Classification of Phonocardiograms with Convolutional Neural Networks

Omer Deperlioglu
Afyon Kocatepe University, Afyonkarahisar, Turkey
Erenler Mahallesi, Gazlıgöl Yolu Rektörlük E Blok, 03200, Afyonkarahisar
Merkez/Afyonkarahisar, Turkey
Tel,: +90 272 228 13 50
deperlioglu@aku.edu.tr

Abstract

The diagnosis of heart diseases from heart sounds is a matter of many years. This is the effect of having too many people with heart diseases in the world. Studies on heart sounds are usually based on classification for helping doctors. In other words, these studies are a substructure of clinical decision support systems. In this study, three different heart sound data in the PASCAL Btraining data set such as normal, murmur, and extrasystole are classified. Phonocardiograms which were obtained from heart sounds in the data set were used for classification. Both Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) were used for classification to compare obtained results. In these studies, the obtained results show that the CNN classification gives the better result with 97.9% classification accuracy according to the results of ANN. Thus, CNN emerges as the ideal classification tool for the classification of heart sounds with variable characteristics.

Keywords: Heart sounds classification, Artificial neural network, Phonocardiograms classifications, Convolutional neural network

1. Introduction

One of the first causes of human deaths in recent years in our world is heart diseases or cardiovascular diseases. Phonocardiograms (PCG) and electrocardiograms (ECG) are usually used for the detection of heart diseases. The most common method used to detect heart diseases is to listen to the sounds produced by the contraction of the heart during blood pump. These sounds are called PCG. Doctors often use a stethoscope to listen or record heart sounds. But it does not always suffice to be able to diagnose heart diseases by simply listening or seeing a record of them. For this reason, studies on heart sounds or PCGs have been increased to make it easier for doctors to make a diagnosis (Deperlioglu, 2018; Bahekar et. al., 2017; Ali et. al., 2017; Shervegar et. al., 2017).

Studies on heart sounds are usually based on classification. These classification studies are being done to create infrastructure for clinic decision support systems, which is the largest reference source for physicians. Naturally, a great majority of these studies are done to increase the classification success. There are the most common methods of improving classification success such as the segmentation of S1 and S2 sounds, determination of the peak values of S1 and S2 sounds, using different filtering methods, or using different classification techniques.

For segmentation of S1 and S2 sounds of heart sounds, energy methods or comparison with ECG signals methods are usually used. In Deperlioglu's work, he proposed a practical method of segmentation by re-sampled energy method. He explained that this method is easier than other segmentation methods and that segmentation can be done efficiently (Deperlioglu, 2018). Choi and Jiang have made a comparative study about Shannon energy, and Hilbert transform and the cardiac sound characteristic waveform (Choi & Jiang., 2008). The algorithm proposed by Saini is an automatic detection of two dominant heart sounds based on a 3-order normalized mean Shannon energy envelope. This proposed automatic detection and analysis algorithm can effectively detect heart sounds S1 and S2 by reducing the effect of noises in heart sounds. Due to the fact that the signal and the envelope calculation was pre-processed, the noises in the heart sounds could be easily suppressed (Saini, 2016). In another study, Shannon-Energy-Envelope based Phonocardiogram Peak Spacing Analysis method was used to examine the characteristics of PCG and cardiac rhythms.

Thus, the average heart rate was calculated from the Shannon energy signal. PCG features were also found using mean, variance and autocorrelation (Sharma et. al., 2014).

El-Segaier et al. have used QRS complexes and T waves in ECG signals to find S1 and S2 segments in their studies. They used ECG signals as a reference for segmentation of S1 and S2 sounds (El-Segaier et. al., 2005). T waves in some ECG signals cannot be clearly selected. For such situations, Carvalho and his colleagues used a new classifier in the selection of S2 sounds for low quality ECG signals. Thus, they tried to come from above the problem of not being classified signals (Carvalho et. al., 2005). Many researchers are trying to define the S1 and S2 sounds with a few signal processing and statistical methods to reduce the excessive workload without using the ECG as a reference. Other approaches include uncontrolled techniques such as envelope self-organizing map (Liang et. al., 1997), spectrogram quantization method (Liang et. al., 1998), and Mel frequency cepstrum coefficients (Kumar et. al., 2006).

Different artificial intelligence methods have been used to enhance classification success with segmentation. Bahekar et al. have attempted to improve the classification success of PCG signals using the Adaptive Neuro Fuzzy Inference System (ANFIS) and wavelet transform. Ali et al. used three different ensemble techniques to improve the classification success. These are: Bagging, AdaboostM1 and Random Subspace ensemble techniques. They have said that the ensemble method has improved the success of classification (Ali et. al., 2017). In their work, Gharehbaghi and colleagues present a new method for discriminating between innocent and pathological murmurs using the growing time support vector machine. They compared the results with conventional support vector machines and found that the growing time support vector machine improves the classification success (Gharehbaghia et. al., 2017). In their work, Zhang and colleagues have proposed a scaled spectrogram and tensor decomposition-based method to improve classification accuracy. In this study, support vector machines were used for classification too. They have shown that the proposed method improves the classification success (Zhang et. al., 2017). Eslamizadeh and Barati used Artificial Neural Network to classify heart sounds as normal and murmur in their study. They used the Modified Neighbor Annealing method for the training of artificial neural networks. They have shown that the Modified Neighbor Annealing method produces good results for heart sounds classifiers (Eslamizadeh & Barati, 2017).

Recently, deep learning methods have also been used to classify heart sounds. For example, Potes and colleagues have proposed a method based on a classifier group that combines the outputs of AdaBoost and CNN to classify normal/abnormal heart sounds (Potes et. al., 2017).

Rubin et al. have proposed an automatic heart sound classification algorithm that allows time-frequency heat map indications to be combined with a CNN (Rubin et. al., 2017). Aykanat et al. used two types of machine learning algorithms for classification of heart sounds; support vector machine (SVM) with mel frequency cepstral coefficient (MFCC) and spectrogram images in a CNN (Aykanat et. al., 2017). Chen et al. have studied the effectiveness of using CNNs to automatically detect abnormal heart and lung sounds and classify them into different classes in their paper. They have tried to increase classification accuracy with 1, 2, and 3 convolutional layers. They have obtained the best accuracy value with 2 convolutional layers (Chen et. al., 2016). Ryu et al. proposed a diagnostic model of cardiac diseases using a CNN. This model can predict whether a heart sound recording is normal and abnormal by classifying phonocardiograms (PCGs) (Ryu et. al., 2016).

In this study, a deep learning method is proposed to increase the success of direct classification without dealing with more complicated methods or algorithms. First, 8-second samples of heart sounds were taken and normalized. After preprocessing, the signal filtering with Elliptic filter was done. Later, the PCG of every signal was created and resized image sizes of 100x75 pixels. At the end of the study, to compare the classification success, the same data set was classified with both ANN and CNN.

These studies are explained in detail in the following sections.

2. Material and Methods

Heart and vascular diseases are the first cause of death in the world. The heartbeat, which is the result of the blood pumping of the heart, gives information about the functioning of the heart valves. Thus, features can be obtained that can differentiate between normal and abnormal heart sound signals. With the ECG signal, it is possible to visualize the parts of the heartbeat signal.

However, ECG measurement is usually expensive and requires extra time. For this reason, studies for the detection of heart diseases generally focus on the analysis of heart sounds. In this context, it is aimed to make a successful classification using deep learning method in this study. The block diagram of the application is shown in Figure 1. The details of each block in the diagram are explained as follows. For all classification study, MATLAB r2017a software was used.

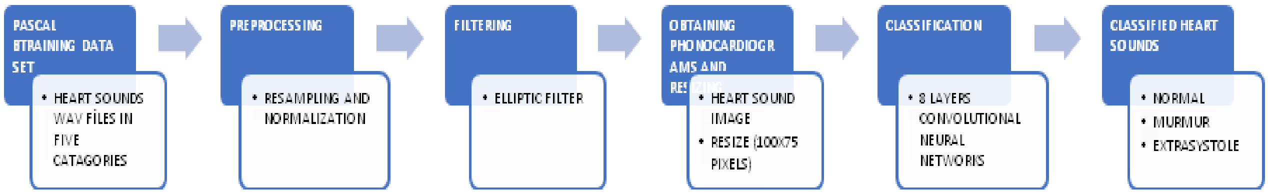

Figure 1. Block diagram of classification process

2.1. Resampling and Normalization

Classification studies require that all heart sounds be at the same duration and at the same sampling frequency. If the sounds are recorded in different media with different devices, they are resampled so that they have the same sampling frequency. The sounds used in this study were recorded with the digital stethoscope DigiScope® in the hospital. Therefore, they are not resampled because they have the same sampling frequency. In this study, normalization was applied to the heart sounds signals [-1 1].

2.2. Filtering

Heart sounds that provide valuable diagnostic information in clinical examinations are among the most important physiological signals in the human body. However, heart sounds include noise, such as external sounds and lung sounds, caused by signal recording conditions. Noisy heart sound signal negatively affects the diagnosis of the doctor (Denga & Hanb, 2018). Digital filters are often used to filter biomedical signal. Digital filtering is defined as the acquisition of desired frequency values according to the characterization of the desired filter in order to improve the signal according to the intended use (Shenoi, 2005; Thede, 1995).

Based on the experience gained from previous studies, an elliptic filter was used in this study (Deperlioglu, 2018; Guraksin et. al., 2009) .

The heart sound signal covering the first two steps is given in Figure 2 for sample sound file of 103_1305031931979_B in the PASCAL Btraining data set.

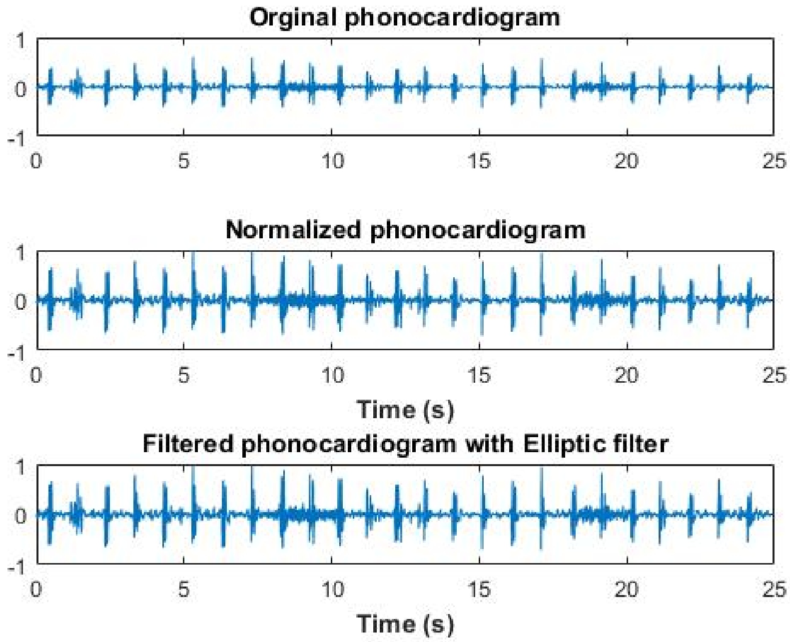

Figure 2. PCGs for sample sound file of 103-1305031931979-B

2.2.1 Elliptic Filter

The elliptic filter combines the properties of the Chebyshev (Type-1 and Type-2) filters. It is a filter type that can change the numbers in the pass and stop band separately. Chebyshev Type-1 when the fluctuations in the dash band approaches zero, Chebyshev Type-2 when the fluctuations in the transmission band approach zero, and Butterworth can also change into the filter when the fluctuations in both bands approach zero. The elliptical filter is the preferred approach when a very sharp transition band filter is desired. The disadvantage of this approach is that there are fluctuations in both the stopper and the transmission band (Agaoğlu, 2008).

2.3. Obtaining Phonocardiograms of Heart Sounds and Resizing

All heart sounds in the PASCAL Btraining data set are wav format. The duration of every sound is arranged as 8 seconds in the Resampling and Normalization step. In this step, PCG images were created image size of 560x420 pixels and RGB format. Then, these images were resized to image size of 100x75 pixels, in order to need a smaller memory of the computer for the classification process.

2.3.1. Classification

Artificial neural networks (ANN) and convolutional neural networks (CNN) were used in this study.

2.3.2. Multilayer feedforward network

ANN is an efficient data processing system compromised by the analogy of centrally based biological neural networks. ANN acquires a large collection of units linked together in a specific way to communicate between units. These units, also called nodes or neurons, are simple parallel processors that operate in parallel. A neural network is an interconnected combination of simple processing elements, units or nodes based on the neuron of a loosely functioning animal. The ability to process the network has been recorded in a number of training examples, either at adaptation or at a combination of weights obtained by the learning process.

Associated memory can be defined as the process of calling patterns or templates stored in a partial or loud version of the original model. Feedforward networks can be used to accomplish this task, but a more powerful tool is provided by the repeating networking class. They may be thought of as not repetitively processing input models to provide new versions approaching a continuously stored memory.

Feedforward network is a non-repeating network with the processing units or nodes in the layer, and all nodes in a layer are linked to the nodes of the previous layers. There are different weights on the connection. There is no feedback loop, the signal input can only flow in one direction. Multilayer feedforward network is feedforward ANN concept with multiple weighted layers as seen figure 3. This network is called hidden layers because it has one or more hidden layers between the input and output layers (Gurney, 2004; Tutorials Point, 2017).

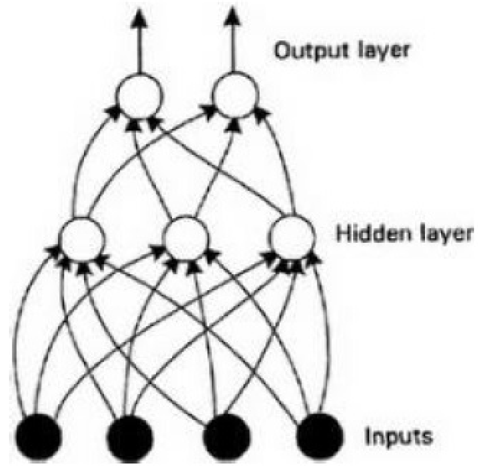

Figure 3. Multilayer feed forward network (Gurney, 2004)

2.3.3. Bayesian regularization

In ANN, some regularization algorithms were developed to solve the problem of extreme compatibility. Levenberg-Marquardt (LM) and Bayesian regularization (BR) learning algorithms are the most widely used methods. In general, they use the mean square error function to minimize the compatibility error between inputs and outputs. After the backpropagation algorithm, the LM editing technique has been developed for further convergence. However, LM is inadequate in environments where connection points and properties increase. Despite its fast operation, it needs a lot of memory. For this reason, different algorithms have been developed that can be modified in large networks. One of them is a BR. BR is a function that includes the sum of the mean squares and the sum of the square weights to minimize the prediction errors and obtain a good generalized model. BR works faster and more efficiently on large networks.

Bayesian regularization technique is different from LM method by updating weight and bias values. The mean square error and weights are reduced together to provide faster convergence. So it tries to find the right combination to create a generalized network model. Sometimes this process is also referred to as Bayesian softening (Kayri, 2016; Aggarwal et. al., 2005).

2.3.4. Convolutional Neural Network

Convolutional Neural Networks (CNN) is an alternative neural network type that can be used to reduce spectral variations and spectral correlation models in sound signals. CNNs are a more effective model for heart sound signals than other Deep Neural Networks (DNNs) because heart sound signals carry both features (Sainath et. al., 2013).

A CNN is a feedforward network comprised of one or more convolutional layers, generally comprising a sub-sampling step. It then consists of one or more completely interconnected layers, such as a standard multilayer neural network. A CNN architecture is designed to interpret the 2D structure of 2D image inputs most efficiently. Local links and related weights are used to achieve this. These are collected so as to allow constantly changing properties. Another benefit of CNNs is that they have fewer trainings and easier parameters than networks that are fully connected to the same number of hidden units (Convolutional Neural Networks, 2018).

A CNNs are biologically inspired variants of a multilayer perceptron. CNNs establish a built-in local correlation by applying a local link model between the neurons of adjacent layers. As shown in Figure 4a, the inputs of the hidden units in the *m*-layer are obtained from a subset of the units having the built-in areas in the *m-1* layer. This ensures that a number of layers arrive consecutively, resulting in a filtration. It can encode 5 features such as a neuron in the *m+1* hidden layer. On CNNs, each filter hi is repeated on the entire image surface. These repeated units form a feature map that shares the weight and bias parameters. 3 hidden units of the same feature map are shown in Figure 4b. The weights shown by parallel lines in the figure were also limited as same. To learn such shared parameters, the gradient method can be used with only a small modification to the original parameters. The sum of the inverse gradients of the shared parameters equals the gradient of the shared weights.

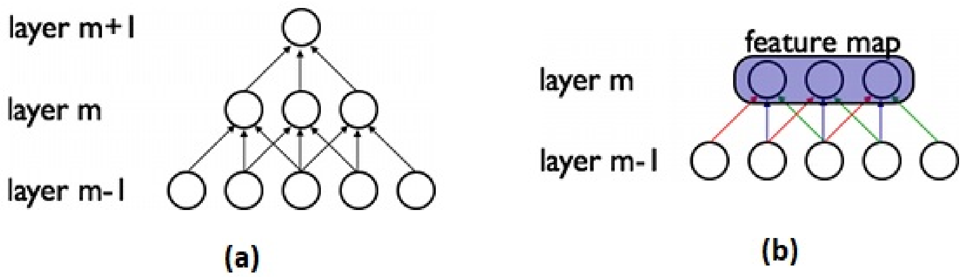

Figure 4. a) Sparse Connectivity, b) Shared Weights (Convolutional Neural Networks (LeNet), 2018)

Figure 5 shows an example of a convolutional layer. Layer *m-1* includes four feature maps. The m is a hidden layer and it includes two feature maps such as h^0 and h^1. The neuron outputs at h^0 and h^1 are calculated from the neuron outputs entering the 2x2 receiving area at the layer below layer *m-1*. Thus, the weights are W^0, and W^1 *and* $h,^0$ and h^1 are weight tensors that have three dimensions. The leading dimension indexes the map entries summaries, pointing to the other two neuron outputs. To combine all of them W_{ij}^{kl} , with each pixel of the layer's minus *k* map, it refers to the weight of the link between neuron outputs (*i, j*) in the coordinates of the feature map *m-1* (Convolutional Neural Networks (LeNet), 2018).

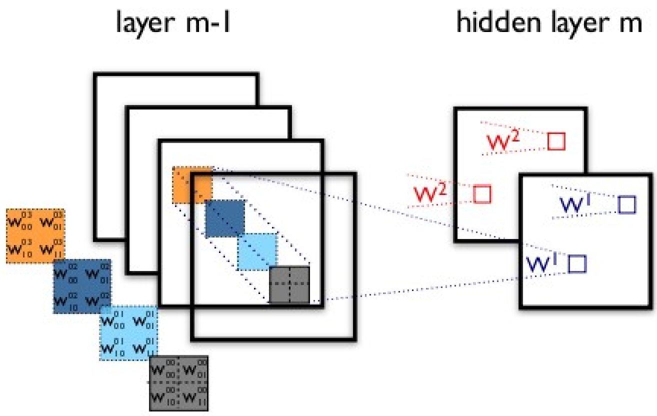

Figure 5. An example of a convolutional layer (Convolutional Neural Networks (LeNet), 2018)

2.4. Performance Evaluation

The accuracy, sensitivity and specificity are commonly used performance measures in medical classification studies. These measures were used to assess the precision of the proposed method. They are calculated as the following:

$$Ac = \frac{T_P}{T_P + F_P} \quad (1)$$

$$Se = \frac{T_P}{T_P + F_N} \quad (2)$$

$$Sp = \frac{T_N}{F_{PTN} + T_N} \quad (3)$$

In the equations, TP and FP represent the numbers of true positives and false positives, respectively. TN and FN the numbers of true negatives, and false negatives, respectively. FPTN also represents the number of false positives and it is calculated from negative samples in the results of classification.

The precision of the classifier's ability to diagnose correctly is determined by the ratio of accuracy. The extent to which the model correctly defines the formation of the target class is defined by the rate of Sensitivity. The extent of the model's target class separation capability is defined by the rate of Specificity (Kahramanli & Allahverdi , 2008).

3. Applications of Heart Sounds Classification

In this study, PASCAL Btraining heart sounds data set was used. Sound files in this data set are wav format and they were obtained from a clinic trial in hospitals using the digital stethoscope DigiScope® (Bentley et. al., 2011). The data set contains 192 selected files of 3 types, as normal, murmur, and extrasystole. Table 1 shows the general characteristics of the heart sounds files. After normalization and filtering are done for all files in the data set, images of heart sounds in the data set have been created. In the study, the classification process was done with ANN and CNN for the same data set. In ANN and CNN, a mean square error function was used for the performance algorithm.

Table 1. The general characteristics of the heart sounds files

	Duration	Sampling Frequency	Number of Files
Normal Category	8 second	4000 Hz.	52
Noisy Normal Category	8 second	4000 Hz.	26
Extrasystole Category	8 second	4000 Hz.	46
Murmur Category	8 second	4000 Hz.	52
Noisy Murmur Category	8 second	4000 Hz.	16
Total			192

3.1. Classification with Artificial Neural Networks

Multilayer feedforward network was used for classification with ANN. In this application, the ANN structure and parameters were obtained after a review of previous studies and very much number of trial runs. There is a total of 10 neurons in the hidden layer in ANN. The Bayesian regularization backpropagation was used for learning algorithm and the mean square error function was also used the performance algorithm. 134 samples in the data set were used for training data, 29 samples were used for validation data, and 29 samples were used for testing data. The confusion matrix obtained at the end of the classification was given in Figure 6. As seen from the confusion matrix, the accuracy of classification 82.8% was achieved in the ANN classification. The ANN performed with a sensitivity of 92.40% and a specificity of 88.82%.

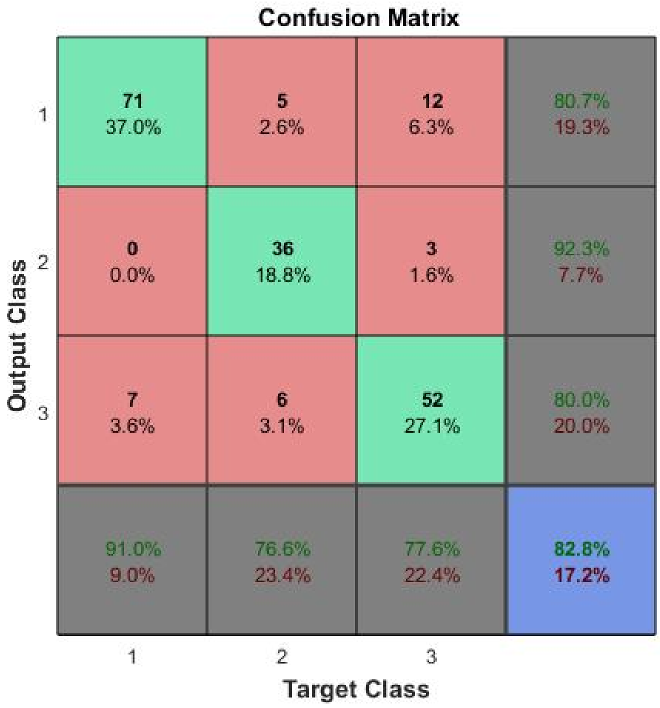

Figure 6. Confusion matrix of multilayer feedforward network

3.2. Classification with Convolutional Neural Networks

The same data set was used in the classification study with CNN. CNNs are a type of deep learning that is particularly suitable for image recognition and classification. CNNs are a deep network type that receives and processes image data as objects together with their label. In this application, the CNN structure and parameters were obtained after a review of previous studies and very much number of trial runs. The CNN has 8 layers. These layers are image input layer, convolutional layer, ReLU layer, cross-channel normalization layer, max pooling layer, fully connected layer, softmax layer, and classification layer, respectively.

In this study, the Image Input Layer is used to specify the image values of 75x100x3. These numbers correspond to height, width, and RGB format of images. Any data conversions, such as data normalization or data augmentation in this layer, can be thought of as randomly flipping and truncating the data. They are often used to prevent overfitting and are done automatically at the beginning of the training. One convolutional layer was used in CNN. The parameters of the recursive layer are the size of the network filtering. These are the height and width of the filter used by the training function when scanning through the images. In this study, the filter size is set to 4. The second parameter, number of neurons that determines the number of feature maps and bound to the same region of the output, is the number of filters selected as 16. The convolutional layer is followed by a nonlinear activation function and it is called ReLU Layer. The rectified linear unit function was used in this application. One cross-channel normalization layer was used in this application. The size of the channel window is set to 2. In other words, it is the channel window size for normalization. The max pooling layer is used for downsampling as another way of reducing the number of parameters and preventing over-fit. This layer returns the maximum values of the rectangular regions of the inputs specified by the first argument pool size. In this application, the size of the rectangle is [4, 3]. Stride function was also used to determine the step size while the training function scans through the image. The fully connected layer combines all the features that previous layers have learned across the image to define larger patterns. The last fully connected layer combines them to classify them. For this reason, the output size parameter in the last fully connected layer is equal to the number of classes in the target table. In this application, the output size is 3 such as normal, murmur, and extrasystole. The fully connected layer usually uses the softmax activation function for classification. The final layer of CNN is the classification layer. This layer uses the possibilities returned by the softmax activation function for each input to mutually assign one of the special classes.

The confusion matrix obtained at the end of the classification was given in Figure 7. As seen from the confusion matrix, the accuracy of classification 97.9% was achieved in the CNN classification. The CNN performed with sensitivity of 99.47% and specificity of 98.42%.

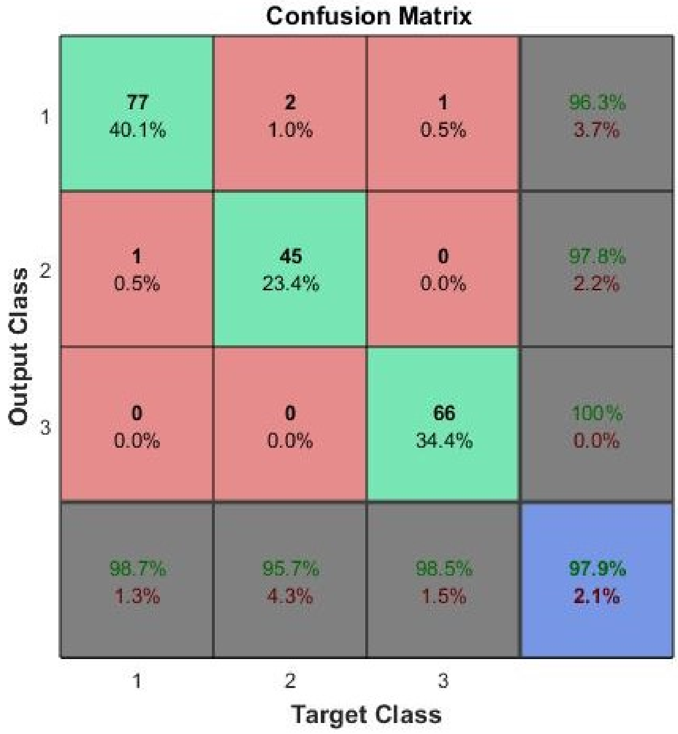

Figure 7. Confusion matrix of convolutional neural network

4. Results and Discussion

At the end of the studies, the results are compared with the different studies conducted with neural networks in order to evaluate the obtained results. The obtained classification accuracies, sensitivities, and specificities were given in table 2.

Table 2. The comparison of classification accuracies, sensitivities, and specificities

Classification method	Accuracy (%)	Sensitivity (%)	Specificity (%)
ANN (this study)	82.80	92.40	88.82
CNN (this study)	**97.90**	**99.47**	**98.42**
AdaBoost and CNN (Potes et. al., 2017)	94.24	77.81	86.02
CNN (Rubin et. al., 2017)	84	73	95
CNN (Aykanat et. al., 2017)	87.0	89.0	95.0
CNN (Ryu et. al., 2016)	79.5	70.8	88.2
Deep Gated RNN (Thomae & Dominik, 2016)	55.0	99.0	11.0
CNN (Nilanon et. al., 2016)	81.3	73.5	89.2
Wavelet-based deep CNN (Tschannen et. al., 2016)	82.8	85.5	85.9
Deep convolutional neural networks (Rubin et. al., 2016)	75	100	88

As seen in Table 2, classification of heart sounds with CNN provides the best classification accuracy rate with 97.90%. Also, it has the rate of sensitivity with 99.47% and has the rate of specificity with 98.42%. It is seen from these results that the proposed CNN model gives better results than the other CNN and deep learning studies.

5. Conclusion

The classification of heart sounds has been a subject for many years. This is the effect of having too many people with heart diseases in the world. Studies on heart sounds are usually based on classification. In this study, three kinds of heart sounds such as normal, murmur, and extrasystole were classified in the PASCAL Btraining data set. In order to make a comparison, both ANN and CNN were used for classification. In the studies conducted, the obtained results showed that CNN classification gave the best results according to the results of ANN, and previous studies. It seems that CNN is the ideal classification tool for the classification of heart sounds with variable characteristics. In future studies, larger images can be used to achieve better classification performance. In addition, segmentation of S1 and S2 sounds can improve the accuracy of classification.

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Omer DEPERLIOGLU received his BSc in Electric and Electronic (1988) Gazi University, MSc in Computer Science (1996) from Afyon Kocatepe University, PhD in Computer Science (2001) from Gazi University in Turkey. Now he is associate professor of Computer Programming in Department of Science, Vocational School of Afyon, and Afyon Kocatepe University of Afyonkarahisar, Turkey. His current research interests include different aspects of Artificial Intelligence applied in Power Electronics, Biomedical, and Signal Processing. He has edited 1 book and (co-) authored 3 books and more than 20 papers, more than 30 conferences participation, member in International Technical Committee of 4 conferences and workshops.