Detecting Abnormal PCG Signals and Extracting Cardiac Information Employing Deep Learning and the Shannon Energy Envelope

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Phonocardiogram (PCG) is a computerized system that represents the heart sound recording. PCG reflects the acoustic behavior of the heart graphically through intensity, frequency, time duration, and other valuable information. An acoustic signal like PCG provides supplemental diagnostic information to Electrocardiogram (ECG) by extracting cardiac information from the heart sound those cannot be identified by hearing the heart sound. PCG is an objective and standard evaluation technique that can record the heart sound continuously for a long period of time and can also overcome the human hearing limitation [1] [2]. So, PCG plays a vital role to examine the heart sound as well as cardiac abnormalities which improves the overall diagnosis efficiency. We proposed a PCG classification method using the deep convolutional neural network (CNN). Our proposed method is not only able to classify PCG signals using CNN but can also segment PCG signals using the Shannon energy envelope method. This signal processing technique provides significant information regarding the heart condition that helps to detect heart diseases in the primary phase.

Machine learning (ML) and deep learning (DL) have enhanced the importance of research on biomedical signals like Electrocardiogram (ECG), Phonocardiogram (PCG), Electroencephalogram (EEG), and so on. ML algorithms are commonly used for the biomedical signal classification. However, one of the major limitations of ML algorithms is the feature extraction. Extracting appropriate features from the raw signal is very challenging. DL algorithms can solve this problem by extracting high-quality optimal features through its own neural network and reduce the need for feature engineering. Thus, DL algorithms lead to better performance and high accuracy compared to ML algorithms.

In our study, we used a very common and powerful deep learning algorithm called CNN to analyze PCG signals. CNN is mainly a deep neural network which is mainly divided into three parts such as convolutional layers, pooling layers, and fully connected layers. Convolution and pooling functions reduce the number of parameters by selecting only important parameters. Hence, they save the memory and increase the overall accuracy [3]. To validate our proposed method, we used 3240 PCG signals from the two datasets known as PhysioNet Computing in Cardiology Challenge 2016 heart sound database and Open Michigan Heart Sound and Murmur Library [4]-[6]. The ratio of normal PCG signals to abnormal PCG signals is 1:4. 90% of the PCG signals were used to train the classification model and 10% PCG signals were used to validate the model. Synthetic Minority Over-sampling Technique (SMOTE) was employed for making the data balanced [7]. Over-sampling technique was not used in the testing set as we wanted to test the model on unseen data. Mel-frequency cepstral coefficients (MFCC) and Mel-scaled power spectrogram were employed to get compact and meaningful information from each PCG signal [8]. These extracted features were used as input to our DL model.

We used a 1D CNN model of 4 hidden layers to classify each PCG signal in the database. Four hidden layers were used with 128, 256, 512, and 1024 filters. The ReLU activation function was used in each hidden layer. Each layer had the same kernel size of 4. A max-pooling layer of kernel size 2 was also used in each layer to downsample the input and to reduce the number of dimensions. The Sigmoid activation function was used in the output layer for the binary classification. To overcome the overfitting problem, we used the dropout technique. The dropout technique usually deletes random samples of the activations during

the training by making them zero and helps the network to learn robust features that are useful to increase classification accuracy. The value of the learning rate was 0.0001. Network weights had been updated iteratively in each epoch based on training data using the Adam optimization algorithm. Finally, the performance of the model was validated by using the unseen test data.

We evaluated the proposed CNN model by calculating sensitivity/recall, specificity, and accuracy metrics. The sensitivity/recall indicates the percentage of the accurately predicted abnormal PCG signal. The specificity is the percentage of the accurately predicted normal PCG signal. The overall classification accuracy indicates the percentage of the accurately predicted normal and abnormal PCG signals out of all PCG signals. These important evaluation metrics were found by analyzing the confusion matrix [8]. An overall accuracy score of 93.20% was achieved by using our proposed model. The sensitivity/recall of the model was 89.20%, whereas the specificity of the model was 94.20%. The overall performance of the proposed PCG classification model was compared with the 11 others recent methods and we got better result in terms of overall accuracy [8].

Classification of the PCG signal does not provide any significant details about cardiac parameters. So, after the classification, it is very important to segment the PCG signal to obtain cardiac information. We have developed a segmentation technique using Discrete Wavelet (DWT) and Shannon energy envelope. Our proposed segmentation method facilitates getting the time duration and amplitude of different heart sounds. Time durations of the systolic and diastolic interval, heartbeat, and cardiac cycle are also possible to detect effectively by using our proposed segmentation technique. These important cardiac parameters can help a cardiologist to detect cardiac abnormalities in the initial stage.

First, we used DWT to denoise the signal and to separate any redundant information from the signal [8] [9]. Shannon energy envelope was then used to detect the boundaries of each heart sound. Normalized average Shannon energy usually shows better performance compare to all other envelope detection algorithms to reduce the negative consequence of low-frequency noise on the PCG signal. Thus, it is possible to detect the envelope difference of high and low amplitude portions of the signal accurately [10]. After detecting the envelope, the location and duration of the heart sounds were calculated using a zero-crossing algorithm. For peak detection, we used the Hilbert Transform (HT) algorithm and the python package peakutils. HT was used to calculate the minimum-phase response from the spectrogram of the PCG signal [11]. Peakutils provides different utilities to detect the peak of a one-dimensional signal. This function detects the local maxima as a peak within a fixed distance and by using a threshold [12]. By using this segmentation technique, it is possible to effectively detect anomalies in the heart during the primary stage of heart diseases. Based on the ability of our classification and segmentation algorithms, we can develop an automatic tool that can continuously monitor the heart sound and can detect early symptoms of cardiac diseases. Our proposed segmentation technique performs poor when the noises are overlapped with heart sounds. It requires further research to solve this complex problem and to increase the accuracy of the PCG classification model.

REFERENCES

[1] R. M. Rangayyan and R. J. Lehner, "Phonocardiogram signal analysis: a review," *Critical Reviews in Biomedical Engineering*, vol. 11, no. 03, pp. 211–369, 1987.

[2] M. T. H. Chowdhury, K. N. Poudel, and Y. Hu, "Automatic Phonocardiography Analysis using Discrete Wavelet Transform," *3rd International Conference on Vision, Image, and Signal Processing*, Vancouver, BC, Canada, August 2019.

[3] V. Nigam, "Understanding Neural Network. From neurons to RNN, CNN, and Deep Learning," Sep. 2018. [online]. (*https://towardsdatascience.com/understanding-neural-networks-from-neuron-to-rnn-cnn-and-deep-learning-cd88e90e0a90*).

[4] "Michigan Heart Sound and Murmur Library," 2015. [Online]. *(https://open.umich.edu/find/open-educational-resources/medical/heart-sound-murmur-library)*.

[5] C. Liu , D. Springer, Q. Li, B. Moody, R. A. Juan, F. J. Chorro, F. Castells, J. M. Roig, I. Silva, A. E. Johnson et al., "An open access database for the evaluation of heart sound algorithms," *Physiological Measurement*, vol. 37, no. 12, pp. 2181–2213, November 2016.

[6] A. Goldberger, L. Amaral, L. Glass, J. Hausdorff, P. C. Ivanov, R. Mark, J. E. Mietus, G. B. Moody, C. K. Peng, and H. E. Stanley. "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," vol. 101, no. 23, pp. 215–220, 2000. [Online]. (*https://doi.org/10.13026/C2ZW2H*).

[7] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "Smote: synthetic minority over-sampling technique," *Journal of artificial intelligence research*, vol. 16, pp. 321–357, 2002.

[8] M. T. H. Chowdhury, K. N. Poudel, and Y. Hu, "Time-Frequency Analysis, Denoising, Compression, Segmentation, and Classification of PCG Signals," in *IEEE Access*, vol. 8, pp. 160882-160890, 2020.

[9] M. T. H. Chowdhury, K. N. Poudel, and Y. Hu, "Phonocardiography Data Compression Using Discrete Wavelet Transform," *2018 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, Philadelphia, PA, USA, pp. 01–03, Dec. 2018.

[10] H. Liang, S. Lukkarinen, and I. Hartimo, "Heart Sound Segmentation Algorithm Based on Heart Sound Envelogram," *Proceedings of The IEEE Computers in Cardiology*, vol. 24, pp. 105–108, 1987.

[11] S. Behbahani, "A hybrid algorithm for heart sounds segmentation based on phonocardiogram," *Journal of Medical Engineering & Technology,* vol. 43, no. 06, pp. 363–377, 2019.

[12] "PeakUtils," [Online]. (*https://peakutils.readthedocs.io/en/latest/*).

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Abstract

Phonocardiography (PCG) is an automatic computer-aided diagnosis tool that represents the condition of the heart sound. PCG reflects the acoustic behavior of the heart graphically through intensity, frequency, time duration, and other valuable information. An acoustic signal like PCG provides supplemental diagnostic information to Electrocardiogram (EKG) by detecting the structural defects of the heart that cannot be detected by EKG. Moreover, PCG allows extracting informative characteristics of the heart sound those cannot be identified by the human ear. So, PCG plays a vital role to examine the heart sound as well as cardiac abnormalities which improves the overall diagnosis efficiency. We have proposed a PCG classification and segmentation method in this paper.

We classified and segmented the PCG signal using the following techniques:

- A total of 3240 unique heart sound recordings were collected from the University of Michigan Heart Sound and Murmur Library database and the 2016 PhysioNet/CinC challenge database.
- As the training dataset was not balanced, an oversampling method named Synthetic Minority Over-sampling Technique (SMOTE) was used to make it balanced .
- We used Mel-scaled power spectrogram and Mel-frequency cepstral coefficients (MFCC) to extract compact and meaningful information from each PCG signal.
- We used a 1D CNN model of 4 hidden layers with 128, 256, 512, and 1024 filters, which were implemented with the ReLU activation function to classify each PCG signal in the database.
- This proposed model detected normal and abnormal PCG signals with a very good testing accuracy of 93.20%. The achieved sensitivity/recall and the specificity of the model were 89.20% and 94.20%, respectively.
- We compared the performance of our proposed PCG classification model with the 11 other recent PCG classification models, and our model outperformed those models significantly in terms of overall accuracy.
- We have developed a segmentation technique using Shannon energy envelope, and a zero-crossing algorithm to extract cardiovascular information representing the current condition of the human heart.

Materials and Methods

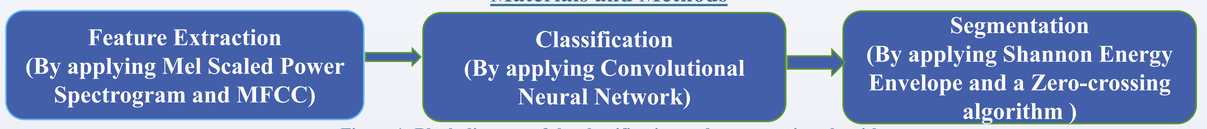

Figure.1: Block diagram of the classification and segmentation algorithm

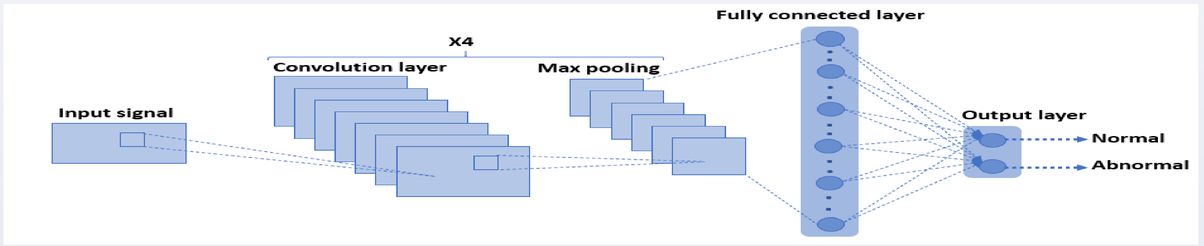

Figure 2: Our Proposed Convolutional Neural Network model to classify PCG Signal.

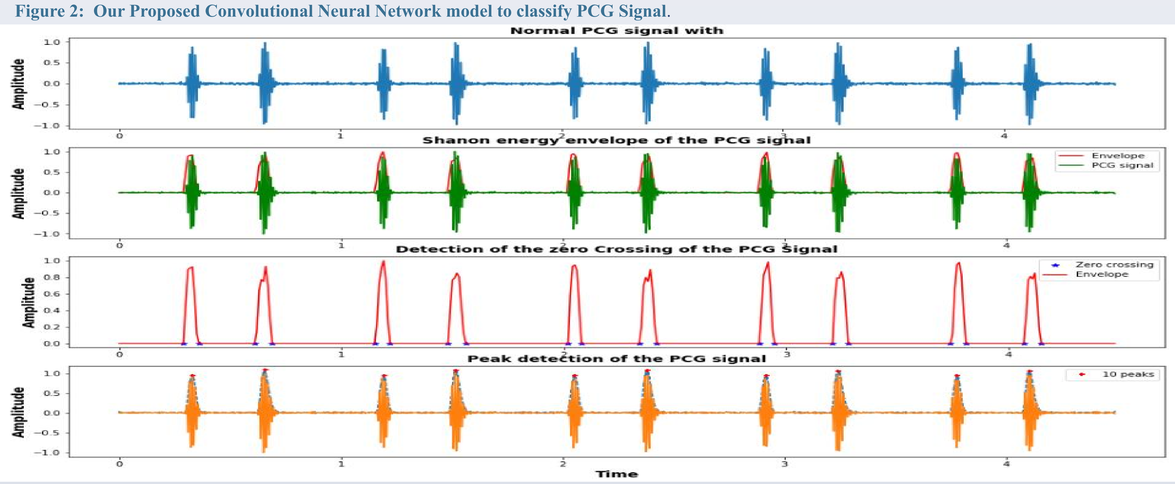

Figure 3: a) Original normal PCG signal. b) Shannon energy envelope of the PCG signal. c) Zero-crossing of the PCG signal. d) Peak detection.

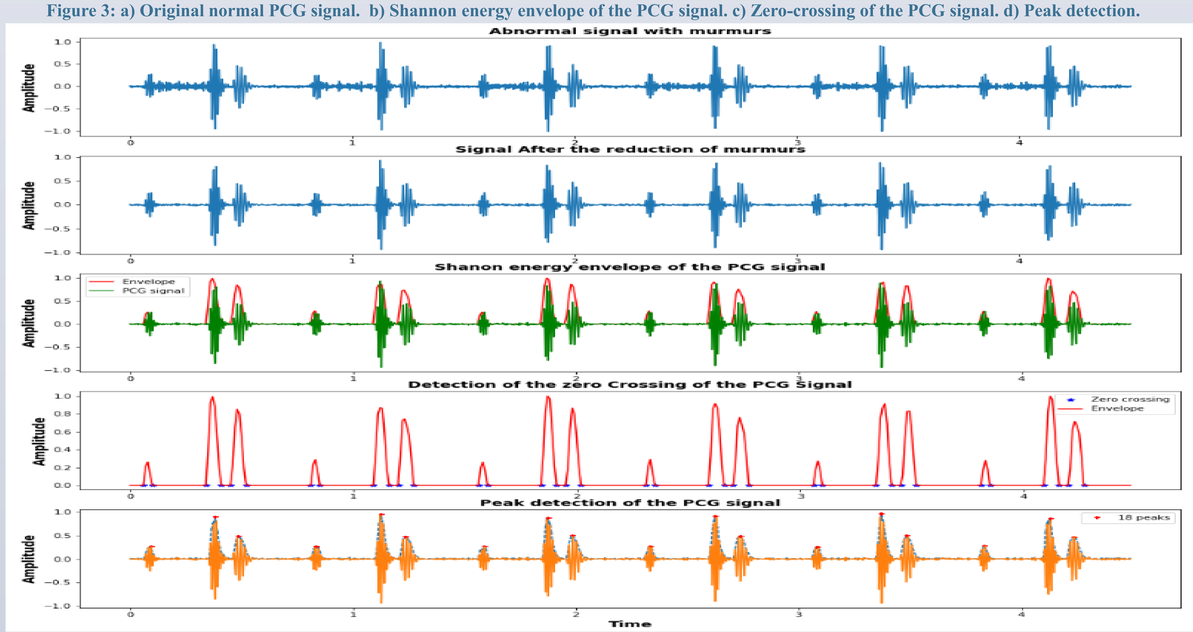

Figure 4: a) Original normal PCG signal. b) Denoising/ Murmurs reduction c) Shannon energy envelope of the PCG signal. d) Zero-crossing of the PCG signal. e) Peak detection.

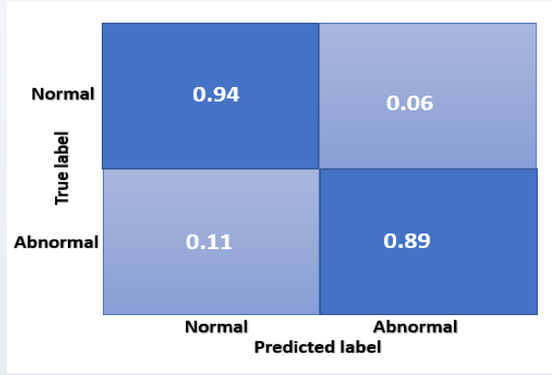

Figure 5: The confusion matrix.

Table 1: Comparison of the proposed model with other models.

Author	Sensitivity (%)	Specificity (%)	Accuracy (%)
Potes et al., (2016)	94.24	77.81	86.02
Nassralla et al., (2017)	78.00	98.00	92.00
Whitaker et al., (2017)	90.00	88.45	89.26
Langley et al., (2017)	77.00	80.00	79.00
Han et al., (2018)	98.33	84.67	91.50
Tang et al., (2018)	88.00	87.00	88.00
Sotaquirá et al., (2018)	91.30	93.80	92.60
Singh et al., (2019)	93.00	90.00	90.00
Nogueira et al., (2019)	90.45	85.25	87.85
Sing et al., (2020)	94.08	91.95	92.47
Krishnan et al., (2020)	86.73	84.75	85.65
Our Study	**89.20**	**94.20**	**93.20**

Table 2: Extraction of the cardiac information from PCG signals.

Cardiac parameter	Value in a normal PCG signal	Value in an abnormal PCG signal
Duration of S1	0.06 second	0.04 second
Duration of S2	0.08 second	0.07 second
Duration of S3	–	0.07 second
Amplitude of S1	0.94	0.30
Amplitude of S2	1.10	0.98
Amplitude of S3	–	0.52
Systole interval	0.32 second	0.30 second
Diastole interval	0.54 second	0.47 second
One cardiac cycle	0.86 second	0.77 second
Heart rate	70 beats per minute	80 beats per minute

Conclusion

Our proposed method is not only able to classify heart sounds using deep learning but can also extract important cardiac information from PCG signals using the Shannon energy envelope. This signal processing technique provides significant information regarding the heart condition and can help cardiologists to take appropriate and reliable steps to diagnosis if any cardiovascular disorder is found in the initial stage. Based on the ability of our classification and segmentation algorithms, we can develop an automatic tool that can continuously monitor the heart sound and can detect early symptoms of cardiac diseases. This tool can be a promising solution to improve the cardiac patient survival rate and decrease the hospitalized and death rate caused by heart diseases.