A Deep Neural Network Model for Automated Heart Disease Classification

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Abstract: Heart related diseases presently pose one of the major threat worldwide. Heart abnormalities show a wide variation because of which accurate diagnosis becomes challenging. Phonocardigram (PCG) signals and their analysis has opened up a new paradigm in telemedicine. The abrupt fluctuations and the randomness of the PCG signals make them difficult to analyze and extract key parameters called features. Conventional Fourier techniques fail in this regard. In this paper, we have proposed a wavelet based technique wherein the discrete wavelet transform (DWT) have been used for the processing and feature extraction of the PCG signals has been done subsequently. The features extracted are energy, variance, entropy and standard deviation. The features extracted can be subsequently utilized for the classification of the PCG signals using the Conjugate Gradient Algorithm. The three categories of classified are: stenosis, regurgidation and normal. It has been shown that the proposed algorithm attains an accuracy of 93%.

Keywords:-
ECG-Electrocardiogram , PCG-Phonocardiogram, AS- Aortic Stenosis , AR- Aortic Regurgitation , MS- Mitral Stenosis, MR- Mitral Regurgitation , DWT- Discrete Wavelet Transform, ENER-Energy ,STD-Standard Deviation,VAR-Variance, NHS- Normal Heart Sound, Conjugate Gradient.

I. Introduction

The heart is divided into chambers namely atrium and ventricles. The upper two chambers are known as atria while the lower two chambers are known as ventricles. Heart muscles squeeze the blood from chamber to chamber. During this squeezing process, the valves help the blood to keep flowing smoothly in and out of the heart. This is done by automatically opening of valves to let blood from chamber to chamber and closing to prevent the backflow of blood [1]. Heart sounds are the composite sounds produced by myocardial systolic and diastolic, hoist valve, blood flow and cardiovascular vibration impact, and contain a great deal of physiological and pathological information regarding human heart and vascular.

Research on diagnosis of cardiac abnormalities using wavelet techniques has been carried out from the past few years, due to its good performance in analyzing the signals that present non stationary characteristics, this technique has eventually become a powerful alternative when compared to the traditional Fourier Transform (FT) [1] [2].Fig.1 shows the normal heart sounds, composed of four different sounds, namely S1, S2, S3 and S4.The pumping action of a normal heart is audible by the 1st heart sound (S1) and 2nd heart sound (S2). During systole, the AV valves are closed and blood tries to flow back to the atrium, causing back bulging of the AV valves. But the taut chordatetendineae (cord-like tendons that connect the papillary muscles to the tricuspid valve and the mitral valve in the heart) stop the back bulging and causes the blood to flow forward. This leads to vibration of the valves, blood and the walls of the ventricles which is presented as the 1st heart sound. During diastole, blood in the blood vessels tries to flow back to the ventricles causing the semi lunar valves to bulge. But the elastic recoil of the arteries cause the blood to bounce forward which vibrates the blood, the walls and the ventricular valves which is presented as the 2nd heart sound . The 3rd heart sound (S3) is heard in the mid diastole due to the blood that fills the ventricles. The 4th heart sound (S4), also known as atrial heart sound, occurs when the atrium contracts and pumps blood to the ventricles. S4 appears with a low energy and is almost never heard by the stethoscope [3].

PCG is the graphical representation of heart sounds and murmurs. The timing and pitch of a heart sound are of significant importance in a diagnosis of a heart condition [4]. The features of a PCG signal such as heart sounds, the number of components for each sound, their frequency content and their time interval, can be measured more accurately by recent digital signal processing techniques [5]. According to the advances of signal processing techniques, PCG can be a useful diagnostic tool, revealing information that the human ear cannot offer. Due to this, expert PCG-based systems can be made. A new tentative to materialize such systems can be found in [5, 6, 7]. Compared to ECG, PCG diagnosis is much easier by just placing the stethoscope against the skin. The current problem with many PCG systems is noises from the sounds of breathes, contact of the stethoscope with the skin and other ambient noises, which may corrupt the heart signals. Consequently, the PCG would be much more useful for diagnosis in home care system, if the noises were eliminated. The PCG is of major importance to achieve a basic diagnosis when high-cost techniques, like echocardiography, are not available [7][12][14]. To record PCG signal waveform, a large amount of data is stored. Therefore, using the compression methods, one can reduce the space of the PCG signal data. The main goal of any compression technique is to attain maximum data reduction while preserving the significant signal morphology features upon reconstruction.[11][15]

II. Materials and methods

Congenital heart defects or acquired heart valve diseases are often the cause of abnormal heart murmurs. Aortic stenosis, mitral regurgitation, aortic regurgitation, and mitral stenosis are among the most common pathological types of murmurs. [13]

A. Input Heart Signal obtainment:

Input heart signals for investigation are downloaded from standard biomedical website, these signals are converted into (.wav) format. They are:

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- Normal Heart Sound
- Aortic Stenosis
- Mitral Stenosis
- Aortic Regurgitation
- Mitral Regurgitation

1) Normal Heart Sound

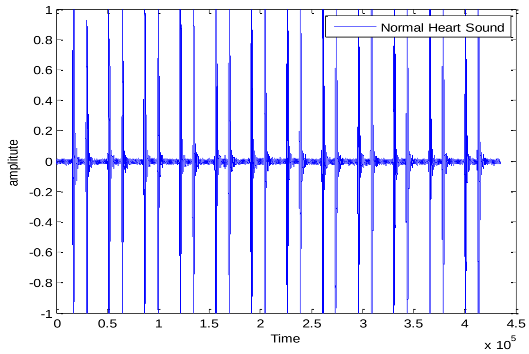

Fig.1 Normal heart sound

2) Aortic Stenosis

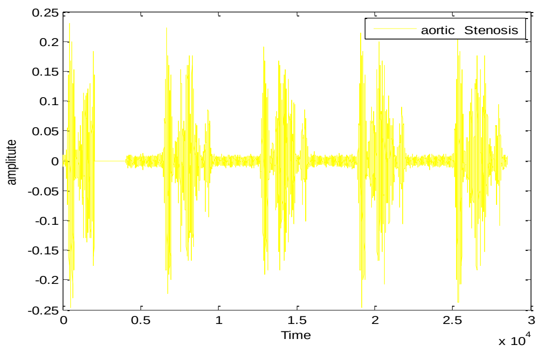

Fig.2Aortic Stenosis

3) Mitral Stenosis

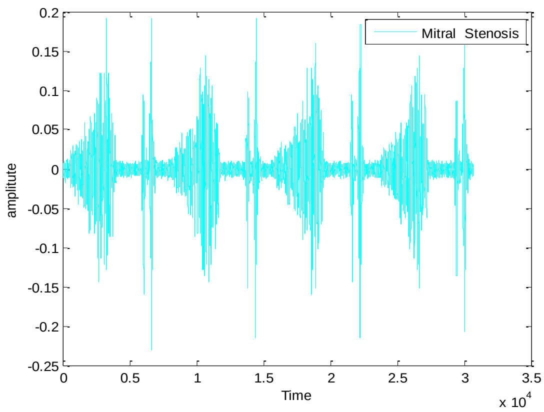

Fig3: Mitral Stenosis

4) Aortic Regurgitation

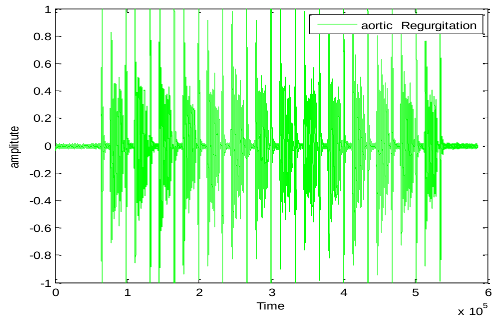

Fig4: Aortic Regurgitation

5) Mitral Regurgitation

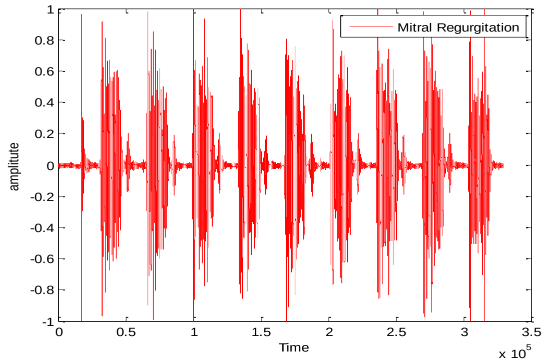

Fig5: Mitral Regurgitation

B. Discrete wavelet transform

Wavelet analysis has practically become a ubiquitous tool in signal processing. Two basic properties, space and frequency localization and multi-resolution analysis, make this a very attractive tool in signal analysis. The wavelet transform method processes perfect local property in both time space and frequency space and it use widely in the region of vehicle faults detection and identification. The general definition of the wavelet transform is given as [9]:

$$W(a, b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{a}} \boldsymbol{\psi} * \left\{\frac{t-b}{a}\right\} dt \quad \text{.............(i)}$$

Where a and b are real and*denote complex conjugate and (t) is wavelet function.

The wavelet acts a signal filter for the fluctuating PCG signal.

C.Parameters

1) Variance

Variance is defined as Mean Square value of the signal, computed after the mean value has been removed.

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(xi-\mu)^2 \quad \text{....... (ii)}$$

σ=Variance, N=no of samples, Xi=input heart signal μ= mean

2) Standard Deviation

Standard Deviation (s) is defined as Square root of the variance i.e. MS value of the signal, computed after the mean value has been removed

$$S=\sqrt{\sigma^2} = \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(xi-\mu)^2} \quad \text{...... (iii)}$$

3) Energy

The energy of the signal can be computed as the squared sum of its spectral coefficients' normalized by the length of the sample window. The energy metric has been used to identify the mode of transport of a user with a single accelerometer, respectively walking, cycling, running and driving.

$$E_f=\sum_{-\infty}^{\infty} \left|x[n]\right|^2 \quad \ldots\ldots\ldots\ldots \text{(iv)}$$

4) Entropy

Entropy is used to measure a system's level of disorder in physics of thermodynamics. Entropy measurement is an ideal method in order to measure the level of disorder of a non-stationary signal. Besides, entropy is also being used for the purpose of measuring the average amount of information that an event contains.

Entropy = -sum (P * log (P)). (P=probability vector) ….(v)

III Scaled Conjugate Gradient (SCG) Algorithm

The algorithm employed in this study is the scaled conjugae gradient or SCG algorithm based on the steepest descent approach which happens to attain faster convergence compard to existing gradient descent approaches.

The scaled conjugate gradient (SCG) algorithm is an algiruthm used for:

1) Low memory applications
2) Applications using large data sets in real time situations.

The training rule for the SCG algorithm is given by:

$$w_{k+1} = w_k - \left[H_k\sqrt{g} - \mu\right] I H_k e_k \ldots\ldots\ldots\ldots \text{(vi)}$$

Here,

W_{k+1} is the weight of next (k+1) iteration

W_k is the weight of the present iteration

H_k is the Hessian Matrix $\frac{\partial e}{\partial w} \cdot \frac{\partial e}{\partial w}^*$

Here * represents the complex conjugate of the matrix

g is the gradient and defined as $\frac{\partial e}{\partial w}$

e_k is the error of the present iteration.

IV Experimental results

In this study, the data set is classified using the DWT and SCG algo.

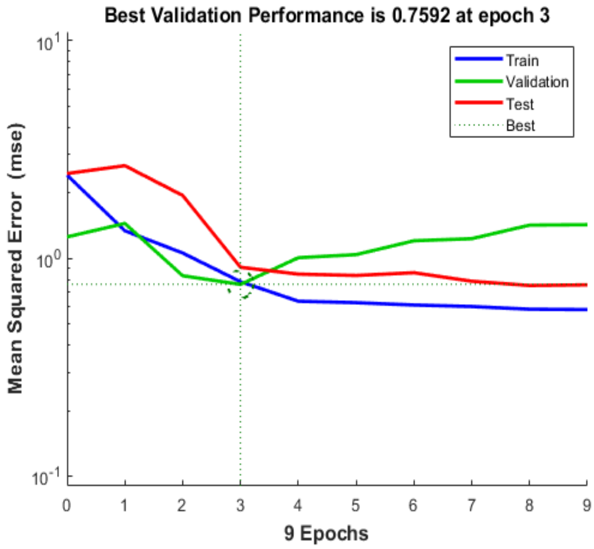

Fig.6 Variation of MSE with respect to epochs

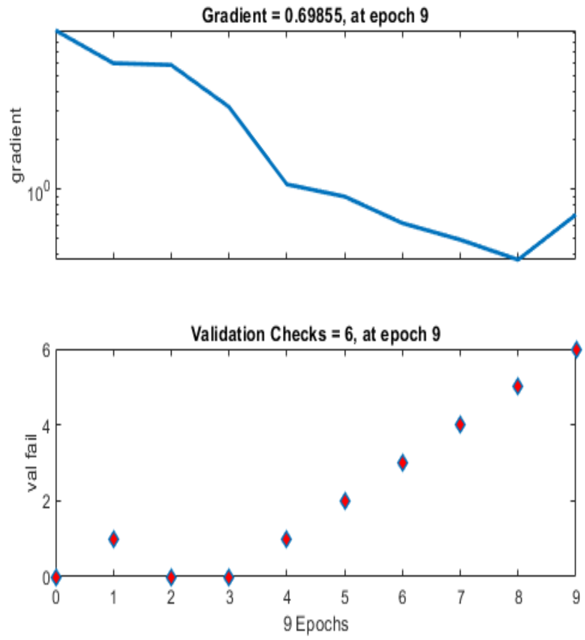

Fig.7 Training States

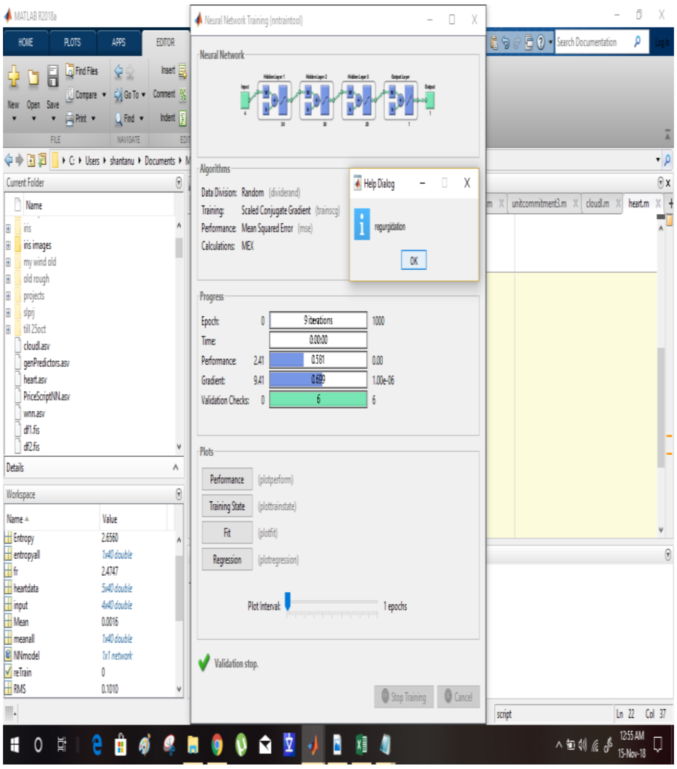

Fig.8 Final Classification using ANN

VI -Conclusion

In this study, a biomedical-based system has been developed for the feature Extraction of heart sound signals obtained from normal and diseased signlas. The diseased signals are stenosis and regurgidation. In the first stage, DWT is used for signal smoothening. This removes the artifacts and noise effects of the signals. The features extracted are energy, variance, entropy and standard deviation. The features extracted can be subsequently utilized for the classification of the PCG signals using the Scaled Conjugate Gradient (SCG) Algorithm. The three categories of classified are: stenosis, regurgidation and normal. It has been shown that the proposed algorithm attains an accuracy of 93%%. It can be seen that it performs better compared to previously existing techniques.[20]

REFERENCES

[1] P.T. Krishnan, P.Balasubramanian, P., S.Umapathy, “Automated heart sound classification system from unsegmented phonocardiogram (PCG) using deep neural network”. Springer, 2023, Vol.43, pp.505–515.
[2] Zhao Ren, Nichols Cummins, Vedhas Pandit, Jing Han, Kun Qian, Bjorn Schuller, “Learning Image-based Representations for Heart Sound Classification”, ACM 2022
[3] TE Chen, SI Yang, LT Ho, KH Tsai, “S1 and S2 heart sound recognition using deep neural networks”, IEEE 2021
[4] MN Homsi, N Medina, M Hernandez, “Automatic heart sound recording classification using a nested set of ensemble algorithms”, IEEE 2020
[5] SK Randhava, M.Singh, “Classification of heart sound signals using multi-modal features”, Elsevier 2019
[6] João Pedrosa , Ana Castro, Tiago T. V. Vinhoza, “Automatic heart sound segmentation and murmur detection in paediatric phonocardiograms, IEEE 2018
[7] Anita Devi, Abhishek Misal, “A Survey on Classifiers Used in Heart Valve Disease Detection”, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Vol. 2, Issue 1, January 2017
[8]Abhishek Misal, G. R. Sinha, “Separation of Lung Sound from PCG Signals Using Wavelet Transform”, Journal of Basic and Applied Physics, Vol. 1 Iss. 2, PP. 57-61, Aug. 2016
[9] Harun Uguz, “Adaptive Neuro-fuzzy Inference System for Diagnosis of the Heart Valve Diseases Using Wavelet Transform with Entropy”, Neural Comput & Applic 2012, Springer-verlag London Limited, Pg No.1617–1628, April 2015.
[10]Abhishek Misal , G.R.Sinha , R. M. Potdar, M. K. Kowar, “Comparison Of Wavelet Transforms For Denoising And Analysis Of PCG Signal”, I-Manager’s Journal On Communication Engineering And Systems, Vol. 1 , No. 1 ,November 2011 - January 2014
[11] B. Ergen, Y. Tatar, and H. O. Gulcur, “Time-frequency analysis of phonocardiogram signals using wavelet transform: a comparative study,” Computer Methods in Biomechanics and Biomedical Engineering, 2013
[12] Hong Tang ; Ting Li ; Yongwan Park ; Tianshuang Qiu, “Separation of Heart Sound Signal from Noise in Joint Cycle Frequency–Time–Frequency Domains Based on Fuzzy Detection, IEEE 2012
[13L. HamzaCherif,S.M.Debbal,F.Bereksi-Reguig, “Choice of the wavelet analyzing in the phonocardiogram signal analysis using the discrete and the packet wavelet transform, ELSEVIER 2011
[14] Zümray Dokur Tamer Ölmez, “Feature determination for heart sounds based on divergence analysis, ELSEVIER 2010
[15] Sepideh Babaeia, Amir Geranmayeh, “Heart sound reproduction based on neural network classification of cardiac valve disorders using wavelet transforms of PCG signals, ELSEVIER 2009
[16] Mustafa Yamacli ; Zumray Dokur ; Tamer Olmez, “Segmentation of S1–S2 sounds in phonocardiogram records using wavelet energies, IEEE 2008
[17] Zümray Dokur, Tamer Ölmez, “Heart sound classification using wavelet transform and incremental self-organizing map, ELSEVIER 2008
[18] S. M. Debbal and F. Bereksi-Reguig, “Automatic measure of the split in the second cardiac sound by using the wavelet transform technique”, Computers in Biology and Medicine, vol. 37, pp. 269-276, 2007
[19] D. Kumar, P. Carvalho, M. Antunes, P. Gil, J. Henriques, L. Eug´enio , “A New Algorithm for Detection of S1 and S2 Heart Sounds”, IEEE transaction,2006
[20] https://www.healthline.com/health/heart-disease/statistics