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Classification of heart disease based on PCG signal using CNN

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ABSTRACT

Cardiovascular disease is the leading cause of death in the world, so early detection of heart conditions is very important. Detection related to cardiovascular disease can be conducted through the detection of heart signals interference, one of which is called phonocardiography. This study aims to classify heart disease based on phonocardiogram (PCG) signals using the convolutional neural networks (CNN). The study was initiated with signal preprocessing by cutting and normalizing the signal, followed by a continuous wavelet transformation process using a mother wavelet analytic morlet. The decomposition results are visualized using a scalogram, then the results are used as CNN input. In this study, the PCG signals used were classified into normal, angina pectoris (AP), congestive heart failure (CHF), and hypertensive heart disease (HHD). The total data used, classified into 80 training data and 20 testing data. The obtained model shows the level of accuracy, sensitivity, and diagnostic specificity of 100%, 100%, and 100% for training data, respectively, while the prediction results for testing data indicate the level of accuracy, sensitivity, and specificity of 85%, 80%, and 100%, respectively. This result proved to be better than the mother wavelet or other classifier methods, then the model was deployed into the graphical user interface (GUI).

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1. INTRODUCTION

The heart is one of the most important organs in humans because it has a vital role, pumping blood throughout the body keeping the blood flow. One of the diseases caused by its malfunction is cardiovascular disease. According to data from the world health organization (WHO), cardiovascular disease is the number one cause of death in the world. An estimated 17.9 million people have died from cardiovascular disease. In 2016, an estimated 31% of global deaths are due to cardiovascular causes. Of these 31%, 85% was approved caused by a heart attack and stroke [1].

Symptoms of cardiovascular disease can often go undetected, but to identify them early, heart attacks and strokes may be the first warning of the disease. Symptoms of a heart attack include pain or discomfort in the center of the chest, pain or discomfort in the arm, left shoulder, elbow, jaw, or back. Also, the person may have breathing difficulty or shortness of breath, nausea or vomiting, dizziness or faint, cold sweats, and paleness [1]. In Indonesia, heart disease is still a very dangerous threat. According to the sample registration system (SRS), heart disease is the second leading cause of death, after stroke. As a result of this disease, the country suffered economic losses. Each year, the data from the Social Security Administrator for Health (BPJS) shows an increase in health expenses for heart disease. In 2014, heart disease consumed around 4.4 trillion of BPJS funds, followed by an increase to 7.4 trillion in 2016, and increased further in 2018 amounting to 9.3 trillion [2]. This proves that there is a very significant increase every year in patients with heart disease. Therefore, disease prevention efforts are needed to reduce the burden of state expenses in tackling the disease. People with cardiovascular disease or who are at high risk for cardiovascular disease need early detection.

Heart disease has many types, some of which are angina pectoris (AP), congestive heart failure (CHF), and hypertensive heart disease (HHD). Each of these diseases is characterized by their respective heart signals. At present, there have been many developments in the analysis of heart signals or sounds. The most commonly used method based on heart signal is the electrocardiogram (ECG) signal, while the phonocardiogram (PCG) signal is often used to analyze the heart sound. An ECG is a recording of heart signal activity [3]. Meanwhile, PCG records the sound of the heart resulting from the beating of various structures of the heart and circulating blood [4]. ECG is recorded by placing the electrodes on the skin, whereas PCG is recorded through an electronic stethoscope [5], [6].

Research on heart disease analysis using ECG has been widely used [7]-[11]. PCG signals consist of two main sounds namely the first sound (S1) and the second sound (S2) [12]. As for the abnormal heart PCG signals, it consists of more than two sounds and murmurs [13]. A murmur is a turbulent sound of blood flowing through the heart due to a physiological abnormality. Murmurs can occur as a result of heart valve dysfunction, septal defect, and coarctation of the aorta [14]. The characteristics of the PCG signal can be analyzed using digital signal decomposition [15]. The decomposition of digital signals can be done by using many methods, including the Fourier transformation or wavelet transformation. Wavelet transform is a mathematical method that is almost similar to Fourier transform. However, the decomposition process is localized both in the time and frequency domains, as opposed to the Fourier transform, which is only localized in the frequency domain [16]. The wavelet transforms are more valid than Fourier transform because the wavelet transform depends on wavelets if the frequency varies in a limited duration. Therefore, the results of using wavelet transforms have more detailed results [17].

In accordance with the world agreement on sustainable development goals (SDGs), the development of information and communication technology (ICT) is one of the SDGs goals [18]. One proof of the development of ICT is the very rapid development of predictive or classification methods [19], [20]. Currently known as artificial intelligence (AI), a mechanical simulation system for gathering knowledge and information distribute them to parties who meet the requirements in the form of actionable intelligence [21]. Machine learning (ML) is part of AI, which is used to design algorithms based on data trends and historical relationships between data [22], [23]. In ML, many methods can be used, including fuzzy systems, artificial neural networks, deep learning, and evolutionary algorithms [24], [25]. Deep learning is an algorithm from ML that uses several layers in the learning process [26], [27].

Research related to the analysis of heart disease based on the PCG signal has been used [28]-[31]. The analysis using wavelet transforms and the ML method for classification also has been used extensively [32]-[36]. Currently, it is widely accepted that the continuous wavelet transform (CWT) method is the most appropriate for analyzing non-stationary PCG signals (having various frequencies and in time) [37], [38]. Research related to the classification of PCG signals with CWT has also been carried out by several researchers [39].

The signal analysis process does not only use feature extraction but through scalogram analysis [40]. Signal analysis using a scalogram is more useful than a spectrogram because a scalogram consists not only of time and frequency but also the magnitude or strength of the signal itself [41]. In several studies, the method used for classification or classifier is convolutional neural networks (CNN). CNN is a type of artificial neural network (ANN) which has a deep learning principle in it. It consists of several layers specifically designed to process two-dimensional data [42]. However, the construction of CNN and CWT in PCG signal analysis has never been used in previous studies. Therefore, the process of classification of heart disease in this study is based on PCG signals using CWT and CNN (CWT-CNN). The reason for using CWT-CNN is that CWT has capability to eliminate the signal noise and then analyze it in the frequency, time, and magnitude domain which is interpreted into a scalogram in the form of a two-dimensional image, whereas CNN is a very suitable method to be used as a classifier.

2. RESEARCH METHOD

The data used in this study are secondary data obtained from the observation of heart disease patients and healthy people at PKU Muhammadiyah Yogyakarta Hospital conducted by and [36] on February 24, 2017, to April 18, 2017. The data were collected in the form of heart rate signal recordings in .wav file format from 75 volunteers with heart disease and 25 normal people. The data recording process is based on research conducted by [43].

This study aims to classify the types of heart disease based on PCG signal patterns. The data were analyzed using continuous wavelet-convolutional neural network (CW-CNN), which is a combined model of continuous wavelet transformation and convolutional neural network (CNN) as a classifier. In principle, the continuous wavelet transform is used to analyze data by extracting and decomposing PCG signals into several components, and later, the result will be used as input on CNN. In brief, the process of classifying heart disease by the CW-CNN method is explained in Figure 1.

After obtaining the CNN model with the most optimal classification of heart disease, the next step is to apply this CNN model into an application based on MATLAB or known graphical user interface (GUI), so that it can be used easily and possess a more attractive appearance. The design of the GUI display for the classification of heart disease is shown in Figure 2.

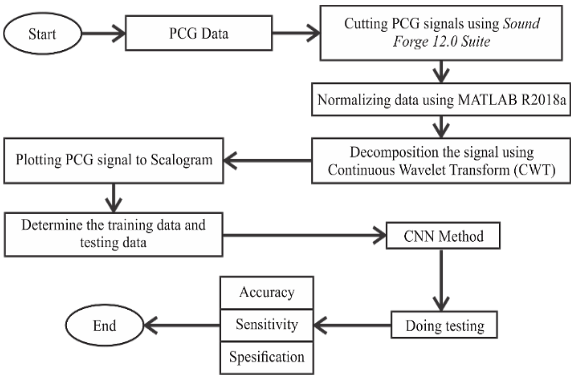

Figure 1. Research diagram

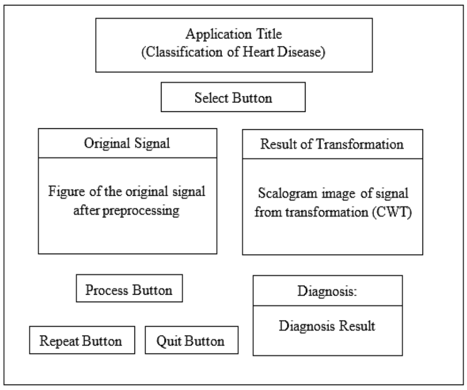

Figure 2. GUI display design

3. RESULTS AND ANALYSIS

3.1. Preprocessing signal

In this study, the data used are in the form of cardiac PCG signal recordings consisting of 75 recordings of heart disease patients from PKU Muhammadiyah Hospital Yogyakarta and 25 recordings of the heart of a normal person. The recording data were stored in the .wav extension. The first step to analyze the heart rate recording data was signal preprocessing. The signal preprocessing was conducted by cutting the heartbeat sound signal and normalizing the signal. Every single heart rate record was cut into several pieces of signal with the same signal length. Normalization process is bringing data to standard normal form (mean=0, standard deviation=1). Normalization is necessary so that the data is in the same range. The steps for preprocessing PCG data are as follows:

3.1.1. Signal cutting process

Each heart PCG signal data record was cut into several pieces of signal with the same cut length. One piece of PCG signal consists of first heart sound (S1) and second heart sound (S2). The process of cutting the signal was done by the rectangle method and then followed by the hamming window method. An example of a normal PCG signal cutting process in the heart with the file name n1.wav is presented in Figure 3.

3.1.2. Signal normalization process

The PCG signal that has been cut was then normalized. The normalization process was carried out so that the data does not affect the size of the recording signal amplitude. This process does not change the information contained in the PCG signal. An example of a cardiac PCG signal for normal data with the normalized file name n1.wav is shown in Figure 4.

3.2. Decomposition of PCG signal

The next step after data normalization was decomposing the signal with continuous wavelet transformation. In this study, the mother wavelet used is the mother wavelet analytic morlet. Wavelet transformation function according to [44] is defined as (1).

$$W_\omega(a,b) = \int_{-\infty}^{\infty} x(t)\, \psi^*_{(a,b)}(t) dt \tag{1}$$

and mother wavelet analytic morlet is defined as (2).

$$\psi(t) = \pi^{-1/4} e^{-(t-t_0)^2/2} U(t) \tag{2}$$

After the transformation, the results were visualized in the form of a scalogram. The following is an example of the wavelet transformation process using a mother wavelet analytic morlet visualized in the form of a scalogram using the file named n1.wav, as shown in Figure 5. In Figure 5, it can be observed that not only frequency and time are visualized in the form of color, but the magnitude or strength of the signal is also presented. From this representation, the data in the form of scalogram images are rich in parameter features that can be used to analyze digital signals. The results of the scalogram will then act as an input for the CNN model.

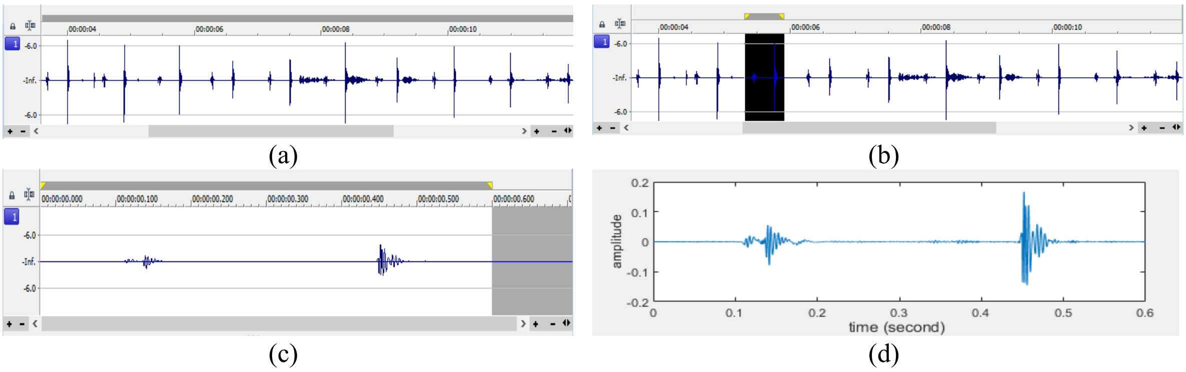

Figure 3. PCG signals: (a) before cutting, (b) cutting process, (c) cutting result of the rectangle method, (d) cutting result of the hamming window method

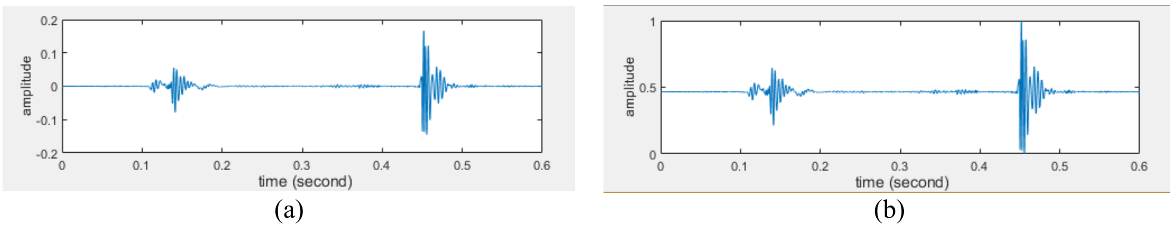

Figure 4. PCG signals: (a) before normalization, (b) after normalization

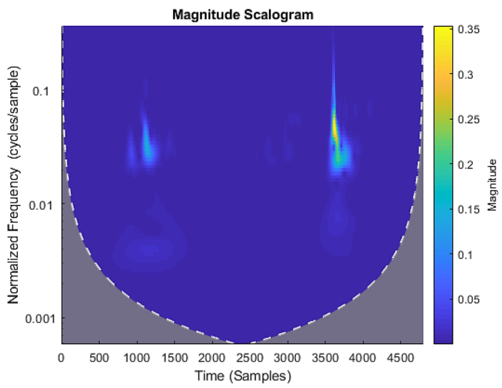

Figure 5. Visualization of wavelet transform results on a scalogram in the time and frequency domain

3.3. CNN

The first thing to do at this stage is image labeling. This labeling was done by training the model with training data that has been labeled according to the image classification. There are 4 classes, namely 0 for normal scalogram images, 1 for AP diagnosed scalogram images, 2 for CHF diagnosed scalograms, and 3 for HHD diagnosed scalograms. The labeling was used to train data based on the predetermined categories. This, then, would be utilized as a reference on the class predictions, so the program could classify according to similarities and categorize them appropriately.

The architecture in this study was inspired by the VGGNet architecture model, but there were slight modifications in the number of convolution layers, pooling, and rectified linear unit (ReLu) layers. Then an appropriate architecture for the heart PCG signal scalogram data was obtained using the trial and error method, as presented in Figure 6.

The input used was matrix information of mxn image from the scalogram. The step was initiated by entering the input into the first stage of the convolution layer, followed by the ReLu activation layer, and then the max-pooling layer. This sequence was repeated three times. The result then entered back to the first convolution layer followed by the ReLu activation layer. After that, the result entered the fully connected layer stage and then the softmax layer. From this process, the final output was generated in the form of image classification into classes. Based on the training results of the training data and architecture used in this study, the resulting model is presented in Figure 7.

Before conducting training to get the model, the first thing to do was data augmentation in which the scalogram image data is resized to facilitate the learning process. This step is necessary because by using data augmentation, the learning process will be faster, better, and have better accuracy [45]. Table 1 presents the results of several scaling experiments conducted for data augmentation. From Table 1 it can be seen that the process of data augmentation by scaling the size to 10% has the best results both in terms of CNN training time and accuracy. Therefore, the results of data augmentation are scalogram images measuring 35x39x3 RGB channels.

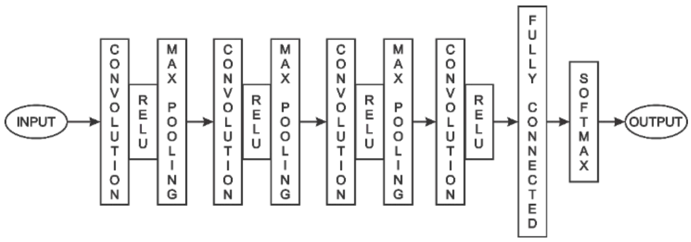

Figure 6. CNN model architecture

```
layers = [
    imageInputLayer([35 39 3])

    convolution2dLayer(4,8,'Padding','same')
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)
    convolution2dLayer(4,8,'Padding','same')
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)
    convolution2dLayer(4,8,'Padding','same')
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)
    convolution2dLayer(4,8,'Padding','same')
    batchNormalizationLayer
    reluLayer
    fullyConnectedLayer(4)
    softmaxLayer
    classificationLayer];
```

Figure 7. CNN model formed

Table 1. Results of several scaling experiments

Scale	Training Time	Accuracy	
		Training	Testing
100%	6 hours	80%	40%
70%	4 hours	80%	50%
50%	1 hour	90%	50%
30%	20 minutes	100%	60%
10%	5 minutes	100%	85%

3.4. Data model result

The experiments for model learning were conducted in a maximum of 200 epochs by varying the number of convolution layers using 4x4 kernel and 8 filters in each convolution parameter. Moreover, 2x2-sized pooling and stride 2 were utilized. The accuracy results of training and testing data obtained through trial and error are presented in Table 2. From Table 2 it can be observed that the best model with 4 convolution layers resulted in 100% accuracy for training data and 85% accuracy for testing data.

The model, which had been formed from the training data, was then tested on all data, both training data and testing data, to determine the accuracy of the model. Model testing was done by calculating the accuracy, sensitivity, and specificity. The results of the output model for training data are: TP=60, TN=20, FP=0, and FN=0. Thus, the obtained value of accuracy, sensitivity, and specificity are as follows:

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP} x100\% = \frac{80}{80} x100\% = 100\%$$

$$sensitivity = \frac{TP}{TP + FN} x100\% = \frac{60}{60} x100\% = 100\%$$

$$specificity = \frac{TN}{TN + FP} x100\% = \frac{20}{20} x100\% = 100\%$$

The performance of the model on training data has a high degree of accuracy because the process of forming the model is based on the training data. Therefore, it is still necessary to test the model on testing data. The prediction results of the model on the testing data are: TP=12, TN=5, FP=0, and FN=3. Thus, the obtained value of accuracy, sensitivity, and specificity with regards to the testing data are as follows:

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP} x100\% = \frac{17}{20} x100\% = 85\%$$

$$sensitivity = \frac{TP}{TP + FN} x100\% = \frac{12}{12 + 3} x100\% = \frac{12}{15} x100\% = 80\%$$

$$specificity = \frac{TN}{TN + FP} x100\% = \frac{5}{5} x100\% = 100\%$$

From the calculation above, it was found that the training data has an accuracy, sensitivity, and specificity of 100%, 100%, and 100%, respectively. This result shows that the CNN model has been built very well based on training data, both on the PCG signal diagnosed with the disease or not. As for testing data, the result showed that the diagnostic accuracy is 85%, whereas the sensitivity is 80%, and the specificity is 100%. These results indicate that the model, which was built based on training data, can very well diagnose PCG signals that are not diseased or normal. This is indicated by the results of the specificity of 100%. However, the sensitivity of 80% in testing data indicates that the model is less able to diagnose diseased PCG signals. Furthermore, the accuracy of 85% on the testing data shows that the CNN model is not able to diagnose PCG signals accurately. Model test results for mother wavelet analytic morlet (amor) were also compared with other mother wavelets such as bump and generalized morse wavelet (morse). The comparison is presented in Table 3.

Additionaly, the results of the model testing were also compared with the other methods besides CNN, such as methods using other classifiers namely fuzzy systems or with other deep learning methods. The comparison of these different methods in terms of accuracy are presented in Table 4. From the results in Table 4 it can be seen that the CNN method has the best accuracy when compared to FCM-Mamdani, FCM-Sugeno Order 0, Backpropagation Neural Network, or LSTM-RNN.

Table 2. The results of training and testing data accuracy (%)

The Number of Convolution Layers	Accuracy (%)	
	Training	Testing
1	100	50
2	100	60
3	100	60
4	100	80
5	100	75

Table 3. The results of the comparison of the accuracy, sensitivity, and specifications of several mother wavelets

		Mother Wavelet		
		Analytic Morlet	Bump	Morse
Accuracy	Training	100%	100%	100%
	Testing	85%	75%	70%
Sensitivity	Training	100%	100%	100%
	Testing	80%	75%	70%
Specificity	Training	100%	100%	100%
	Testing	100%	100%	100%

Table 4. The comparison with other methods (%)

	Accuracy (%)	
	Training	Testing
FCM-Mamdani	57.5	20
FCM-0 Order Sugeno	73.75	35
CNN	100	80
BPNN	80	60
LSTM-RNN	70	60

3.5. Display of GUI

After the model has passed the testing stage, the next step was to construct the CNN model into a GUI. The main purpose is to make it look simpler, more attractive, and easier for users to use it. Figure 8 presents the user interface of the heart disease classification system with a GUI. The GUI display can be used directly to classify heart disease from a PCG signal input. First, the PCG signal input is selected by using the Select Signal button. As an example, the picture above uses PCG signal input from training data with CHF diagnosis. The PCG signal is then entered into the GUI. Then through the preprocessing stage, namely normalization, and by performing a continuous wavelet transformation, a scalogram plot is obtained. This, then, will be used to input the CNN model. Afterward, the processing is done by using CNN that has been built, and the results obtained are successfully diagnosed with CHF. The results of the GUI design are in accordance with the initial design using the CNN model which has been tested in terms of accuracy.

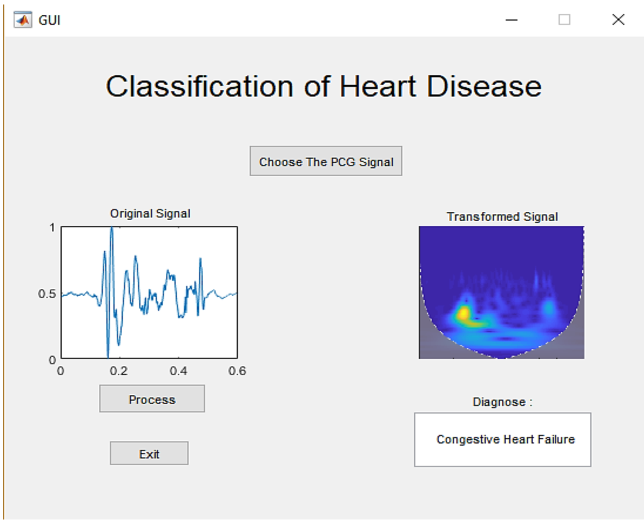

Figure 8. GUI display for classification of heart disease

4. CONCLUSION AND RECOMMENDATION
4.1. Conclusion

This research was initiated with data preprocessing, in which each heartbeat recording (PCG signal) was cut into several pieces of signals, followed by the normalization of each piece of the signal. The data that had been cut and normalized was then described by using continuous wavelet transforms with a motherly wavelet analytic morlet. The results of the transformation were plotted into a scalogram, which then became the input for the CNN method. The scalogram image that had been generated was then augmented against the data so that it could facilitate the learning process of the CNN model. Entering the stage of data types division, image data was divided based on training data and testing data with a ratio of 3:1. After that, the classification stage was done by the CNN method. This method used 4 convolution layers, 3 pooling layers along with the ReLu activation function, a fully connected layer, and was ended with the Softmax activation function to create image probabilities based on the corresponding class similarity. The accuracy, sensitivity, and specificity were then calculated from training and testing data. The final step was implementing the CNN model with a GUI.

PCG signal patterns can be broken down based on the type of mother wavelet used. The accuracy, sensitivity, and specificity obtained by using the CNN method as the classifier were 100%, 100%, and 100% for training data, respectively, and 85%, 80%, and 100% for testing data, respectively. Based on the level of accuracy, sensitivity, and specificity of training and testing data compared with other mother wavelets and other methods, it can be concluded that the mother wavelet analytic morlet can decipher PCG signals better than other mother wavelets. Furthermore, from the aspects of accuracy, sensitivity, and specificity using training and testing data of the CNN model that was built, it can be concluded that the CNN model is a good method to classify heart disease as compared to the other methods.

4.2. Recommendation

For further research, we recommend increasing the dataset size, so potential overfitting problem can be identified. Moreover, updating the PCG data with new and precise PCG recordings can better interpret the circumstances that occur in accordance with the illness suffered. And also, finding the best method in cutting the signal as an attempt to free the input data from human errors is also advisable. Lastly, we also recommend optimizing or manipulating the methods to get a more optimal model, such as by using genetic algorithms, ant colony algorithms, particle swarm optimization, or other optimization methods in the formation of neural network weights to minimize trial and error in the model search process.

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