1. Asmaa N. Khaleel [1], 2. Abdulhamed M. Jasim, Abdulsattar M. Khidhir [2]

College of Electronics Engineering, Ninevah University, Ninewa, Mosul City, Iraq (1), Mosul Technical Institute, Northern Technical University, Mosul, Iraq (2)
ORCID: 1.0000-0001-8352-7884; 2. 0000-0002-2491-9789

doi:10.15199/48.2023.08.25

Efficient PCG classification system based on Slantlet transform

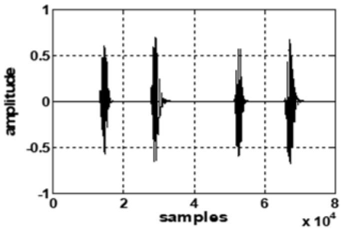
***Abstract**. Phonocardiogram (PCG) signals represent the recording of sounds and murmurs, which result from heartbeats. PCG signals analysis is critical in the diagnosis of normal and abnormal cases of the heart. A variety of methods have been proposed for PCG signals analysis. In this paper, a classification system for PCG signals is introduced based on SLT filters with detailed statistical functions and ANN algorithm. The proposed system is able to diagnose normal and four abnormal cases. The extracted features from heart sound signal are based on 3-scale slantlet filters and three statistical equations; power, average and standard deviation of the SLT filter coefficients. Based on these important features, ANN were trained and tested to obtain high overall classification accuracy. The results show that the proposed classification system is capable to diagnose the normal PCG case and other four different abnormal cases with an overall diagnosis accuracy of 98.67%. This result of the proposed system overcome other recent works.*

Streszczenie.** Sygnały fonokardiogramu (PCG) reprezentują zapis dźwięków i szmerów, które są wynikiem bicia serca. Analiza sygnałów PCG ma kluczowe znaczenie w diagnostyce prawidłowych i nieprawidłowych przypadków serca. Zaproponowano różne metody analizy sygnałów PCG. W artykule przedstawiono system klasyfikacji sygnałów PCG oparty na filtrach SLT ze szczegółowymi funkcjami statystycznymi i algorytmem ANN. Proponowany system jest w stanie zdiagnozować przypadki normalne i cztery przypadki nieprawidłowe. Cechy wyodrębnione z sygnału tonu serca są oparte na 3-skalowych filtrach skośnych i trzech równaniach statystycznych; moc, średnia i odchylenie standardowe współczynników filtra SLT. W oparciu o te ważne cechy SSN zostały przeszkolone i przetestowane w celu uzyskania wysokiej ogólnej dokładności klasyfikacji. Wyniki pokazują, że proponowany system klasyfikacji jest w stanie zdiagnozować normalny przypadek PCG i inne cztery różne przypadki nieprawidłowe z ogólną dokładnością diagnozy na poziomie 98,67%. Ten wynik proponowanego systemu przewyższa inne ostatnie prace.* (Wydajny system klasyfikacji PCG oparty na transformacji Slantleta***)

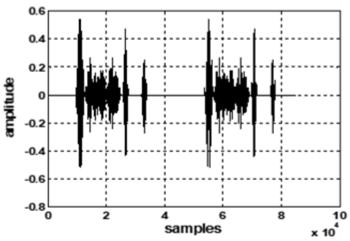
Keywords PCG Signals, Slantlet transform, Statistical Function, and ANN classifier.
Słowa kluczowe: fonokardiogram PCG, transdoemacja Slantlet

Introduction

Phonocardiogram (PCG) represents the heart sound recording and defined as the graphical representation of heart sound produced due to the mechanical activity of the heart valves and muscles through intensity, time duration, frequency and other information [1][2]. The auscultation of heart sound represents four sounds named: S1, S2 (primary major sounds) and S3,S4 (minor sounds), S1 is a low pitch sound (lub), which is longer in duration due to the closure of atrioventricular valves and when the blood flows from atri-um to ventricle. S2 is a high pitch sound (dub) produced when the blood flows from heart to the lung, which is shorter in duration [3]. The duration from S1 to S2 is known as sys-tolic period, on the other side, the duration from the next S2 to S1of the second cycle is known as diastolic period. The systolic and diastolic period together known as one cardiac cycle [2]. Normal heart sound signal can be represented with these four sounds (S1,S2,S3,S4) .



(a) normal signal



(b) abnormal signal

Fig.1 . PCG signals.

Murmurs can appear during systolic or diastolic phase, which is defined as a low frequency noise and indicates structural or functional abnormalities of the heart like stenosis or regurgitation[4] [5].

Due to the malfunctioning of the valves, if the valve dose not close or open completely, the systolic murmurs (SMs) comprise of aortic stenosis (AS) and mitral insufficiency (MI). The diastolic murmurs (DMs) comprise of aortic insufficiency (AI) and mitral stenosis (MS) and make the heart don't work properly and a certain disease occur [1]. Figure 1 shows normal and abnormal cases of PCG sign

PCG is a technique that can record the heart sound continuously for a long period of time and can also overcome the human hearing limitation. Thus, PCG plays an important role to examine the heart sound as well as abnormality of heart sounds, which improves the overall diagnosis efficient-ly [6].

The heart sound results from the movement when the valve is opening and closing; it is greatly affected by the electrical activity of the heart muscle. Heart sound auscultation can help differentiate abnormal signals from normal heart sound signals and therefore, provide effective information for the perfect diagnosis of cardiovascular diseases [7].

The heart activities have been studied and analyses previously through recordings in order to diagnose different heart cases [8]. Thus, slantlet and neural networks have been widely used in biomedical applications for analysis and classification of various signal types [9] [10].

Firstly, heart sound is obtained, it processed through a 3-scale slantlet filter, then we use a statistical calculation to decrease errors and increase the overall accuracy of the system. Many different automated classifying approaches have been used, including artificial neural network (ANN), SLT and neural networks.

Literature Review

Deep learning such as RNN, LSTM has been employed to classify PCG signals based on LSTM and GRU, where

LSTM has shown to provide better results [5]. An improved automatic classification algorithm for cardiac disorder by heart sound signal has been reported in [11]. They used Mel Frequency Cepstral Coefficient (MFCCs) and Discrete Wavelets Transform (DWT) to extract important features of PCG, then a classification was introduced to these features based on three classifiers; support vector machine (SVM), deep neural network (DNN) and centroid displacement

based on nearest neighbor. The overall maximum accuracy was reached 97.9%. On the other hand, several studies reported in literature have investigated the normal and abnormal cases classification of the heart sound. In [2], the researchers diagnosed different cardiac abnormality from the PCG signals by using the Fast Fourier Transform(FFT), with a classification accuracy reached up to 82%. Furthermore, the multi-classifier algorithms (KNN, and SVM) for recognizing the normality status of the heart sound recordings was studied. Fine-KNN classifier outperformed SVM classifier by achieving an accuracy of 93.5%.

Another study was proposed an algorithm to analyze the PCG signal beat by beat for human identification [12]. The wavelet transform used to denoising the PCG signal followed by the Hilbert envelope that was used to extract the PCG beat by beat. Based on those features, AR Burg reflection coefficients have been used for estimating each beat. The proposed work satisfied good performance compared with other methods.

In [13], several signal processing techniques were combined and applied a deep learning method to denoise, compress, segment, and classify PCG signals effectively and accurate-ly. Mel-scaled power spectrogram and Mel-frequency cepstral coefficients (MFCC) are implemented to extract many features from the PCG signal, which are then fed into a classifier to classify each PCG signal into a normal or an abnormal signal by using a deep learning approach The final accuracy of training was 98.25% with a testing accuracy of 97.10%. In addition, murmur detection system is proposed depending on the significance of frequency domain features of PCG records. The accuracy calculated reached about 87.35% [14]. Another classification algorithm of nor-mal/abnormal PCG signals by using a dynamic recurrent network called the nonlinear autoregressive network with exogenous inputs (NARX) was proposed in [15].

Moreover, deep hybrid models that took advantage of deep learning techniques to extract important features from un-structured data without the need for feature engineering have been proposed [16]. The proposed models have overcome the overfitting problem of deep learning by applying machine learning techniques to classify PCG signals accurately with less computational complexity. Additionally, a deep neural network structure based on a one-dimensional convolutional neural network (1D-CNN) and a long short-term memory network (LSTM) was introduced in [17], which can directly classify unsegmented PCG to identify the abnormal signals. Results show that the CNN-LSTM model provided a good overall balanced accuracy of 0.86 with a sensitivity of 0.87, and specificity of 0.89. Finally, a combined noise reduction method based on variational modal decomposition (VMD) and wavelet soft threshold algorithm (WST) was proposed. Features were extracted after denoising and employed for an intelligent diagnosis model to verify the effect of the denoising method. Intelligent classification showed that the accuracy, sensitivity and specificity of the classification system for congenital heart diseases were 92.23, 92.42, and 91.89%, respectively and better than those with WST only [18].

Theoretical Background

In this proposed work, the PCG signals can be analyzed and classified based on the slantlet transform (SLT) followed by a set of statistical functions to extract the reduced heart signals characteristics. These features can be used as an input data for the artificial neural network ANN to obtain an efficient classification system.

Slantlet Transform

Slantlet Transform (SLT) is a multi-resolution technique which is suitable for a piecewise linear data. Just like DWT, the SLT is orthogonal and can offer multi-resolution decomposition. Moreover, they provide an octave band and zero-moment characteristics, SLT filters can take the same minimum number of levels of decomposition like DWT [19]. The filters of SLT are implemented in a parallel structure by employing different filters for each scale, whereas the DWT filters are usually implemented as a tree structure based on filter bank iteration. In this paper, the PCG feature extraction can be obtained based on 3-scale SLT. The three scale of SLT structure is shown in Fig.(2)

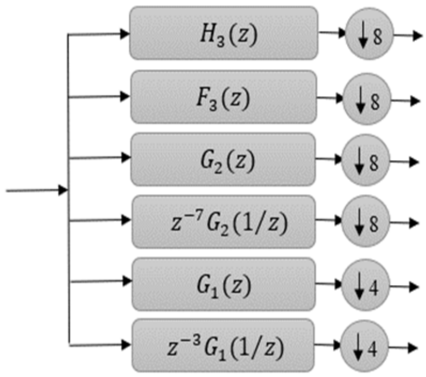


Fig. 2. SLT (3-scale) filter banks structure.

Table 1: Coefficients values of SLT filters.

H3 Coefficients	F3 Coefficients	G2 Coefficients	G1 Coefficients
h(0)=0.167	h(0)=-0.0526	h(0)=-0.5062	h(0)=-0.5117
h(1)=0.2112	h(1)=-0.0665	h(1)=-0.0874	h(1)=0.8279
h(2)=0.2554	h(2)=-0.0804	h(2)=0.3314	h(2)=-0.1208
h(3)=0.2996	h(3)=-0.0943	h(3)=0.7502	h(3)=-0.1954
h(4)=0.3438	h(4)=-0.1082	h(4)=-0.0793	
h(5)=0.388	h(5)=-0.1221	h(5)=-0.1078	
h(6)=0.4322	h(6)=-0.1360	h(6)=-0.1362	
h(7)=0.4764	h(7)=-0.1500	h(7)=-0.1646	
h(8)=0.1866	h(8)=0.5926		
h(9)=0.1424	h(9)=0.4522		
h(10)=0.0982	h(10)=0.3118		
h(11)=0.054	h(11)=0.1715		
h(12)=0.0098	h(12)=0.0311		
h(13)=-0.0344	h(13)=-0.1093		
h(14)=-0.0786	h(14)=-0.2497		
h(15)=-0.1228	h(15)=-0.3901		

The SLT filters; H3, F3, G2, and G 1 are set of parallel filters which have set of coefficients. These coefficients can be calculated based on the equations reported in [19]. The SLT filters coefficients values of each filter are explained as shown in Table 1.
H3 Coefficients F3 Coefficients G2 Coefficients G1 Coefficients

Statistical Functions

The size of slantlet coefficients which are extracted from the PCG signals can be reduced based on set of statistical equations. The statistical functions used are as follows [20]:

Power Equation

The average power of the slantlet coefficients in each sub filter can be calculated based on equation (1):

(1) $$\mathbf{P} = \frac{1}{\mathbf{N}}\sum_{\mathbf{n}=\mathbf{0}}^{\mathbf{N}}(\mathbf{Xn})^{2}$$

Average Equation

The average value for each SLT filter can be calculated based on equation (2):

(2) $$\mathbf{av} = \frac{1}{\mathbf{N}}\sum_{\mathbf{n}=\mathbf{0}}^{\mathbf{N}} \mathbf{Xn}$$

Standard Deviation (sd)

The standard deviation (sd) for each SLT filter is computed due to the following equation:

(3) $$\mathbf{sd} = \sqrt{\frac{\sum_{\mathbf{n}=\mathbf{1}}^{\mathbf{N}}(\mathbf{x_n}-\mathbf{P})^{2}}{\mathbf{N}}}$$

The general structure of the proposed algorithm for PCG signals classification can be illustrate in Fig.3 below:

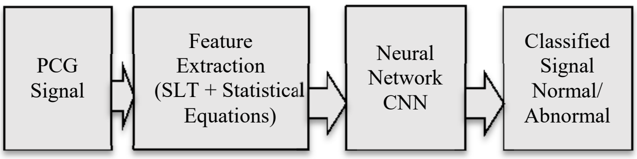


Fig.3. General Structure of Proposed system.

The features extracted from PCG signals are based on the 3-scale SLT which can be concatenated as an one vector. It followed by some of statistical functions to select the most important features of PCG signals. The resulted features used as input vectors to ANN. The ANN classifier used to classify the normal and 4-abnormal cases of PCG signals.

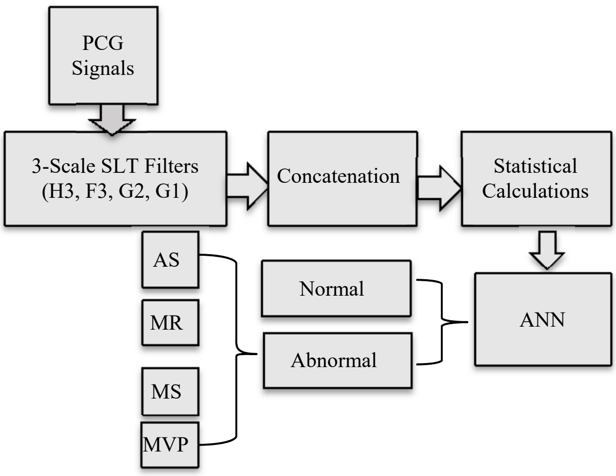


Fig.4. Proposed classification system diagram

Artificial Neural Networks

Artificial Neural Networks (ANNs) are machine learning algorithms based on studies of the brain and nervous system, which involves computations and mathematics. Many fields have used this technique such as signal classification, image identification, voice recognition …etc. Similar to the human brain structure, ANN models have a specific architecture inspired by a biological nervous system. The ANN models are formed of neurons in a nonlinear form. The neurons are connected to each other by weighted links. Data collection and analysis, network structure design and simulation, number of hidden layers, and weights/bias trade-off, are all computed throughout learning and training methods. The ANN falls into three categories: pattern classification, prediction, and control and optimization [21].

In this paper, beside the input and output layers, the proposed classifier has one hidden layer with 30 neurons with tansig activation function. The proposed MLP ANN classifier can diagnose normal and four abnormal cases (AS, MR, MS, or MVP). Figure (5) illustrates the proposed designed ANN for PCG classification. Figure (6) illustrates the performance of the proposed classifier.

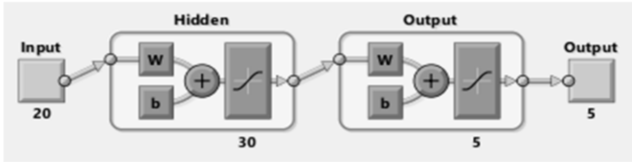


Fig.5. proposed ANN classifier

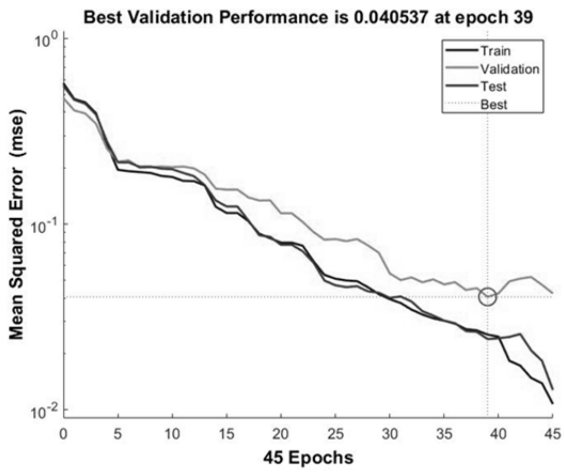


Fig.6. Performance of proposed classifier.

Experimental Results

In this section, the database of PCG collection of heart sound cases according to (normal & abnormal) and then the classifier diagnoses the 4 abnormal cases into (AS, MR, MS & MVP). These dataset collections of normal and abnormal cases are given by the worldwide challenge PhysioNet that offers a free download of the dataset in their website. The dataset includes 51 normal PCG records, 48 Aortic stenosis, 41 Mitral Regurgitation murmur signal, 51 Mitral stenosis and 37 MVP signals, as shown in Table 2 .

The format of all these signals is in s.wav. In this paper, PhysioNet Computing in Cardiology Challenge database is used, 228 PCG signals distributed into normal and abnormal cases with sampling frequency 8KHZ and these were used for evaluating the performance and accuracy of the desired algorithm.

Table 2 PCG dataset collection

Total data	Normal data	Abnormal data
226	51	AS = 48 case
		MR = 39 case
		MS = 51 case
		MVP = 37 case

The ANN is training 25 cases for each of the normal and the four abnormal PCG signals, the remaining of the overall signals of each case that is called a (test cases) is entered to a desired algorithm then the actual accuracy and error for each case is computed. The actual accuracy is defined as the number of correctly predicted data points out of all the data points [22].

(4) Accuracy= N/A

Where N is the number of testing samples which are correctly classified, A denotes to the total testing samples in that class [12]. The obtained results of proposed system shown in Table 3, with overall accuracy reached up to 98.67%.

Table 3. Accuracy of the proposed system

Experiment	Actual class	Predicted class		Accuracy (%)
		True	False	
Normal	51	51	0	100%
AS	48	48	0	100%
MR	39	39	0	100%
MS	51	51	0	100%
MVP	37	34	3	91.89%
Total	226	223	3	98.67%

Tabke e 4. Comparison between the proposed PCG classification and other recent works

Recent Works	Features Extraction	Classifier	Accuracy (%)
Ref. [18]	combined algorithms (VMD and WST)	ANN	92.42%
Ref. [23]	Transfer learning with MFCC	CNN	89.5%
Ref. [24]	MFCC, CQT, variable-Q transform, and HCQT	CNN	96%
Ref. [11]	MFCCs + DWT	SVM, DNN,and KNN	97%
Ref. [20]	DWT with some statistical functions	ANN	96.33%
Proposed work	SLT with some statistical functions	ANN	98.67%

From the results shown in Table 3, it is clear that the pro-posed system for PCG features extraction showed impres-sive results compared with the classification systems re-sults of some other recent works in this field. The perfor-mance of the introduced classification system in this work with other works are compared in Table 4. It can be seen from Table 4 that the PCG features extracted based on 3-scale SLT filters with statistical equations led to promising results and an efficient classification system .

Conclusion

This paper introduced classification system for PCG signals based on SLT filters with some statistical functions and ANN algorithm. The proposed system is able to diagnose normal and four abnormal cases (AS, MR, MS, and MVP). The extracted features from heart sound signal are based on 3-scale slantlet filters and three statistical equations; power, average and standard deviation of the SLT filter coefficients. Based on these important features, ANN has been trained and tested to obtain high overall accuracy classification. The proposed classification system is capable to diagnose the normal PCG case as well as other four different abnormal cases with an overall accuracy of diagnosis that reached up to 98.67%. This result of the proposed system overcome other recent works reported in literature.

REFERENCES

[1] Varshney, Shivam, and Satyendra Singh. "Murmur Detection in PCG signals using DWT Entropy and Feature Clustering." In 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), pp. 1-6. IEEE, 2020.

[2] Gopika, P., V. Sowmya, E. A. Gopalakrishnan, and K. P. Soman. "Performance improvement of deep learning architectures for phonocardiogram signal classification using fast fourier transform." In 2019 9th international conference on advances in computing and communication (ICACC), pp. 290-294. IEEE, 2019.

[3] Al Ghawas, Mohamad, and Rand Al Muallem. "Electronic Stethoscope And Heart Rate Monitor." Near East University (2015).

[4] Bashar, Md Khayrul, Samarendra Dandapat, and Itsuo Kumazawa. "Heart Abnormality Classification Using Phonocardiogram (PCG) Signals." In 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES), pp. 336-340. IEEE, 2018.

[5] Sujadevi, V. G., K. P. Soman, R. Vinayakumar, and AU Prem Sankar. "Deep models for phonocardiography (PCG) classification." In 2017 International Conference on Intelligent Communication and Computational Techniques (ICCT), pp. 211-216. IEEE, 2017.

[6] Chowdhury, Md, K. Poudel, and Y. Hu. "Detecting Abnormal PCG Signals and Extracting Cardiac Information Employing Deep Learning and the Shannon Energy Envelope." In 2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB), pp. 1-4. IEEE, 2020.

[7] Niedziejko, P., P. Dobrowolski, and I. Krysowaty. "Współczesne metody analizy dźwięku serca." Przegląd Elektrotechniczny 87, no. 9a (2011): 1-7.

[8] Gradolewski, Dawid, Piotr Tojza, and Grzegorz Redlarski. "Adaptacyjny algorytm filtracji sygnału fonokardiograficznego wykorzystujący sztuczną sieć neuronową." Przegląd Elektrotechniczny (2014): 227-230.

[9] Mrad, Mohamed Azouz, Kristóf Csorba, Dorián László Galata, Zsombor Kristóf Nagy, and Brigitta Nagy. "Spectroscopy-Based Partial Prediction of In Vitro Dissolution Profile Using Artificial Neural Networks." Periodica Polytechnica Electrical Engineering and Computer Science 66, no. 2 (2022): 122-131.

[10] Thabit, Rasha. "Multi-biometric watermarking scheme based on interactive segmentation process." Periodica Polytechnica Electrical Engineering and Computer Science 63, no. 4 (2019): 263-273.

[11] Son, Gui-Young, and Soonil Kwon. "Classification of heart sound signal using multiple features." Applied Sciences 8, no. 12 (2018): 2344.

[12] Fahad, Imran, Md Ashiqur Rahman Apu, Abesh Ghosh, and Shaikh Anowarul Fattah. "Phonocardiogram heartbeat segmentation and autoregressive modeling for person identification." In TENCON 2019-2019 IEEE Region 10 Conference (TENCON), pp. 1942-1946. IEEE, 2019.

[13] Chowdhury, Tanzil Hoque, Khem Narayan Poudel, and Yating Hu."Time-frequency analysis, denoising, compression, segmentation, and classification of PCG signals." IEEE Access 8 (2020): 160882-160890. [11] P. Careena1, M. Mary Synthuja Jain Preetha and P. Arun "Significance of Frequency Domain Features of PCG Records for Murmur Detection - An Investigation",2020

[14] Careena, P., M. Mary Synthuja Jain Preetha, and P. Arun. "Significance of Frequency Domain Features of PCG Records for Murmur Detection--An Investigation." Biomedical and Pharmacology Journal 13, no. 2 (2020): 555-570.

[15] Khaled, Sara, Mahmoud Fakhry, and Ahmed S. Mubarak. "Classification of pcg signals using a nonlinear autoregressive network with exogenous inputs (narx)." In 2020 International Conference on Innovative Trends in Communication and Computer Engineering (ITCE), pp. 98-102. IEEE, 2020.

[16] Chowdhury, M., C. Li, and K. Poudel. "Combining Deep Learning with Traditional Machine Learning to Improve Phonocardiography Classification Accuracy." In 2021 IEEE Signal Processing in Medicine and Biology Symposium (SPMB), pp. 1-5. IEEE, 2021.

[17] Chen, Ding, Weipeng Xuan, Yexing Gu, Fuhai Liu, Jinkai Chen, Shudong Xia, Hao Jin, Shurong Dong, and Jikui Luo. "Automatic Classification of Normal–Abnormal Heart Sounds Using Convolution Neural Network and Long-Short Term Memory." Electronics 11, no. 8 (2022): 1246.

[18] Zhang, Anqi, Jiaming Wang, Fei Qu, and Zhaoming He. "Classification of Children's Heart Sounds With Noise Reduction Based on Variational Modal Decomposition."

Frontiers in Medical Technology 4 (2022).
[19] Ivan, W. S. "The slantlet transform." IEEE Trans Signal Proces 47 (1999): 1304-1313.
[20] MOHAMED, BOUSSAA, BENRABH MOHAMED, ATOUF ISSAM, ATIBI MOHAMED, And BENNIS ABDELLATIF. "IMPLEMENTATION OF A PCG SIGNAL CLASSIFICATION SYSTEM IN THE FPGA EMBEDDED PLATFORM." Journal Of Theoretical & Applied Information Technology 96, No. 7 (2018).
[21] Park, Y-S., and S. Lek. "Artificial neural networks: Multilayer perceptron for ecological modeling." In Developments in environmental modelling, vol. 28, pp. 123-140. Elsevier, 2016.
[22] Chowdhury, Tanzil Hoque, Khem Narayan Poudel, and Yating Hu. "Time-frequency analysis, denoising, compression, segmentation, and classification of PCG signals." IEEE Access 8 (2020): 160882-160890.
[23] Alafif, Tarik, Mehrez Boulares, Ahmed Barnawi, Talal Alafif, Hassan Althobaiti, and Ali Alferaidi. "Normal and abnormal heart rates recognition using transfer learning." In 2020 12th International Conference on Knowledge and Systems Engineering (KSE), pp. 275-280. IEEE, 2020.
[24] Tiwari, Shamik, Anurag Jain, Akhilesh Kumar Sharma, and Khaled Mohamad Almustafa. "Phonocardiogram signal based multi-class cardiac diagnostic decision support system." IEEE Access 9 (2021): 110710-110722.