signal alone is used as a primary diagnosis, and in case of primary diagnosis, by ECG and etc are used for the final determination of the disease.

Listening to the sound of the heart, which is done in the most traditional way, using medical stethoscopes, can diagnose some diseases if it is done carefully and expertly. In some medical centers, diagnos heart diseaes based on PCG is not possible due to lack of specialists or lack of facilities.

There are four main valves in the heart, for each of which there are two disorders including stenosis or insufficiency, in total these eight disorders are known as heart valvular disorders (HVD) and can be diagnosed by a specialist doctor in appropriate conditions from the murmurs created in a PCG are recognizable.

In this article, using the data obtained from the PCG signal, after removing the noise and normaleization the signal, with the help of deep learning, the existence of valvular stenosis disorders of the heart is detected.

Keywords: PCG, valvular heart disease, deep learning, heart, artificial intelligence

Introduction

According to the latest statistics from the World Health Organization (WHO), 17.7 million people die each year from cardiovascular diseases, which is approximately 31% of all deaths worldwide. WHO predicted that by 2030, approximately 23.6 million people will die from cardiovascular diseases, mainly from heart disease and stroke. Some sudden deaths can be prevented by designing health care systems based on hearing heart. [1].

Heart diseases have a wide range and cardiologists diagnose all kinds of diseases such as mitral valve prolapse, benign murmur, aortic diseases, coronary artery disease, various pathological conditions, etc. [2]. Listening to the sound of the heart or PCG is very accessible and common in the examination of heart function and early diagnosis of the disease. This signal is generated from the mechanical activity of the heart (see Figure 1). Of course, an electrocardiogram (ECG) is a measurement of the heart's electrical activity, but it requires expertise and special equipment to perform this test [2].

Timely diagnosis of the disease and the necessary care for the patients are very important in the topic of prevention. Diagnosis based on PCG requires a lot of expertise and accuracy, which is often not available in public centers.

On the other hand, due to the simple and accessible structure of PCG, this method is used for examination in most general medical centers [3]. The sum of the last two topics leads to the conclusion that many cases of wrong or not diagnosis cause irreparable effects. Therefore, in recent years, a lot of work has been done using artificial intelligence in detecting abnormalities on PCG results [4]. After this stage, if needed and the patient's is diagnosed, he will be referred to a specialized treatment center.PCG can be useful in diseases related to heart valve problems, communication between atria and ventricles, etc. At least 15 diseases can be diagnosed by listening to the sound of the heart, among which 8 valvular heart diseases can also be diagnosed in the same way [5].

Another important function of this proposed method is to use it in the training of medical students as a help in correcting the diagnosis in the training stages.

Heart sounds produce when the cardiac valves open and close during the cardiac cycle. Fig. 1 shows that Heart sounds are S1, S2, S3, and S4. S1 and S2 are most common type of sounds usually produced by the heart. The first sound (S1) is due to the closure of Atrioventricular valves that is Tricuspid and mitral valves(Bicuspid). S1 is low-pitched with a long and soft sound that resembles the word LUBB. The second sound(S2) is produce when the semi-lunar valves of the Aortic valve and pulmonary valve closes. S2 is high-pitched with a short and sharp sound that resembles the word DUB. The third sound (s3) is blood rushing into the ventricles and low pitched sound. S3 is usually seen in youth, well-trained athletes, and sometimes in pregnancy. The fourth sound (S4) is due to the contraction of the Aortic musculature and it is inaudible sound. It is audible when the vibration is form due to ventricular wall while atrial contraction [5].

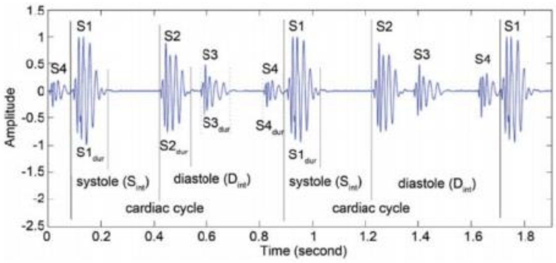

Figure 1. Normal PCG Signal

In most of the past articles, methods based on feature extraction such as KNN, decision tree, etc. have been used to diagnose the disease (reference). Of course, deep neural networks have also been used for diagnosis in limited cases in terms of the number of diseases. In this article, PCG classification approach based on Convolutional Neural Network (CNN) is used [1]. A convolutional neural network is used as a feature extractor, and the features extracted by the convolutional neural network are entered into an SVM for heart sound classification. The structure of the proposed convolutional neural network consists of five layers: input, convolution with maximum integration, two fully connected layers, and output layer [6].

In this paper, we detect Regurgitation heart diseases from PCG signal and provide a comparative analysis of different deep neural network algorithms vrsus the help of previous studies. In the previous study, more features are used, which takes more time to train and is less accurate. To avoid this problem, we used Deep Learning Neural Network(DNN) to obtain better accuracy.

Of course, because we are trying to diagnose more diseases than the previous articles, the work has been done in a hierarchical manner. At first, the normal or abnormal heart sound is diagnosed. Then, the input of the deep neural network is limited by using some general modes.

Methodology

PCG Signal

Phonocardiogram (PCG) is a plan of recording the sounds and murmurs produced by the heart and heard with the help of a device called a stethoscope [7]. Therefore, phonocardiography is the recording of all the sounds made

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by the heart during a cardiac cycle. A phonocardiograph is a microphone that removes unnecessary sounds (noise) and converts the obtained signal into a visible and interpretable form [1].

As mentioned in the introduction, PCG generally has four components. Figure 2 shows examples of the frequency distribution of different components in the heart sound (A from a normal heart sound and B from a heart sound with S3 component, both recorded in the tricuspid region). As shown, components S1-S4 overlap each other in the frequency domain. Similarly, murmurs and effects from breathing and other non-physiological events also overlap significantly. The arrows show typical (theoretical) frequency regions for each type of heart sound: S1 for 10-140 Hz, S2 for 10-200 Hz, and S3 and S4 for 20-70 Hz. Murmurs show different frequency ranges and depending on their nature, they can be up to 600 Hz [7]. Breathing usually has a frequency range of 200-700 Hz [8]. This makes it impossible to separate heart sounds from each other and from unusual noises or artifacts in the frequency domain. The morphological similarity of the noise to normal and abnormal heart sounds makes it very difficult to identify the second way, i.e. the time domain [7].

Introducing the heart

In the heart, the blood with carbon dioxide goes from the right ventricle of the heart to the lungs. There it is purified and the oxygenated blood returns to the left atrium of the heart, and the blood enters the left ventricle from the left atrium, and in this way, with the contraction of the left ventricle, the blood leaves the left ventricle through the aorta and blood circulation in the body begins. This process describes the overall circulation of a cardiac cycle. [2]

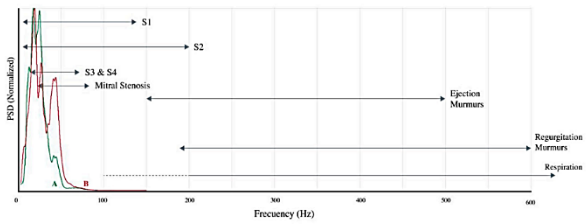

Figure 2. PSD of PCG component

Figure 3 shows the state of the heart in the systole state, which means contraction and pumping of blood to the vessels, and also in the diastole state, which means the heart is resting and the heart is filled with returned blood.

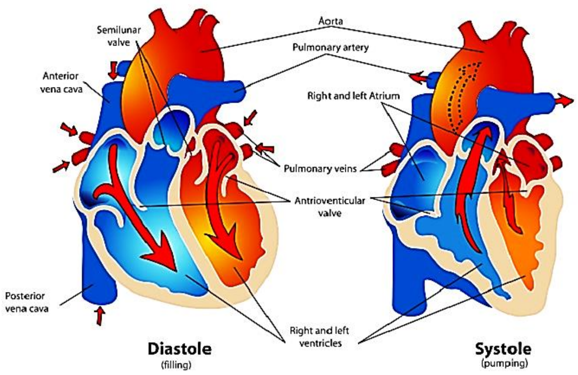

Figure 3. PSD of PCG component

The heart has 4 valves, each of which connects a certain area to the other and maintains the blood flow in the right direction:

- Mitral valve and tricuspid valve that control the flow of blood from the atria to the ventricles.

- Aortic valve and pulmonary valve that control the flow of blood leaving and entering the ventricles.

A normal and healthy heart valve minimizes any blockage and allows blood to flow easily and freely in one direction. Also, the valve is completely and quickly closed when necessary and prevents the return of any blood. In heart valve disease, one or more valves do not function properly [2]. In diseases caused by heart valve Regurgitation, the leaflets of the valve are not closed properly and cause the blood to return back [3].

The normal signal has already been shown in Figure 1, most valvular heart diseases are diagnosed through abnormal sounds called murmurs. A murmur is actually defined as a difference in sound. The characteristics of the murmur in the time domain make the PCG signal can be examined and classified from several aspects to diagnose the disease or health of the person being examined [9]. In the following, we will introduce some of the most important of these items:

Timing

Shape

Pitch

Location

Radiation

Grade

Above items shows in Fiure 4:

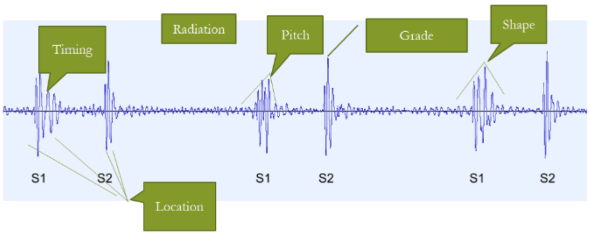

Figure 4. Most important of PCG items in time domain

Of course, in fields other than time, we may also obtain information that will be investigated in future works.

Convolutional Neural Network

CNN is a powerful deep neural network that was inspired by visual neuroscience and was used for the first time in the field of computer vision and is now very advanced. If the input data is a two-dimensional image, the convolutional neural network can effectively learn hierarchical features to build a final feature set from high-level abstraction, which can be a classifier. It is easier to feed a whole connection neural network or a support vector machine in order to realize the purpose of cluster identification in the proposed method. The patterns in the images are automatically learned by the convolutional neural network and stored in the parameters of the network connections. Therefore, the convolutional neural network requires very little manual engineering. In addition, the convolutional neural network has a greater ability to discover complex patterns in high-dimensional data compared to manual feature engineering [10].

Considering that we intend to use other fields for the CNN input, apart from the time domain, we chose this network, domains such as Mel frequency, Fourier transform, wavelet transform, etc. In fact, consider an image where each line is a vector resulting from the transformation of one of the previous items on the time domain.

DataSet

Due to the variety of diseases used, several databases have been used in this section:

- The database, which was recorded under the influence of different conditions, and in order to check the accuracy of the detection of signal limits in the previous pages, this database, which stored PCG and ECG for a healthy person at the same time, will be used. This database, from 24 healthy adults between 23 and 29 years old (mean: 25.4 ± 1.9 years) in 30-minute stress test sessions in the conditions of rest, walking, running and cycling have been obtained using it [11].

Other items are given in Table 1:

TABLE 1. Strouhal number for different geometric cases

Dataset	Sample type
Physionet 2016 (EPHNOGRAM)	Normal and disordered
MITHSDB	Normal and disordered
AADHSDB	Normal and disordered
Congenital Heart Disease Sounds	9 states of disorder
2019 Adult Congenital Heart Disease Sounds	7 state of disorder
Michigan Heart Sounds	Normal and disordered
Peterjbentley Web site	Normal and disordered

Methods

In previous works, two fields have been investigated, including detection of systole and diastole limites in a PCG signal and diagnostic measures with deep neural network or other methods. Due to the variety of PCG structure in different diseases, the diagnostic tasks outside the deep neural network are very diverse.

Detection of systole and diastole limits

Considering that one of the most important indicators in the diagnosis of murmurs is the need to know the position of S1 and S2, in previous works, various methods have been tried to identify the position of different parts of the PCG signal. Each of the valvular disorders of the heart shows the same valve during movement, so if the heart sound areas are divided, it will be easier to diagnose different types of diseases and the deep neural network will have a less complicated task. All proposed segmentation methods can be basically divided into five groups [12]:

1- ECG reference based methods use R-peak and T wave to locate heart sounds. this approch strictly requires simultaneous recording of ECG and PCG signals but is robust in performance and computationally efficient [13].

2- Envelope-based methods are the techniques that are mostly used in non-ECG segmentation. They use the signal energy to perform morphological transformation, their performance is not suitable in the presence of noise and environmental noise [13].

3- Methods based on time-spectral parameters use time-frequency domain features of heart sounds, murmurs and noise to segment heart sounds [14].

4- Wavelet-based PCG segmentation methods are the evolution of methods based on temporal-spectral parameters, they decompose signals to emphasize heart sounds and suppress the effects of murmurs and sounds. The main challenge of the wavelet-based segmentation method is the selection of suitable filters, level of decomposition and sub-bands required to detect heart sounds and murmurs [13].

5- Hidden Markov models(HMM) have also been used for segmentation in recent years and have good performance (low value) in terms of signal-to-noise ratio [15].

Considering that we intend to use the HMM method and this method has one of the best performance accuracy according to [15], I will introduce it further. The sensitivity criterion in this method is equal to 98.8% and in most cases it can correctly detect the first and second heart sounds.

If S states and Q are defined as a continuous sequence of states, the matrix $A = \{a_{ij}\}$ defines the probability of transition from state i to state j between time t and t+1 as follows:

$$a_{ij} = P(q_{t+1} = S_j | q_t = S_i) \qquad (1)$$

The density function of the probability distribution of observations is $B = \{b_j(O_t)\}$ and it shows the probability that state j will output O_t. The probability distribution density function for each state is calculated according to the following Gaussian function:

$$b_j(O_t) = \varphi_{\mu_j.j}(O_t) \qquad (2)$$

φ is a univariate or multivariate Gaussian distribution with μ_j and j, which are the mean and variance of observations in state j, respectively. The initial state distribution is defined as $\pi_i = \{\pi_i\}$ which

$$\pi_i = P(q_1 = S_i) \qquad (3)$$

Since the start of the signal recording can be at any time of the cardiac cycle, the initial state distribution is equal to the state distribution:

$$\pi_i = P(q_1 = S_i) = P(q_t = S_i) \qquad (4)$$

The parameters are shown as λ before applying HMM:

$$\lambda = \{a_{ij}.\mu_j.j.\pi_i\} \qquad (5)$$

A sequence of states must be found that are most likely to be the observations and parameters of the current model.

$$Q^* = arg\,max\,P(Q|O.\lambda) \qquad (6)$$

Q^* is the state sequence of all the possible state sequences, it has the maximum probability of the main state sequence from the observations. To reduce the effects of noise, the signal is passed through a Butterworth filter with a cutoff frequency of 25 Hz and 400 Hz. Additional sounds whose amplitude is greater than the sound of the heart are removed from the signal by the following algorithm:

The signal is divided into a window of 50 milliseconds.

A larger domain is found in each window.

If this amplitude was three times larger than the average amplitude of that window, it is known as noise.

Known noise is removed from the signal.

The works done in the field of diagnosis of heart diseases

As mentioned, the heart signal has some features that were introduced. Considering these features and also various operations on the signal in different fields such as autocorrelation, wavelet transform, Fourier transform, etc., in various articles, efforts have been made to extract features from cardiac signals. In the following, we will briefly introduce some of these cases [16]:

1- Characteristic of the time domain

2- Mel-Frequency Cepstral Coefficient

3- Statistical information

4- Spectral characteristics [17]

Disease diagnosis from PCG using deep neural network

One of the reasons that inclined us to investigate the deep neural network in this proposal is the lack of diversity in the diagnosis of diseases with the deep neural network. In most of the current articles, the deep neural network has been used only specifically on one or a disease with a similar murmur, and in other cases, no action has been taken in this regard. For example, works in this field have been done in sources [1],[18], [19].

DISCUSSION

In this section, first, the work process is reviewed based on the chart presented in Figure 5, the working plan for a hypothetical test data from the PCG signal.

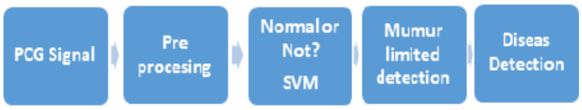

Figure 3. PSD of PCG component

Signal Pre-Procesing

Considering the variety of signals from different databases in terms of time length, fluctuation range, etc., it is necessary to standardize. In the first stage, it is necessary to identify a periodic period of the signal in order to separate the initial point and, accordingly, systole and diastole and other recognizable features in the time domain.

Also, due to the use of different databases, especially for the time domain, all samples will be normalized between a specific domain. Due to the popularity and reference of the Phiziont database, the basis of normalization has been seen in the time domain of this database.

Abnormal detction with SVM

Considering that the deep neural network requires a large amount of data and processing for diagnostic work [31], one of the proposals of this paper is to distinguish healthy heart PCG from unhealthy with a method other than deep neural network. Considering the variety of murmurs and the concern of the deep neural network being biased towards healthy samples, it is suggested to distinguish between normal and abnormal samples by using one of the feature-based methods. Time domain is seleted for this step, most valvular heart diseas have a sofel at least in time chart. To do this part, some characteristics must be determined and classification should be done based on it. Several different methods have been investigated from different aspects, among which the result of SVM is more suitable (TABLE 2).

TABLE 2. Strouhal number for different geometric cases

Method	accuracy	precision	recall	Time(s)
SVM	82.96	82.69	78.59	21.6
KNN	57.8	54.8	48.5	0.182
Mdl	82.07	84.7	68.3	0.179
MLP(NN)	79.91	80.2	75.59	3.5
MSVM	81.85	79.89	75.59	27.18
Classification Tree	74.44	73.9	65	0.19

Determining the limits of systole and diastole by HMM method

As it has been mentioned, one of the best methods for signal analysis and segmentation is the use of hidden Markov model. The PCG signal will be used for this send and output structure. Four diseases under investigation are located in only two regions in terms [20].

Figure 4 taken from [20] shows the identification of different parts of the signal using the HMM method. The simulation of this article using the HMM method is available and can be used in different stages.

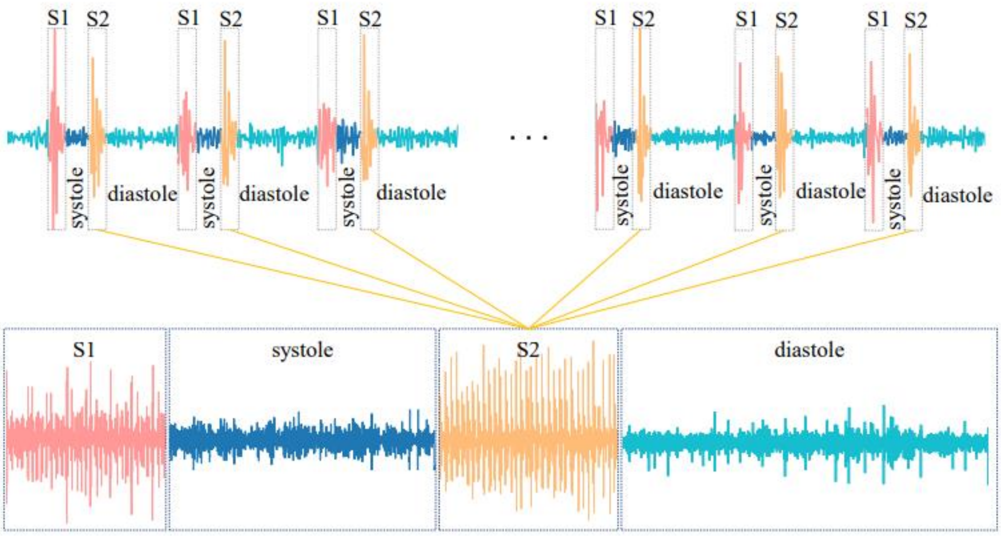

Figure 4- Classification of heart sound dynamics into four basic components based on the results

Diseas Detection with CNN

It is important to remember which lesions lead to systolic murmurs and which lead to diastolic murmurs. For example, narrowing of the aortic or pulmonary valves leads to a systolic murmur, as blood escapes through the narrow opening [6]. Conversely, regurgitation of the same valves results in a diastolic murmur because blood flows backward through the diseased valve when ventricular pressure decreases during relaxation. In the case of mitral and tricuspid valves, stenosis leads to diastolic murmur and systolic murmur insufficiency[6]. Therefore, considering that in the next step, the signal is compared with its different periods, if the detection accuracy is accurate in this step, it will be more achievable to accurately determine the limits of the murmur in the signal.

In this section, in Table 6, all diseases are shown in terms of time of occurrence in the time domain. Considering that the current basis for disease diagnosis is only the time domain, in order to reduce the processing volume of the deep neural network, in this article, the input signal is sent to a convolutional neural network once, and six types of output are recognized according to the location of the murmur.

TABLE 3. deasis and location in time domain

Location	DISORDERS
Mid systole	Aortic stenosis(AS)
Mid systole	Pulmonic Stenosis(PS)
Mid systole	Atrial Septal Defect(ASD)
Mid systole	Hypertrophic Obstructive Cardiomyopathy (HOCM)
Holosystolic	Mitral Regurgitation(MR)
Holosystolic	Tricuspid Regurgitation(TR)
Holosystolic	Ventricular septal defect(VSD)
End of systole	Mitral Valve Prolapse(MVP)

first diastole	Aortic Regurgitation(AR)
first diastole	Pulmonic Regurgitation(PR)
first diastole	Austin-Flint
Mid/end diastole	Mitral Stenosis(MS)
Mid/end diastole	Tricuspid Stenosis(TS)

A convolutional neural network is used as a feature extractor, and the features extracted by the convolutional neural network will have four outputs. The time, time-frequency characteristics of a PSD-based spectrogram using STFT were considered as input to the convolutional neural network model. The structure of the proposed convolutional neural network consists of five layers: input, convolution with maximum integration, two fully connected layers, and output layer. The convolutional neural network treated these different transformations as images in the input layer. Then, the convolutional neural network model was trained with stochastic gradient descent using an optimizer, while the output layer contained four single neurons with sigmoid activation function. The final result diagnosed four different diseases and the results are compared in Table 4.

Performance measures such as accuracy, precision, recall, and kappa score values are also evaluated for each retention validation test. Also, the number of samples used is given in Table 4.

TABLE 4. Resault of CNN

Classes	Number Of Dataset	deep CNN
AR (%)	23	95.76
MR (%)	15	97.97
PR (%)	16	96.87
TR (%)	13	91.44
Normal (%)	68	100
Average accuracy (%)	-	98

CONCLUSION

In order to detect heart diseases that can be detected by using the auditory heart and with the help of the neural network, the PCG signal is checked and after pre-processing, in case of detecting an abnormal beat using SVM, the recorded sound is limited to a The HMM network is used and different ranges of the signal are obtained, after that the type of disease will be diagnosed two time using the deep neural network.

In the first time, according to the result of the previous step, a part of the signal that has a disturbance is detected.

In the second time, these limits are given to a second deep neural network and the result of the disease is obtained

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