Discrete Wavelet based Features for PCG Signal Classification using Hidden Markov Models

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Abstract: This paper proposes the use of several features based on Discrete Wavelet Transform as novel descriptors for the application of classifying normal or abnormal phonocardiogram (PCG) signals, using Hidden Markov Models (HMM). The feature extraction of the first descriptor called “DWE” consists in converting each PCG signal into a sequence of features vectors. Each vector is composed of the energy of the wavelet coefficients computed at each decomposition level from an analysis window. The second descriptor “LWE” consists in applying the logarithm of DWE features, while the third descriptor “WCC” applies the DCT on the LWE features vector. This work aims to find the relevant descriptor using PCG Classification Rate criterion. This is achieved by implementing a standard system of classification using the HMM classifier combined with MFCC features descriptor. Each class is modeled by HMM model associated to GMM model. Several experiences are carried out to find the best configuration of HMM models and to select the optimal mother wavelet with its optimal decomposition level. The results obtained from a comparative study, have shown that the LWE descriptor using Daubechies wavelets at order 2 at level 7, gives the highest performance classification rate, with a more compact features representation than the MFCC descriptor.

1 INTRODUCTION

Before the 19th century, physicians used the ear as a way to listen to the sound emitted by heartbeats in order to identify heart operation state, which can be useful for diagnosing heart disease. This method of "immediate hearing" on the chest or the back is a very rudimentary approach for physicians having led to dissatisfaction with it. In 1816 Isaac invented a medical instrument called the "stethoscope", which is an exciting and practical new method of bedside examination. This instrument is widely used to diagnose heart disease (Hanna & Silverman, 2002). Despite its approval, this requires a long-term practice and several years of clinical experience is necessary and is difficult to obtain. This led doctors and researchers to develop techniques for helping cardiac auscultation. This need gave birth to electronic stethoscopes, which have the advantage of being able to record, store and replay the sounds in better conditions, for diagnostic purposes (Jiang & Choi, 2006) (Moukadem, Dieterlena, Hueberb, & Brandtc, 2013).

The heart sound signal of a normal heartbeat has two sounds. The first heart sound, a lub of "lub-dub" (S1), corresponds to the systolic period. The second heart sound, a dub (S2) of "lub-dub", corresponds to the diastolic period. These sounds are caused by the closing and opening of valves inside the heart (Kumar, et al., 2006). A normal heartbeat sound has an out of rhythm "lub ... dub...". Doctors can find heart additional or abnormal sounds from listening to sound with rhythm “lub-lub…dub, lub…dub-dub” (Gomes & Pereira, 2012) (Raza , et al., 2019).

The classification phase usually comprises three steps: pre-processing, feature extraction and classification model. First, pre-processing is an important step in the data mining process for eliminating noise and cleaning the heartbeat signal, and this is done using a band pass filter. The

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extraction of characteristics is an essential stage, from which the classification system is carried out; this step transforms each heartbeat sound signal into to sequence of vectors. The choice of characteristics is essential and is done by the system designer following many considerations: the main motivation is to choose features as discriminatory as possible; also the greater the number of characteristics, the more complex the classification system and the longer the learning time, which makes the real-time implementation more difficult. Several studies related to classification and pattern recognition have been introduced in the past using techniques such as wavelet transform (WT), Mel-Frequency Cepstral Coefficients (MFCC), ensemble empirical mode decomposition, multi-fractal decomposition and Shannon energy (Chen, et al., S1 and S2 heart sound recognition using deep neural networks, 2016) (Chen, Yang, & Ho, S1 and S2 Heart Sound Recognition Using Deep Neural Networks, 2017) (Gupta, Palaniappan, Swaminathan, & Krishnan, 2007) (Alajarin, 2007). In many studies, Hidden Markov Models (HMM) were used for PCG modelling and analysing, in conjunction with short-time Fourier transform coefficients (STFT). The mel-scaled WT were used to classify signals of heart sounds in (Wang, Lim, Chauhan, Foo, & Anantharaman, 2007). Conjunction of signal amplitude and MFCC coefficients with HMM were used in (Chauhan, Wang, Lim, & Anantharaman, 2008) and the same idea were also applied using DFT and principal component analysis in (Saracoglu, 2012).

In this study, we propose to apply a feature extraction method based on Discrete wavelet Transform (DWT), mostly inspired by research in speech processing (Didiot, Illina, Fohr, & Mella, 2010) and in electrical appliances identification (Hacine-Gharbi & Ravier, 2018). This method can extract three descriptors called respectively DWE (Discrete Wavelet Energy), LWE (Log Wavelet Energy) and WCC (Wavelet Cepstral Coefficients). The DWE descriptor extraction consists to convert each PCG signal into a sequence of features vectors obtained each one by computing the energy at each level of dyadic wavelet decomposition from an overlapping analysis window. The LWE descriptor applies the logarithm on the features of DWE descriptor, while the WCC descriptor applies DCT transform on the features of LWE descriptor. The aim of this work is to investigate the relevance of these descriptors by comparing them with the traditional MFCC descriptor for the task of PCG signals classification, in terms of classification rate and complexity.

The remainder of this paper is organized as follows. In Section 2, we discuss sound classification, features extraction approaches and we introduce the proposed approach and detail each algorithm step. Experimental results and discussion are presented in Section 3. We end up by a conclusion and perspectives concerning future work.

2 CLASSIFICATION OF PCG SIGNAL

2.1 Dataset

In order to test our methods, we used the PASCAL Classifying Heart Sounds Challenge database (Bentley, Nordehn, Coimbra, Mannor, & Getz, 2011). Database comprises 176 recordings for heart sound segmentation. More details about the challenge dataset can be found in (Liu, et al., 2016). During evaluation, we use only 621 cardiac cycles (beat) including 204 pathological cardiac cycles. This extraction and recording is carried out using the PRAAT software. For each version of the signal, a labelling file is created in text format, containing the transcription of the signal in a sequence of labels. These labels are the normal and abnormal classes Each beat belongs either to the normal class (label ‘N’) or to the pathological class (label ‘AN’). Each PCG signal was then resampled to 16000Hz.

Table 1 summarizes the distribution of the training and testing sets composing the PASCAL database.

Table 1: Distribution of the testing and training record numbers of the PASCAL database.

Classes	Normal	Abnormal
Number	417	204
Test/Train	121/296	58/146

2.2 Proposed Feature Extraction Method

In order to classify the heart sound components, many authors have proposed the use of the MFCC descriptor (Rahmandani, Nugroho, & Setiawan, 2018) (Nilanon, Yao, Hao, & Purushotham, 2016) (Numan, et al., 2019). This last descriptor is a perceptual representation of the power spectrum of a sound signal. It is obtained by taking the Discrete Cosine Transform (DCT) of the logarithmic power spectrum on a nonlinear mel-scale of frequency by using the following frequency transformation (Wu, Kim, & Bae, 2010):

$$Mel(f) = 2595log_{10}\left(1 + \frac{f}{700}\right) \tag{1}$$

The features extraction operation from PCG signals requires the computation of 39 dimension vectors per frame including static features and energy with their dynamic features. When MFCC is used, acceptable results for clean heart sounds are obtained. However, the results are sensitive to the recording frequency and the performance is not as good in a noisy environment. This is based on the results of many studies (Numan, et al., 2019) (YaseenSonG & Kwon, 2018) (Li, et al., 2019), whereby the latter indicates that the new extracted feature is more suitable and shows stronger anti-interference ability for heart sound signals representation than that of the MFCC. The results show a remarkable classification performance in detecting the noisy class accurately. At least, the MFCC feature vectors require high dimensionality computation.

To overcome this limitation P. Wang et al. have proposed to replace the MFCC by the mel-scaled WT. This method applies the wavelet transform to the mel-spectrum of the phonocardiogram (Wang, Kim, & Soh,2005). Their suggested method has produced encouraging results compared with those obtained achieved using the MFCC.

Many other wavelet features can be further computed from discrete wavelet coefficients, namely Discrete Wavelet Energy (DWE), Log Wavelet Energy (LWE) and Wavelet Cepstral Coefficients (WCC), as depicted in Figure 1.

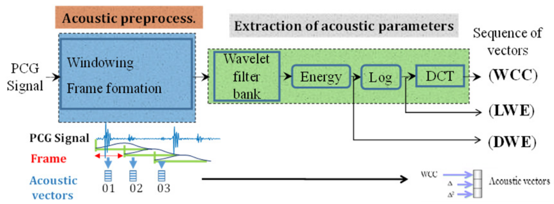

Figure 1: block diagram describing the process of wavelet cepstral coefficient (WCCs), discrete wavelet energy (DWE) decomposition-based calculus and log wavelet decomposition-based energy (LWE) features extraction with Hamming windowing.

The idea of using DWE, LWE and WCC as the feature set for a PCG classification system comes from the success of wavelet cepstral coefficients for speaker identification (Lei & Kun, 2016) and also because PCG and speech are both acoustic signals. Our acoustic analysis approach consists in extracting the DWE, LWE and WCC descriptors for short-term feature extraction with low dimensionality of the features vectors. The LWE descriptor consists in calculating the log of the energy of the wavelet coefficients at each decomposition level without DCT transform in order to keep the interpretation of a descriptor representing energies in frequency bands. The flowchart of DWE, LWE and WCC extraction method used in this paper is shown in Figure 1. The whole procedure was carried out in the four steps given as follows:

Step 1: Preprocessing: this step goes through the following operations (Nabih-Ali, EL-Sayed, El-Dahshan, Ashraf, & Yahia, 2017):

- The PCG data is segmented into 20ms-overlapping frames, with 10ms overlap between them.
- Hamming window is applied on these 20ms portions.

Step 2: CWT is the continuous version of WT which principle remains similar when going to the DWT discrete version. However, the application of DWT requires that the scales used by the wavelet and their positions are sampled down by a factor of two (or up for the inverse DWT). This is called the dyadic scale. In practice, DWT is simply computed by using a filter bank for constructing the multi resolution time-frequency plane. The filter bank is achieved using a half-band low pass filter and a half-band high pass filter. In the iterative wavelet decomposition procedure, the low-frequency coefficients are called the approximations (a_j), while the high-frequency coefficients are called the details (d_j).

The DWT coefficients $a_j[n]$ and $d_j[n]$ are calculated, at each level j, by the following formula:

$$a_j[n] = \sum_l a_{j-1}[l-2n]\,L(l) \quad \text{for } j = 1, \dots, p \tag{2}$$

$$d_j[n] = \sum_l a_{j-1}[l-2n]\,H(l) \tag{3}$$

where the analyzed signal is of length $\mathrm{N} = 2^p$. The notations L and H represent the low-pass and high-pass filters, respectively.

As a result of this step, we obtain a feature vector, which is called Discrete Wavelet decomposition-based calculus Energy (DWE) and which is evaluated as:

$$DWE[d_j] = \sum_{n=0}^{N_j-1} \left|d_j[n]\right|^2 \text{ for } j = 1, \dots, p \tag{4}$$

$$DWE[a_p] = \sum_{n=0}^{N_p-1} |a_p[n]|^2 \quad (5)$$

The number of samples is $N_j = N/2^j$ at each level j, which means that this number is reduced by a factor 2 at each iteration from (1 to p).

Step 3: The previous step allows the calculation of another descriptor called LWE. This last is the log of energy at each level of dyadic decomposition. It writes:

$$LWE[d_j] = log \sum_{n=0}^{N_j-1} |d_j[n]|^2 \text{for } j = 1, \dots, p \quad (6)$$

$$LWE[a_p] = log \sum_{n=0}^{N_p-1} |a_p[n]|^2 \quad (7)$$

Step 4: The previous step finally allows further computation of WCCs, which are the results of the application of the inverse discrete cosine transform (DCT) on the logarithmic values of energies. This homomorphic analysis has the effect of making the obtained coefficients less correlated with each other.

Previous results described in (Hacine-Gharbi & Ravier, 2018), in the field of electrical appliances identification, showed that the WCC performed good results, in terms of appliance identification rate.

2.3 Hidden Markov-based Classification System

The classification system design of heartbeat sound is divided into two phases, the training and testing phases as shown in Figure 2. Therefore, we split the dataset (Bentley, Nordehn, Coimbra, Mannor, & Getz, 2011) into two sets with a proportion of 70% for training and 30 % for testing data. The two phases require feature extraction step, which consists in dividing each signal in overlapped windows and converting each window into features vector.

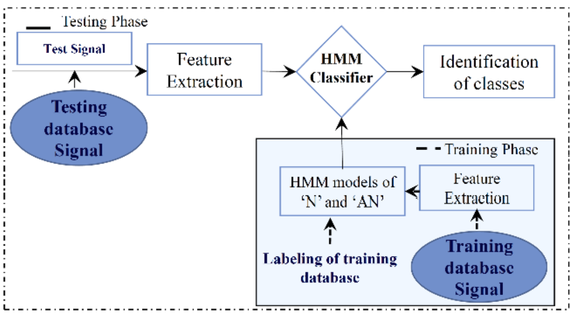

Figure 2: Flow chart outlining the procedure of the proposed classification system.

Hence, this step converts each signal into a sequence of features vectors.

In the training phase, the data are learned by modelling the signals of each class by a HMM model associated with GMM (Gaussian Mixture Model) model. The feature extraction techniques are applied in order to produce input data to the system for class learning.

In the testing phase, the temporal signal is transformed into a sequence of feature vectors which are used as input data for the HMM classifier.

Finally, the evaluation of the implemented system is done by using the decision results given by the classifier knowing the ground truth given by the expert notations. Appropriate statistics will be used for this performance evaluation task.

2.4 Performance Evaluation

The overall performance of the PCG signal classification was evaluated by the computation of classification rate (CR) given by the Accuracy value (Acc_{HTK}) provided by the HMM Toolkit library software (HTK) (Young, Kershaw, Odell, & Ollason, 1999) and is calculated as follows (Young, Kershaw, Odell, & Ollason, 1999):

$$Acc_{HTK} = \frac{H}{N} \quad (8)$$

where N is the total number of PCG signals given at the input of the classifier, and H is the number of the PCG signals correctly classified.

3 EXPERIMENTAL RESULTS

3.1 Experiments

Each heartbeat is modeled by a $\mathrm{N_{States}}$ HMM. Each state is modeled by a GMM with $\mathrm{N_{Gaussians}}$ Gaussians of frame size of 20ms. The implementation of the system is carried out using the HTK library (Young, Kershaw, Odell, & Ollason, 1999). The performance of this classification is performed in terms of CR.

The following section, which is structured in two parts, presents the experimental results. In the first part, we compare the performance of the new features to that of other features. In a second part, we carry out an experiment to select the optimal mother wavelet for the best previous descriptor and decomposition level.

3.2 Results and Discussion

3.2.1 Comparative Study between Different Features

Table 2 shows the best possible classification results with optimal number of states and optimal number of Gaussian components $N_{Gaussians}$ when varying the States from 2 to 12 and varying the $N_{Gaussians}$ from 1 to 96 (taking 8 values of $N_{Gaussians}$: 1,2,3,6,12,24,48,96). The features vector was computed with sliding Hamming windows of 20ms and 50% of overlapping (Nabih-Ali, EL-Sayed, El-Dahshan, Ashraf, & Yahia, 2017).

By observing the results of each column, we can find that the best performance is achieved when the optimal number of states is set to 10 for the feature descriptor (LWE) with CR of 92.74%.–Using the MFCC features, the baseline algorithm yielded the poorest CR of 87.71 % with the configuration of 39 dimensional feature vector. In the light of these results, we can conclude that the model, which uses LWE features, obtained higher CR with respect to the other wavelet features and the MFCC descriptors.

Table 2: Comparison of ACC_HTK(%) for different features extractions descriptors techniques using Daubechies (db2) at level 7 for the hmm optimal number of states *(Lekram & Abhishek, 2014)*. The features number is given for each descriptor.

	MFCC (39)	**DWE (8)**	**LWE (8)**	**WCC (8)**
$\mathbf{N_{States}}$	9	8	10	8
$\mathbf{N_{Gaussians}}$	2	2	3	3
$\mathbf{Acc_{HTK}}$ (%)	87.71	88.27	**92.74**	89.94

3.2.2 Optimal LWE Parameterization

Window Duration. Table 3 shows the CR results for different window duration values. The Db 2 wavelet and a decomposition level 7 are considered in this experiment for the classification system (Lekram & Abhishek, 2014). By analyzing the results in Table 3, we can find that the maximum CR (Acc_{HTK}) in each column is achieved when the window size equals 20ms, the best CR of 92.74% was reached in this table. Therefore, it is desirable to select a window duration of 20ms.

Table 3: Acc_{HTK} (%) for different combinations of the window size.

Wind. size	60ms	50ms	40ms	30ms	20ms
Acc_{HTK} (%)	87.71	88.27	88.83	89.39	**92.74**

Wavelet Family and Decomposition Depth. In this part, the smoothness and the impact of the wavelet family on the CR is evaluated. This study intended to define the optimal mother wavelet with its optimal decomposition level. In the present work, the following wavelet families are considered:

- ✓ the Daubechies family with orders going from 1 to 8: Db1, Db2, ..., Db8;
- ✓ the Coiflets family with orders going from 1 to 5: Coif1, Coif2..., Coif5;
- ✓ the Symlets family with orders going from 1 to 8: Sym1, Sym2, ..., Sym8.

We used the optimal system configuration identified in the previous studies, which is composed of ten HMM states, where each state is represented by a three Gaussian mixture.

The results are given in Table 4, where the highest CR value of 92.74% was achieved when using Daubechies wavelet of order 2 and a decomposition level of 7.

Table 4: Comparative results between different kinds of wavelet families. The table shows the Acc_{HTK} values for the optimal decomposition level as well as the optimal order for each wavelet family.

	Daubechies	Symlet	Coiflets
level	7	2	6
order	2	2	1
$\mathbf{Acc_{HTK}}$ (%)	92.74	89.94	89.39

Table 5 also gives the detailed results of AccHTK for the best Daubechies wavelet family when changing levels and orders. The Table gives some credit to our study because of the high variability observed in Acc_{HTK} values between the lowest of 72.07% and highest value of 92.74%.

Table 5: Acc_{HTK} (%) of LWE for different Daubechies orders and different decomposition levels.

	1	2	3	4	5	6	7	8
db1	86.03	86.03	86.59	85.47	81.01	87.15	85.47	87.15
db2	87.15	89.94	86.03	85.47	86.03	87.71	**92.74**	90.50
db3	84.36	85.47	86.03	77.65	78.77	83.80	87.71	
db4	79.89	82.68	82.12	77.09	81.56	81.56	85.47	
db5	*72.07*	79.89	80.45	77.65	79.89	79.33		
db6	76.54	78.77	85.47	82.12	83.80	86.03		
db7	79.89	83.80	85.47	82.68	84.92	84.92		
db8	78.77	83.24	87.15	83.24	87.71	82.68		

Moreover, results were obtained with the Coiflets and Symlets wavelet families by following the same experimental protocol. The order 2 at level 2 showed the best performance within the Symlet family with CR of 89.94%. Finally, the order 1 at level 6 showed the highest performance within the Coiflets family with CR of 89.39%.

As a conclusion, from the experiments carried out, the LWE descriptors, obtained using Daubechies and Symlets wavelets at low orders and high decomposition levels (order 2 with level 7 and order2 with level 2, respectively), gave the best CR values. On the other hand, taking Coiflets wavelets, the best results were obtained at order 1 with level 6 and the performance dropped of about 0.99%.

4 CONCLUSIONS

In this study, three features descriptors called DWE, LWE and WCC, based on discrete wavelet transform are proposed for the classification of normal and abnormal PCG signals using HMM classifier. Different experiments have been carried out to find the best configuration of the HMM classifier and to select the optimal wavelet mother with its decomposition level. The results have shown that the combination of HMM model of 10 states associated to GMM of 3 Gaussian components, with LWE descriptor computed on analysis window of 20 ms duration using the mother wavelet Db2 with decomposition level 7 presented the highest performance level with CR of 92.74%. The results demonstrate the relevance and the efficiency of LWE descriptor compared to the MFCC, WCC and DWE in terms of CR and compact feature representation.

In future works, we are planning to evaluate the reference system on a larger database. The LWEs will also be tested under different noise conditions in order to observe their robustness towards noisy PCG.

REFERENCES

Alajarin, J. (2007). Classification and diagnosis of heart sounds and murmurs using artificial neural networks. 7th Proceedings of the 2nd international work-conference on The Interplay between Natural and Artificial Computation. Part I:Bio-inspired Modeling of Cognitive Tasks. SpringerVerlag Berlin. Heidelberg,.

Bentley, P., Nordehn, G., Coimbra, M., Mannor, S., & Getz, R. (2011). The PASCAL classifying heart sounds challenge. www.peterjbentley.com/heartchallenge/.

Chauhan, S., Wang, P., Lim, C., & Anantharaman, V. (2008). A computer-aided MFCC based HMM system for automatic auscultation. Comput. Biol. Med. 38 221–33.

Chen, T., Yang, S., & Ho, L. (2017). S1 and S2 Heart Sound Recognition Using Deep Neural Networks. IEEE Trans. Biomed. Eng. 64, 372–380.

Chen, T., Yang, S., Ho, L., Tsai, K., Chen, Y., Chang, Y., . . . Wu, C. (2016). S1 and S2 heart sound recognition using deep neural networks. IEEE Trans. Biomed. Eng.64.372–380 –10.

Didiot, E., Illina, I., Fohr, D., & Mella, Q. (2010). A Wavelet-Based Parameterization for Speech/Music Discrimination. Computer Speech & Language, 341-357.

Gomes, E., & Pereira, E. (2012). Classifying Heart Sounds Using Peak Location for Segmentation and Feature Construction. Aistatspp. 1–5.

Gupta, C., Palaniappan, R., Swaminathan, S., & Krishnan, S. (2007). Neural network classification of homomorphic segmented heart sounds. in Appl Soft Comput.7. 286-97.

Hacine-Gharbi, A., & Ravier, P. (2018). Wavelet cepstral coefficients for electrical appliances identification using hidden markov models. International Conference on Pattern Recognition Applications and Methods (ICPRAM).

Hanna, I., & Silverman, M. (2002). A history of cardiac auscultation and some of its contributors. Am.J. Cardiol, 90, 259–267.

Jiang, Z., & Choi, S. (2006). Cardiac sound characteristic waveform method for in-home heart. Expert Syst. Appl. 31. 286–298.

Kumar, D., Carvalho, P., Antunes, M., Gil, P., Henriques, J., & Eugenio, L. (2006). New Algorithm for Detection of S1 and S2 Heart Sounds. in Proceedings of the ICASSP. IEEE International Conference on Acoustics, speech and Signal Processing-Proceedings. Toulouse. France. Vol 2. pp.1180–1183.

Lei, L., & Kun, S. (2016). Speaker recognition using wavelet cepstral coefficient, I vector, and cosine distance scoring and its application for forensics. Journal of Electrical and Computer Engineering.

Lekram, B., & Abhishek, M. (2014). Heart sounds segmentation analysis using daubechies wavelet (db). International Journal of Research in Advent Technology. Vol.2. No.2.

Li, F., Liu, M., Zhao, Y., Kong, L., Dong, L., Liu, X., & Hu, M. (2019). Feature extraction and classification of heart sound using 1D convolutional neural networks. EURASIP J. Adv. Signal Process. p.59.

Liu, C., Springer, D., Li, Q., Moody, B., Juan, R., Chorro, F., . . . Clifford, G. (2016). An open access database for the evaluation of heart sound algorithms. Physiological Mea-surement.

Moukadem, A., Dieterlena, A., Hueberb, N., & Brandtc, C. (2013). A robust heart sounds segmentation module based on s transform. BiomedSignal Process Control. 8 273–81.

Nabih-Ali, M., EL-Sayed, A., El-Dahshan, Ashraf, H., & Yahia. (2017). Denoising of heart sound signals using discrete wavelet transform. circuits Syst Signal Process. 36. 4482–4497.

Nilanon, T., Yao, I., Hao, J., & Purushotham, S. (2016). Normal/abnormal heart sound recordings classification using convolutional neural network. Computing in Cardiology Conference (CinC), pp. 585–588, IEEE.

Numan, F., Salleh, S., Ting, C., Samdin, S., Ombao, H., & Hussain, H. (2019). A markov switching model approach to heart sound segmentation and classification. Journal of Biomedical and Health Informatics. IEEE.

Praat. (n.d.). - Télécharger praat.fr.softonic.com/.

Rahmandani, M., Nugroho, H., & Setiawan, N. (2018). Cardiac sound classification using mel-frequency cepstral coefficients MFCC) and artificial neural network (ANN). International Conference on Information Technology Information System and Electrical Engineering (ICITISEE). pp. 22-26.

Raza , A., Mehmood, A., Ullah, S., Maqsood, A., Choi, S., & Won, B. (2019). On Heartbeat Sound Signal Classification Using Deep Learning. Sensors. 19.4819. doi: 10.3390/s19214819, www.mdpi.com/journal/sensors.

Saracoglu, R. (2012). Hidden markov model-based classification of heart valve disease with PCA for dimension reduction. Eng. Appl. Artif. Intell. 25 1523–8.

Wang, P., Kim, Y., & Soh, C. (2005). Feature extraction based on Mel-Scaled wavelet transform for heart sound analysis. Medicine and Biology –Proceedings,7572-7575.

Wang, P., Lim, C., Chauhan, S., Foo, J., & Anantharaman, V. (2007). Phonocardiographic signal analysis method using a modifed hidden Markov model Ann. Biomed. Eng. 35 367–74.

Wu, H., Kim, S., & Bae, K. (2010). Hidden Markov Model with heart sound signals for identification of heart diseases. Proceedings of the International Congress on Acoustics.

YaseenSonG, Y., & Kwon, S. (2018). Classification of heart sound signal using multiple features. pplSci(Basel). 8:2344.

Young, S., Kershaw, D., Odell, J., & Ollason, D. (1999). The HTK Book. Cambridge: Entropic Ltd.