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A New Method to Improve Automated Classification of Heart Sound Signals: Filter Bank Learning in Convolutional Neural Networks

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ABSTRACT

Introduction: Recent studies have acknowledged the potential of convolutional neural networks (CNNs) in distinguishing healthy and morbid samples by using heart sound analyses. Unfortunately the performance of CNNs is highly dependent on the filtering procedure which is applied to signal in their convolutional layer. The present study aimed to address this problem by applying filter bank learning concept in CNNs.
Material and Methods: In proposed method, the filter bank of CNN is updated based on a cross-entropy minimization rule to extract higher-level features from spectral characteristics of the heart sound signal. The deeper level of the extracted features in parallel with their spectral-based nature leads to better discrimination between healthy and morbid heart sounds. The proposed method was applied to three different heart sound datasets of PASCAL-A, PASCAL-B, and Kaggle, including normal and abnormal categories.
Results: The proposed method obtained a true positive rate (TPR) between minimally 86% and maximally 96% (if FPR=0%) among all the examined datasets. In addition, the false-positive rate (FPR) was obtained as 7-8% (if TPR=100%) among the mentioned datasets. Finally, the accuracy was achieved in the range of 93-98% when the FPR was 0% and within the range of 96-96.5% when the TRP was 100%.
Conclusion: Increased TPR in the proposed method (96% for the proposed method vs. 87% for CNN) in parallel with a decrease in its FPR (7% for the proposed method vs. 10% for CNN) showed the proposed method's superiority against its well-known alternative in automated self-assessment of the heart.

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Introduction

Cardiovascular diseases are one of the main causes of death worldwide. Frequent evaluation of the cardiovascular system is necessary for early detection of the heart pathologic conditions and physical examination is the simplest way for such diagnosis [1]. Heart sounds provide important information about the performance of the cardiovascular system; therefore, playing an important role in the early detection of heart pathologic conditions, such as arrhythmias, valve disease, and heart failure [2].

The heart sounds in the traditional methods are analyzed by experts. The progress of this method is hampered because of its time-consuming nature and human errors [3]. Therefore, based on the computerized detection and classification, automated methods have been substituted the traditional methods regarding the analysis of the heart sound. Automated methods help to improve patient care by eliminating the need for a highly-skilled examiner [4]. This feature makes these methods an ideal candidate for the self-evaluation of at-risk patients. Furthermore, advances in heart sound processing have resulted in considerable improvements in the results' quality. These advantages turned the automated methods into a useful, cost-effective, and non-invasive diagnostic modality for cardiac pathology. One of the major challenges of automatic methods is distinguishing healthy and morbid samples, which is a well-known classification problem. Several methods have been proposed for such a classification as grouped into the categories described below.

In several studies, the instance-based learning concept was incorporated in the procedure of distinguishing healthy and pathologic cardiovascular systems. For instance, the k-nearest neighbors classifier has been utilized for detecting morbid heart systems based on their sound signal [5]. In other researches, the support vector machine (SVM) approach was applied to classify heart sounds [6]. For instance, the least square SVM (LSSVM) method was utilized to distinguish normal and abnormal heart sounds. In another type of SVM-based methods, growing-time SVM was examined to classify pathological and healthy heart sounds [7]. Hidden Markov model (HMM) was applied for the heart sound

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classification in some studies. Although HMM-based approaches were widely employed for speech recognition, their results in classifying heart sounds have not yet been satisfactory [8].

Recently, several types of neural networks were applied to separate healthy and pathological samples of heart sounds. The performance of the *artificial neural network* classifiers is highly sensitive to discriminative signal features as their inputs, including time, frequency, and time-frequency features. For instance, several types of wavelet transform (as the most famous member of time-frequency features family) have been applied on heart sound to classify healthy and morbid samples.

Recently, the use of deep learning approaches has been extended to address the heart sound classification problem. Deep structure and multi-level data representation enable the above algorithms to obtain a better separation between healthy and unhealthy signals [9, 10]. Deep neural networks performance is seriously hampered by three main factors, namely their large-scale dimensions, high process volume, and undesirable convergence [11, 12]. Convolutional neural networks (CNNs) are an important type of deep learning paradigm applying in heart sound classification [13]. The CNNs are graphical models which model the joint distribution between the observed vector and hidden layers. This model enables them to extract a deep hierarchical representation of the training data; therefore, they can confirm a better diagnosis regarding the detection of the high-level features type.

This paper introduced a new method to improve the performance of CNNs in the classification of heart sounds based on filter bank learning. In the proposed method, the higher-level information of the heart sound signal is integrated with the capabilities of the deep architectures to construct a learning filter bank on CNN. To perform this plan, the spectral mid-level features of heart sound are incorporated in the deep structure and then higher-level features are updated during filter bank based on minimization of cross-entropy. This logic leads to better discrimination over the target heart situation.

Materials and Methods

Although deep neural networks have significant similarities with CNN in the microscopic scale (i.e., basic components), they are quite different from the macroscopic perspective (i.e., learning protocol).

In this architecture, as the layers increase, the input data are transformed into mid-level and high-level representations which may be utilized to make the final decision for classification. A more complex structure and a number of layers in such networks lead to more extraction of the abstract features from the input signal. These deeper features allow the neural network to produce a more fitted model to express signal behavior; therefore, neural network decision will be more accurate [14]. The CNN is a category of large-scale neural networks that may extract deep features that represent target classes and it consists of different layers with each layer performing a certain task. Convolution layer is one of those layers which may be regarded as a set of filters (e.g., filter bank), which is a powerful tool to extract discriminative features.

In heart sounds classification, there are certain formal acoustic features which are commonly extracted from the time-frequency representations (i.e., spectrograms). This strategy may also be used as a basis to learn filter banks of convolutional layers. Therefore, in the proposed method the filter banks in the convolution layer are learned based on the spectrogram of heart sound signals (i.e., mid-level features) and then passed through the network to train the whole CNN architecture.

As shown in figure 1, $\mathcal{S}$ represents the matrix of spectrogram and ω refers to the weights of the filter bank which scrolling over a local region of the spectrogram. Furthermore, m and n are concerned with the spectrogram, while those of i and j deal with that of the filter bank [15].

$$\omega * \mathcal{S} = \sum_j \sum_i \omega_{j.i}\, \mathcal{S}_{m-j,n-i} \tag{1}$$

Equation 1 creates a feature map as an output of the convolution layer and the subsampling of feature maps enhances robustness against noise. As shown in Figure 1, pooling would progressively convert its input feature map to a downscale form of representation using either maximum or average functions. The max-pooling results in faster convergence during the training process. Therefore, applying ReLU non-linearity gives the coefficient of each filter bank (Figure 1).

The Adadelta algorithm was employed to learn some weights optimizing the loss function. A window of total past gradient was defined as σ size. Then, all past squared gradients were recursively subtracted using a decay term which is the sum of gradients. Therefore, the previous average and current gradient are two effective elements which influence the running average $E[\Phi^2]_t$ at time step $\boldsymbol{t}$ [16].

$$E\left[\Phi^2\right]_t = \delta\, E\left[\Phi^2\right]_{t-1} + (1-\delta)\,\Phi_t^2 \tag{2}$$

In the abovementioned equation, parameter δ is a momentum term and Φ is the gradient of $\omega_{j,i}$. The updated vector $\Delta\omega_{j,i_t}$ is defined as follows, in which β refers to the learning rate.

$$\Delta\omega_{j,i_t} = -\beta\,\Phi_t$$
$$\omega_{j,i_{t+1}} = \omega_{j,i_t} + \Delta\omega_{j,i_t} \tag{3}$$

Finally, the parameter update vector takes the form of the following equation:

$$\Delta\omega_{j,i_t} = -\frac{\beta}{\sqrt{K_{t+\epsilon}}}\,\Phi_t \tag{4}$$

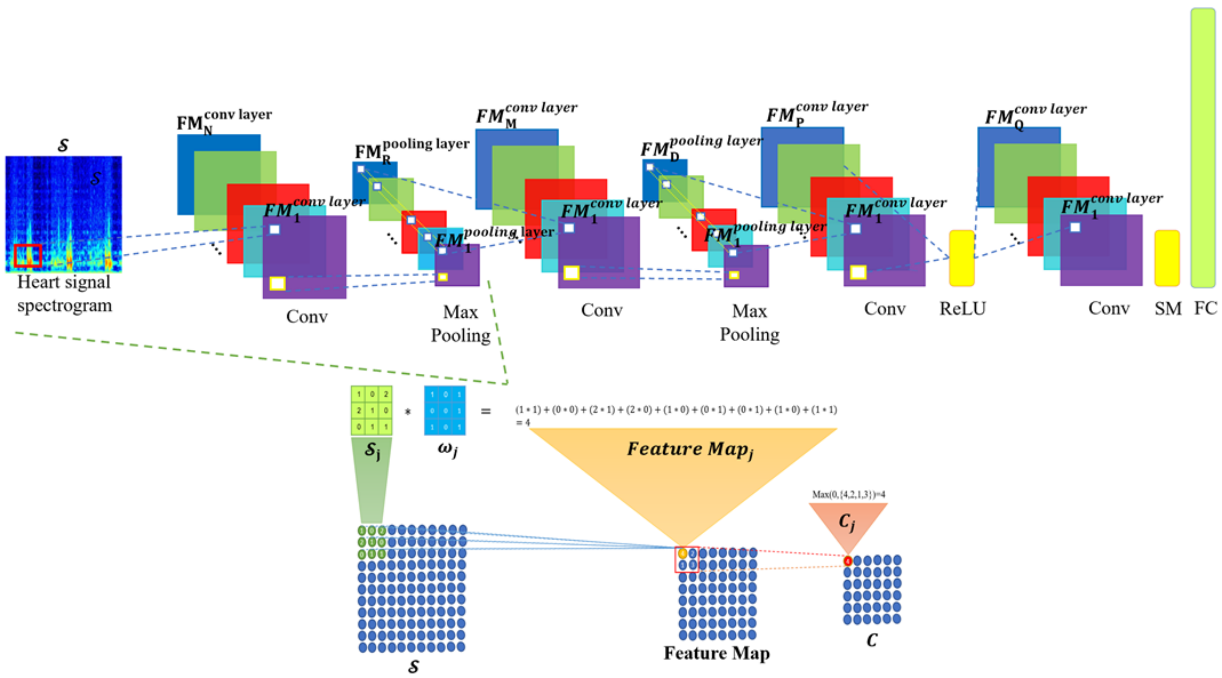

Figure 1. Proposed structure for heart sound signal classification composing of four layers in the figure pooling, one non-linearity layer and three fully connected layers

Requirements: raw segments of heart signals, batch size

1. Convert each segment of the heart signal to the equivalent spectrogram
2. Make train, validation, and test sets using the step 1 data
3. While (training data is available)
4. Feed the number of batch size of samples to the convolutional neural networks (CNN)
5. While (the current layer is available)
   A. current layer=get the current layer name
   B. Switch (current layer)
      Conv: While (the filter-bank in current layer is available)
         I. Learn the filter-bank of each layer using the spectrogram and make the output of each filter-bank
         II. Pass the output of step 5, through the non-linearity
      Max-Pooling: apply the max pooling layer
      Non-linearity: apply the ReLU activation function
      Softmax: apply softmax function
   C. End of Switch
6. End of While
7. End of While
8. While (validation data is available)
9. Get the number of batch size samples
10. The trained model is used to tune on samples
11. End while
12. Use the pre-trained CNN to heart sound classification over test set

Figure 2. Pseudo code of the proposed method based on filter-bank learning

In the abovementioned equation, ϵ is the value that prevents the division error from zero, and K_t refers to the sum of squares of previous gradients. The diagonal matrix K is replaced with the decaying average over past squared gradients $E\left[\Phi^2\right]_t$:

$$\Delta\omega_{j,i_t} = -\frac{\beta}{\sqrt{E\left[\Phi^2\right]_t+\epsilon}}\Phi_t \qquad (5)$$

A shorthand form of equation (5) is defined using the root squared error of the gradient in the form of:

$$\Delta\omega_{j,i_t} = -\frac{\beta}{RMS[\Phi]_t}\Phi_t \qquad (6)$$

As a result, equation (2) may be rewritten as follows:

$$E\left[\Delta\omega_{j,i}^{2}\right]_t = \delta\, E\left[\Delta\omega_{j,i}^{2}\right]_{t-1} + (1-\delta)\Delta\omega_{j,i}^{2} \qquad (7)$$

The root mean squared (RMS) error of parameter updates is demonstrated as:

$$RMS\left[\Delta\omega_{j,i}\right]_t = \sqrt{E\left[{\Delta\omega_{j,i}}^2\right]_t + \epsilon} \quad (8)$$

The $RMS[\Delta\,\omega_{j,i}]_t$ is approximated using the RMS of the parameter in the previous step (i.e., $t-1$). Finally, the learning rate α is replaced with $RMS[\Delta\,\omega_{j,i}]_{t-1}$ as:

$$\Delta\omega_{j,i_t} = -\frac{RMS\left[\Delta\omega_{j,i}\right]_{t-1}}{RMS\left[\Phi\right]_t}\,\Phi_t$$

$$\omega_{j,i} = \omega_{j,i_t} + \Delta\omega_{j,i_t} \quad (9)$$

The pseudo-code of the proposed method is delineated in Figure 2.

Results

The proposed method was applied to three different heart sound datasets, including PASCAL-A, PASCAL-B, and Kaggle. The two PASCAL datasets are available at [17] and the Kaggle supports a heartbeat sound database that is available from [18]. More information regarding these datasets is presented in Table 1.

In figure 3 two examples of healthy and unhealthy heart signals were illustrated.

Table 1. Datasets details

Dataset	Time Length	Source	Size
PASCAL-A	Varying lengths between 1-30 sec	General public via the iStethoscope Pro iPhone app	(n=65)
PASCAL-B		Clinic trial in hospitals using the digital stethoscope DigiScope	(n=415)
Kaggle	over 30 sec long	Clinic trial in hospitals using the digital stethoscope DigiScope	(n=47)

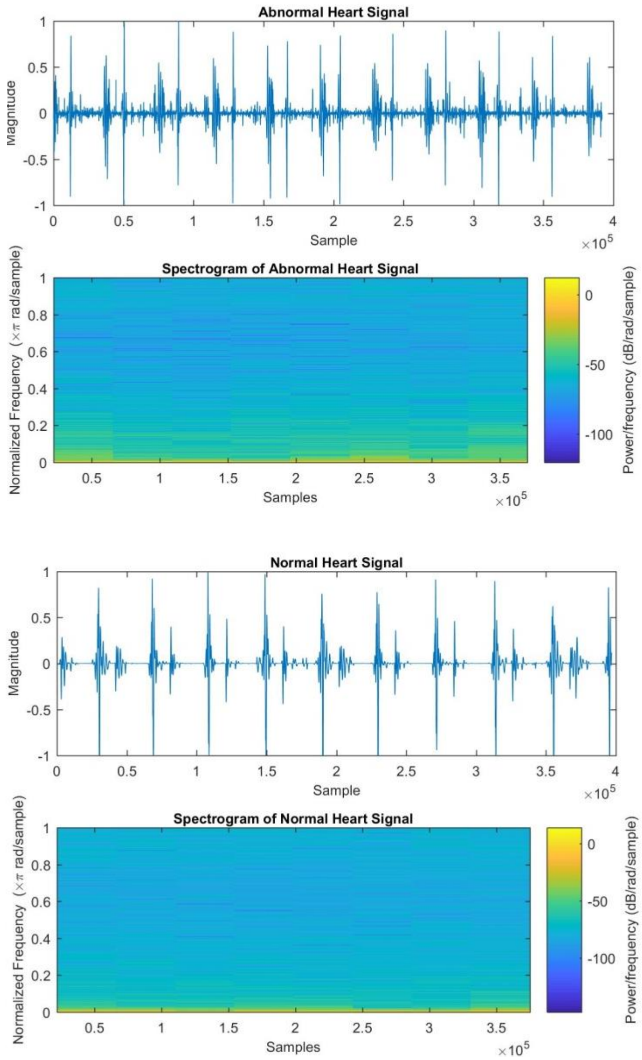

Figure 3. Two examples of abnormal and normal heart signals and their spectrogram

Table 2. Architecture of the proposed structure

Layer	Kernel	Stride	Pad	Neuron
Convolution	3x3	1	2	20
Max-pooling	2x2	2	0	20
Convolution	5x5	1	0	50
Max-pooling	2x2	2	0	50
Convolution	5x5	1	0	500
ReLU (activation function)	-	-	-	-
Convolution	2x2	1	0	2
Fully connected	2x2	1	0	2
Softmax (activation function)	-	-	-	-

The proposed algorithm was simulated using MATLAB R2017a package on a laptop with an Intel Core i7 processor and 16 GB DDR4 RAM. Furthermore, CNN without a filter bank learning scheme was simulated [19, 20]. Accordingly, the effectiveness of the proposed method was evaluated using their receiver operating characteristic (ROC) curves [21]. This curve describes the change of True detections, such as true positive rate (TPR) [22] of a classifier versus its false alarms, such as false-positive rate (FPR) [23]. Each record of the heart sound signal had a max length of 30 sec. The frames were selected in 500ms windows and the short-time Fourier transform length was equal to 256 used to calculate the spectrogram.

The specifications of the proposed architecture are represented in Table 2, as well as the results of applying this structure is demonstrated in Figure 4. This figure shows the obtained ROC curves for both examined algorithms when they were applied on PASCAL-A.

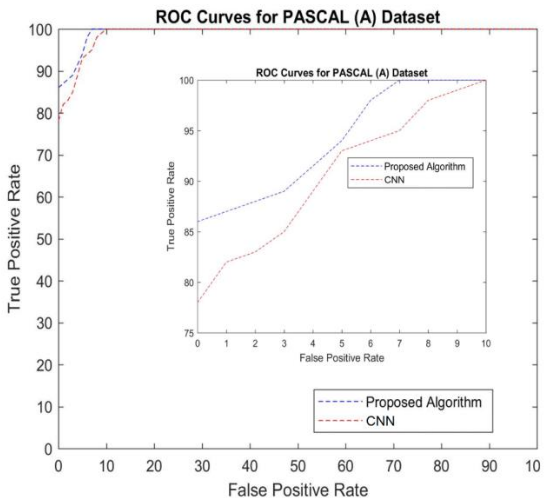

Figure 4. Receiver operating characteristic curves resulted from applying the proposed algorithm and convolutional neural network algorithms on PASCAL-A dataset

These curves clearly show the superiority of the proposed method, compared to its alternative, as well as the effectiveness of the filter bank learning in distinguishing healthy and unhealthy heart sounds. Based on the ROCs, area under curve (AUC) [21] was obtained at 0.9167 and 0.8973 for the proposed and alternative methods, respectively, showing the superiority of the proposed algorithm against its alternative. Figure 5 shows the ROC for both the above

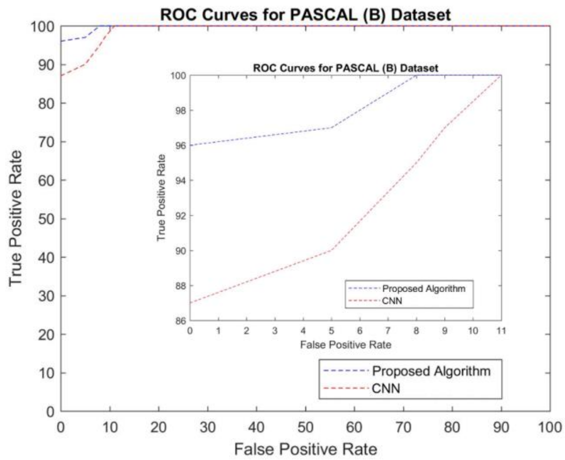

Figure 5. Receiver operating characteristic curves resulted from applying the proposed algorithm and convolutional neural network on PASCAL-B dataset

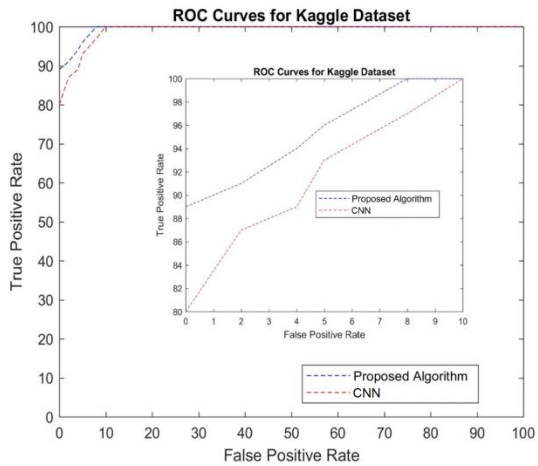

Figure 6. Receiver operating characteristic curves resulted from applying the proposed algorithm and convolutional neural network on Kaggle dataset

Table 3. Confusion matrixes of the proposed algorithm and convolutional neural network

Method	Dataset	Actual	Prediction P	Prediction N
Proposed algorithm	PASCAL A	P	86	7
		N	14	93
	PASCAL B	P	96	8
		N	4	92
	Kaggle	P	89	8
		N	11	92
convolutional neural network	PASCAL A	P	78	10
		N	22	90
	PASCAL B	P	87	11
		N	13	89
	Kaggle	P	80	10
		N	20	90

*P: Positive, N: Negative

These curves and computed AUC were estimated at 0.9358 and 0.9025 for the proposed and alternative methods, respectively.

Therefore, confirming the superiority of our method over its alternative as shown in the previous dataset. A similar gain has been proved for our scheme against its alternative by comparing their ROCs obtained from tests on the Kaggle dataset (Figure 6). The computed AUCs were obtained at 0.9312 and 0.9072 which is indicative of the superiority of our scheme in the classification of heart sounds over its alternative.

The confusion matrixes of the examined and proposed methods based on each dataset are illustrated in Table 3.

Discussion

Real data that were obtained from the three mentioned datasets were analyzed. The proposed algorithm and its alternative (i.e., classical CNN without filter bank learning) were applied on each dataset separately and the results were compared using the ROC curves.

For a better interpretation of ROC curves, $FPR = 0\%$ and $TPR = 100\%$ were regarded as ideal values for false and true detections; therefore, Table 4 was constructed using extremes of curves (4-6). For the PASCAL-A dataset in FPR=0%, the proposed algorithm showed 8% superiority in its detection rate against CNN without filter bank learning (Table 4). In another extreme (e.g., $TPR = 100\%$) the false detections of the proposed algorithm was observed 3% lower than its alternative.

A similar fact may also be shown for dataset PASCAL-B in such a way that FPR and TPR of the proposed algorithm were obtained at 9% and 3% better than the classic CNN algorithm, respectively. In a similar manner, the results showed the superiority of the filter bank learning against the classical CNN by extents of 9% and 2% for TPR and FPR, respectively, regarding the Kaggle dataset.

To present a more practical interpretation, $FPR = 5\%$ and $TPR = 90\%$ were regarded as marginally acceptable false and true detection values, then the performances of algorithms were analyzed under these conditions as reported in Table 4.

Table 4. Results of the proposed algorithm and CNN

Dataset	Parameter	Examined algorithm	
		Proposed	CNN
PASCAL-A	Detection rate against 0% false positive	86	78
	False detection rate against 100% detection	7	10
	Detection rate against 5% false positive	94	93
	False detection rate against 90% detection	3.2	4
PASCAL-B	Detection rate against 0% false positive	96	87
	False detection rate against 100% detection	8	11
	Detection rate against 5% false positive	97	90
	False detection rate against 90% detection	0	5
Kaggle	Detection rate against 0% false positive	89	80
	False detection rate against 100% detection	8	10
	Detection rate against 5% false positive	96	93
	False detection rate against 90% detection	1	4.6

CNN: convolutional neural network

Table 5. Evaluation parameters over each dataset (FPR=0%)

Algorithm	Dataset	TPR	FNR	Accuracy
Proposed algorithm	PASCAL-A	86	14	93
	PASCAL-B	96	4	98
	Kaggle	89	11	94.5
CNN	PASCAL-A	78	22	89
	PASCAL-B	87	13	93.5
	Kaggle	80	20	90

TPR: True negative rate, FNR: false negative rate, CNN: Convolutional neural network

Table 6. Evaluation parameters over datasets (TPR=100%)

Algorithm	Data set	FPR	TNR	Accuracy
Proposed algorithm	PASCAL-A	7	93	96.5
	PASCAL-B	8	92	96
	Kaggle	8	92	96
CNN	PASCAL-A	10	90	95
	PASCAL-B	11	89	94.5
	Kaggle	10	90	95

TPR: True negative rate, FNR: false negative rate, CNN: Convolutional neural network

The reported values showed that detection and false detection rates of the proposed algorithm obtained at 1% and 0.8% were better than the classic CNN when they were applied on the PASCAL-A dataset. The above superiorities reached 7% and 5% when the tests were performed on the PASCAL-B dataset. Similar evaluation parameters (i.e., $FPR=$5% and $TPR=$ 90%) led to 3% and 3.6% improvement for the detection and false detection rates of our method against the classical CNN when the tests were performed on the Kaggle dataset. The results of the present study demonstrated that the proposed algorithm made a great improvement against basic CNN (up to 9% superiority) when the main criteria were the absence of false detection (FPR= 0%). However, the proposed algorithms gradually lost its superiority against basic CNN with increasing FPR in such a way that for FPR=5% this gain was obtained only as 1-3%.

To investigate the capabilities of the proposed scheme in greater detail, some standard evaluation parameters were added to TPR and FPR as depicted in tables 5 and 6. These parameters consisted of true negative rate (TNR), false-negative rate (FNR), and classification accuracy [24].

In $FPR=0$%, the proposed scheme outperformed overall datasets against its alternative in terms of all the above parameters (Table 5). Note that the TNR parameter was dropped out in this table because of the same value (100%) overall datasets.

As shown in Table 5, the achieved results over the PASCAL-A dataset were depicted according to TPR, FNR, and accuracy. The best values obtained by the proposed algorithm were 8%, 8%, and, 4% better than the best values gained using the alternative algorithm.

In the same token, the obtained results over the PASCAL-B dataset showed the superiority of the proposed algorithm against its alternative were 9%, 9%, and 4.5%, in terms of TPR, FNR, and accuracy, respectively.

The Kaggle dataset results confirmed the previous results. The obtained results from applying the proposed algorithm on heart sounds of this dataset were 9%, 9%, and 4.5% better than its alternative in terms of TPR, FNR, and accuracy, respectively.

As illustrated in Table 6, the proposed structure in TPR=100% outperformed overall datasets against its alternative in terms of all parameters. Note that the FNR parameter by the same value of 0% for all datasets was removed from table 6.

The results of the PASCAL-A dataset indicated that according to FPR, TNR, and accuracy, the best values obtained by the proposed algorithm were 3%, 3%, and 1.5% better than the best values of the alternative algorithm, respectively. Regarding the PASCAL-B dataset, the superiority of the proposed algorithm against its alternative was reported as 3%, 3%, and 1.5% for FPR, TNR, and accuracy, respectively.

Evaluating the algorithms of the Kaggle dataset showed the superiority of our algorithm by extents of 2%, 2%, and 1%, in terms of FPR, TNR, and accuracy, respectively. Detailed analyses confirmed the trend in Table 4. This trend had shown that the considerable superiorities of the proposed method occurred in low false detection rates. In parallel with the increasing false detection rate, the performance of the proposed method becomes closer to classic CNN in terms of all evaluation parameters (e.g., TPR, TNR, FNR, and accuracy).

The proposed method learns more discriminative features during the training process leading to confident decisions; therefore, it may be an effective step to design an expert system for healthcare. Furthermore, the weights of the filter bank result in a better tuning of the network in order to obtain better optima. On the other hand, the filter bank learning procedure may increase the computational complexity, compared to the existing schemes. Finally, the spectrogram features may only improve the results of the present application because of their congruence with the nature of the heart sound signal. Consequently, their use does not guarantee an improvement in other applications. However, it is recommended that further investigation be conducted concerning this critical issue.

Conclusion

In the current paper, a new method was developed to improve the classification of heart sound signals. The proposed algorithm introduced filter bank learning as an innovative paradigm in deep neural structure to predict normal and abnormal heart sound signals based on their spectral higher-level information.

To evaluate the performance of the proposed method, it was compared with the classic CNN in such a way that both algorithms were trained and tested using the same datasets. The standard parameters of TPR, TNR, FPR, FNR, and classification accuracy were also utilized to compare the effectiveness of the proposed idea. The obtained results concluded that the proposed filter bank learning scheme improved the detection rate (e.g., TPR) by extents of 8%, 9%, and 9% compared to its alternative on datasets of PASCAL-A, PASCAL-B, and Kaggle, respectively. Moreover, based on the FPR, the proposed structure resulted in 3%, 3%, and 2% better than its alternative in the above databases, respectively. In addition, the obtained TNR and FNR confirmed the superiority of our filter bank learning-based scheme against the classical CNN structure in all the examined datasets of PASCAL-A, PASCAL-B, and Kaggle. The proposed algorithm classified heart sounds by extents of 3%, 3%, and 2%, it was better than its alternative in terms of TNR. Similar improvement may be observed in terms of FNR by extents of 8%, 9%, and 9% for the mentioned datasets, respectively.

Exploiting the mentioned results accompanied by the investigation of the occurring trend in the ROC curves resulted in considerable improvements caused by the proposed method in terms of all standard classification evaluating parameters. The most impressive superiorities have occurred in low false detection rates; however, increasing false detections gradually decreases this superiority.

Based on the findings of the present study, it is concluded that the proposed method may be considered a suitable option for the detection of the heart pathologic conditions based on the recorded heart sound signals.

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References

1. Brown EM. Heart sounds made easy. Elsevier Health Sciences. 2008.
2. Wilkins R, Hodgkin J, Lopez B. Fundamentals of Lung and Heart Sounds, 3/e (Book and CD-ROM). CV Mosby. 2004.
3. Feigen LP. Physical characteristics of sound and hearing. The American journal of cardiology. 1971;28(2):130-3.
4. Thiyagaraja SR, Dantu R, Shrestha PL, Chitnis A, Thompson MA, Anumandla PT, Sarma T, Dantu S. A novel heart-mobile interface for detection and classification of heart sounds. Biomedical Signal Processing and Control. 2018; 45:313-24.
5. Avendano-Valencia LD, Godino-Llorente JI, Blanco-Velasco M, Castellanos-Dominguez G. Feature extraction from parametric time‑frequency representations for heart murmur detection. Annals of Biomedical Engineering. 2010;38(8):2716-32.
6. Patidar S, Pachori RB, Garg N. Automatic diagnosis of septal defects based on tunable-Q wavelet transform of cardiac sound signals. Expert Systems with Applications. 2015;42(7):3315-26.
7. Zheng Y, Guo X, Ding X. A novel hybrid energy fraction and entropy-based approach for systolic heart murmurs identification. Expert Systems with Applications. 2015;42(5):2710-21.
8. SaraçOğLu R. Hidden Markov model-based classification of heart valve disease with PCA for dimension reduction. Engineering Applications of Artificial Intelligence. 2012 ;25(7):1523-8.
9. Potes C, Parvaneh S, Rahman A, Conroy B. Ensemble of feature-based and deep learning-based classifiers for detection of abnormal heart sounds. In2016 Computing in Cardiology Conference (CinC). IEEE. 2016; 621-4.
10. Rubin J, Abreu R, Ganguli A, Nelaturi S, Matei I, Sricharan K. Classifying heart sound recordings using deep convolutional neural networks and mel-frequency cepstral coefficients. In2016 Computing in cardiology conference (CinC). IEEE. 2016; 813-6.
11. Dauphin YN, Pascanu R, Gulcehre C, Cho K, Ganguli S, Bengio Y. Identifying and attacking the saddle point problem in high-dimensional non-convex optimization. InAdvances in neural information processing systems. 2014; 2933-41.
12. Pascanu R, Dauphin YN, Ganguli S, Bengio Y. On the saddle point problem for non-convex optimization. arXiv preprint arXiv:1405.4604. 2014.
13. Allahverdi N, Altan G, Kutlu Y. Diagnosis of Coronary Artery Disease Using Deep Belief Networks. 2 Int Conf Eng Nat Sci, Sarajevo, Bosnia. 2016;40-6.
14. Bengio Y. Learning deep architectures for AI. Now Publishers Inc; 2009.
15. Stutz D. Understanding convolutional neural networks. In Seminar Report, Fakultät für Mathematik, Informatik und Naturwissenschaften Lehr-und Forschungsgebiet Informatik VIII Computer Vision. 2014.
16. Ruder S. An overview of gradient descent optimization algorithms. arXiv preprint arXiv:1609.04747. 2016.
17. Bentley P, Nordehn G, Coimbra M, Mannor S, Getz R. Classifying heart sounds challenge. Retrieved from Classifying Heart Sounds Challenge: http://www. peterjbentley. com/heartchallenge. 2011 Nov.

18. Kaggle, heart sound signals. https://www.kaggle.com/sachinvernekar
19. Nilanon T, Yao J, Hao J, Purushotham S, Liu Y. Normal/abnormal heart sound recordings classification using convolutional neural network. In2016 Computing in Cardiology Conference (CinC). IEEE. 2016; 585-8.
20. Lifu K, Weilian W. Heart sound signals based on CNN classification research. InProceedings of the 6th International Conference on Bioinformatics and Biomedical Science. 2017; 44-8
21. Georgoulas G, Stylios D, Groumpos P. Predicting the risk of metabolic acidosis for newborns based on fetal heart rate signal classification using support vector machines. IEEE Transactions on biomedical engineering. 2006;53(5):875-84.
22. Dash S, Quirk JG, Djurić PM. Fetal heart rate classification using generative models. IEEE Transactions on Biomedical Engineering. 2014; 61(11):2796-805.
23. [23] Bonomi AG, Schipper F, Eerikäinen LM, Margarito J, Van Dinther R, Muesch G, et al. Atrial Fibrillation Detection Using a Novel Cardiac Ambulatory Monitor Based on Photo-Plethysmography at the Wrist. Journal of the American Heart Association. 2018;7(15):e009351.
24. Poddar MG, Birajdar AC, Virmani J. Automated classification of hypertension and coronary artery disease patients by PNN, KNN, and SVM classifiers using HRV analysis. InMachine Learning in Bio-Signal Analysis and Diagnostic Imaging; Academic Press. 2019; 99-125.