Classification of Heart Sound Signals for the Detection of Heart Diseases

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***Abstract*—This paper proposed the classification of heart sound signals for the detection of heart diseases. The heart sound signals were acquired from pediatric patients of National Heart Institute, Kuala Lumpur. Each signal was characterized by applying Nonlinear ARX (NARX) model and weight parameters of each disease were estimated. Prior to classification, the spectrogram was applied to the modeled signal for feature extraction and selection. The obtained frequency pattern features were fed to the FFNN and trained using Resilient Backpropagation (RPROP) algorithm. With optimized learning parameter of 0.07, the network gave its best performance at 32-220-6. The accuracy of the network when validated with the diagnostic test was above 97% which suggested that the network performed well and was operating as gold standard. The classification of heart diseases was further improved to 100% when overall testing was performed.**

***Index Terms*— heart sounds, heart valve disease, MLP, NARX model, and Spectrogram.**

I. INTRODUCTION

Cardiovascular Disease (CVD) is a disease affecting the heart or blood vessel [1]. It begins when cholesterol, fatty material and calcium build up in the arteries causing them to narrow so that oxygen delivery to the heart is reduced. In Malaysia, the CVD has been the principle cause of death in government hospitals accounting for 23% to 26% of deaths from 1994 to 2001 [2].

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Heart Valve Disease is among majority cases of CVDs occurred in Malaysia. It can be acquired due to heart problems in someone's life or can be a defect of the heart structure of a newborn. It happens when the valves do not open (stenosis) or close (regurgitation) completely to permit blood flow in one direction during the cardiac cycle [3]. Heart sounds are created during the closure of these heart valves. One way of detecting the abnormality of the heart at an early stage is through auscultation process, by using a stethoscope. It is economic, efficient [4] and of great assistance to every doctor and medical students.

There are a lot of studies being done to quantify the heart sound characteristics using Digital Signal Processing (DSP) techniques [5-8]. Previous literature works had demonstrated the analysis of heart sound using linear modeling and classification technique was designed and implemented using various methods and algorithms. From the analysis, various heart valve-related diseases can be detected and classified in an automatic way. The accuracy of the resulting model for classifying certain heart diseases with linear modeling varies from 88.5% to 91.6% [9]. Lately, it has been suggested that the heart dynamics may be nonlinear [10][11]. Xu *et. al.* [11] adapted a nonlinear transient chirp signal modeling approach and successfully extracted the Aortic (A_2) and Pulmonary (P_2) component of pig's heart. He validated the result by using Normalised root-mean-square error (NRMSE) to estimate the error between the original signal and its reconstructed version. Another research on nonlinear analysis was done by Hadjileontiadis *et. al* [10] who had introduced higher-order statistics to discriminate the heart sounds. The proposed analysis takes into account the non-linearities of the signal, since it preserves

the phase information, and assumes that heart sounds are non-Gaussian process. Shamsuddin and Taib [12] had also successfully modeled selected heart sounds using nonlinear ARX (NARX) model with the average R-square above 99.9%. The proposed model uses ARX model as regression vector and Neural Network as nonlinear model structures. In her analysis, six NARX models have been successfully developed for modeling six different heart diseases.

This paper describes the work of classifying the modeled heart sound signals which consist of Normal and several heart-valve related diseases such as Atrial Septal Defect (ASD), Pulmonary Stenosis (PS), Patent Ductus Arteriosus (PDA), Ventricular Septal Defect (VSD) and Mitral Regurgitation (MR). The study extends the work done by Shamsuddin and Taib [12] in which the analysed weight parameters estimated from each disease are used to model the signals prior to its classification. For feature extraction, spectrogram is used to extract the heart sound frequency patterns. These patterns together with their simulated noise of Signal to Noise Ratio (SNR) ranging from 1dB to 20dB are fed into the Feed Forward Neural Network (FFNN). The number of hidden neurons is optimized at 60, 100, 220 and 260. With hidden neurons of 220, the accuracy of the network to detect Normal and all diseases is 97%. The accuracy of the network is further improved to 100% when the heart sound signals are tested in the overall system.

II. Nonlinear ARX (NARX) Model

The NARX model has been shown to perform well in a variety of applications [13-17]. It has not been popular in the analysis of biomedical area but its applications elsewhere has shown high success rate. The NARX structure is an extension of the linear ARX structure and has a more flexible nonlinear mapping function such that:

$$\hat{y}(t) = F[\, y(t-1), \ldots, y(t-n_y), u(t-1), \ldots, u(t-k-n_u)] \quad (1)$$

$$= F\,[\varphi(t)] \quad (2)$$

where F is a MLP network as nonlinear function, $y(t)$ and $u(t)$ represents the output and input respectively. n_y and n_u are their associated maximum lags and k is the system deadtime ($k \geq 1$). The regression vectors, $\varphi(t)$, are the input to the MLP Network.

III. Spectrogram

Spectrogram is one of the Time Frequency representations (TFR) of a signal. It uses the periodogram power spectrum estimation method and plot the signal in time and frequency axis. The spectrogram uses Short Time Fourier Transform (STFT) formula to localize the signal by modulating it with a window function before performing the Fourier Transform (FT) [18]. It segments the signal into a number of small overlapping records, each record is assumed to be stationary. All sub records are multiplied with an appropriate window in order to reduce the effect of leakage due to time truncation of the signal. Then, a FFT algorithm is applied to each segment. The STFT is represented as [19] :

$$S(t,f) = \left| \int_{-\infty}^{\infty} h(\tau)\, x(t-\tau) e^{-j2\pi f \tau}\, d\tau \right|^2 \quad (3)$$

where $h(\tau)$ is the window function and $x(\tau)$ is the heart disease signal.

The window function used in the study was Hamming window which is given by :

$$w[i] = 0.42 - 0.5\cos(2\pi\, i/M) + 0.08\cos(4\pi\, i/M) \quad (4)$$

where M is the number of points used in the moving average filter.

The length of the intervals for the spectral analysis to be performed must be a power of two in order to use FFT. There is a trade off between frequency resolution and the resolution of details in the time domain. The higher the samples of NFFT, the better the frequency resolution is, and the poorer the temporal solution and vice versa. To improve the resolution in the time domain the time intervals can be overlapped to each other.

IV. Classifier

The FeedForward Neural Network (FFNN) is chosen to classify Normal and other heart diseases into ASD, VSD, PDA, MR and PS. The network consists of two layers: a hidden layer of S^1

neurons with tangent-sigmoid transfer function, and an output layer of two-neurons with linear transfer function. The multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between inputs and outputs. The proposed neural network architecture is illustrated as in the Fig. 1.

The inputs to neural network are from each individual point of the heart-sound in frequency domain. The training targets are denoted by logic 0 or 1. If a FFT signal of a certain heart sound is input to the neural network, the associated output will be "on" and produces 1, the rest of outputs will be "off" and produces 0.

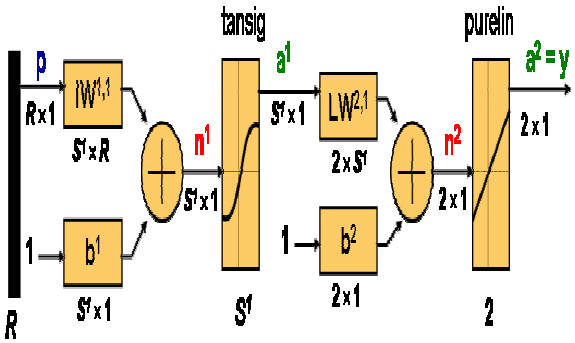


Fig. 1. The proposed network

$$a^2 = \text{purelin}(LW^{2,1} \times \text{tansig}(IW^{1,1}p + b^1) + b^2) = y \qquad (5)$$

V. Performance Validation

This study uses two methods to validate the network performance. The first is by comparing the classification result with the Gold Standard by using a Diagnostic Test accuracy Table as shown in the Table 1.

The classification is based on the heart diseases in their own categories. The Gold Standard is considered the current preferred diagnostic tool in diagnosing a particular disease. The estimated heart diseases are compared with the result obtained from a two-dimensional (2D) echocardiogram. The second one is by performing an overall testing and check the accuracy of the classification result.

TABLE 1.
DIAGNOSTIC TEST ACCURACY TABLE

		Disease as determined by Gold Standard		
		Disease present	Disease absent	
		TRUE	**FALSE**	
Test Outcome	**Positive**	True Positive (TP)	False positive (FP)	Positive Predictive Value (PPV) →
	Negative	False Negative (FN) ↓	True Negative (TN) ↓	Negative Predictive Value (NPV) →
		Sensitivity	**Specificity**	**ACCURACY**

VI. Methods

The heart sound data were acquired from the patients of the Pediatric Unit, National Heart Institute (IJN), Malaysia. It was observed that most children here suffers from ASD, PS, PDA, VSD and MR as these are the most common heart diseases occurring to newborns and children. The data of the patients' age during the time they were acquired ranged from 21 days to 15 years old. There were 4 experiments conducted in the year of 2005 and 2006 for data collection of abnormal heart sounds. In total, there were 116 abnormal and 17 normal heart sound samples acquired from 18 pediatric patients and 11 normal patients respectively.

For classification of heart disease, MATLAB Neural Network Toolbox version 4.0 is used [20][21]. In [12], six NARX network model representing Normal and five other heart diseases are used to predict the heart sounds accordingly. All 133 heart sound signals are grouped separately according to its disease and modeled with its corresponding NARX network. The modeled heart sound signals are later extracted to determine their distinctive features by employing the STFT to the signal. Various levels of background white noise are simulated and injected to each modeled signal prior to feature extraction. The background noise is added in order to make the network system more robust and improve its generalization ability [22-24]. Such SNR levels as 5, 10, 15 and 20 dB are selected to represent the SNR ranging from 1 to 20dB. The block diagram of the classification process is shown in the Fig.2.

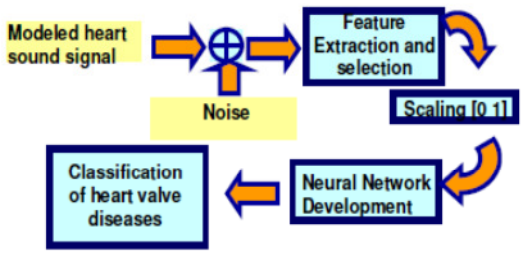


Fig. 2. The block diagram of classification process

For features extraction, the heart sound signal is cut into several segments. Each segment of 2048 points is observed and multiplied with a Hamming window before applying FFT algorithm to the segment.

Then, 50% or 1024 points of this segment is overlapped with the next 1024 points for the next segment calculation. For each segment, the maximum power energy is calculated and plotted against time. The features are investigated and selected based from ten highest points of energy derived from the graph of each heart sound. The time occurring at these points are determined. These points are selected based on the assumption that they represent the position of S_1, S_2 and murmur signals. For each point, the signal is plotted against frequency. The signal pattern is later fed into the neural network. There would be ten patterns from each heart sound signal to be fed in the network. The total patterns are 6650 patterns (1150 ASD, 850 PS, 1200 for each PDA and VSD, 1400 MR and 850 Normal patterns) generated from the spectrogram based on the following calculations :

$$No.\ of\ patterns = HS \times PPHS \times BN \qquad (6)$$

where HS = Total Heart Sounds = 133,
$PPHS$ = No. of patterns per heart sound sample = 10
BN = No. of Signals with and without background noise injected = 5

For classification purpose, the number of patterns for each disease is made equal to 1200 so that the processing of the network during training and validation would be fast. To achieve this, some ASD, PS and Normal patterns are repeated whereas a few of MR patterns are not used. The patterns are divided randomly into training and test set to ensure they generalize well. Based on trial and error, out of 7200 patterns, 80% of these patterns or 5760 are selected and used as training set and the remaining of 20% (1440) is used for the test set or validation. The summary of data distribution is tabulated in Table II. These patterns are scaled or normalised at [0 1] to facilitate the training later by the neural network.

TABLE II
. SUMMARY OF DATA DISTRIBUTION

	Normal	**ASD**	**PS**	**PDA**	**VSD**	**MR**	**Total**
Modeled signal	17	23	17	24	24	28	133
patterns	850	1150	850	1200	1200	1400	6650
Data preparation	1200 each						7200
Training set	80% of 7200						5760
Test set	20% of 7200						1440

The training patterns are fed into the FFNN and trained using the RPROP algorithm. RPROP is chosen as the training algorithm of the classifier since it is fast and requires a modest increase in memory requirements [25][26]. The RPROP performs better in solving pattern recognition problems in which it is suitable for classifying the heart sound signal into its corresponding group of disease. The learning rate and number of hidden neurons is optimized by selecting the least MSE generated by the network. The learning rate ranging from 0.01 to 0.1 is first investigated for hidden neurons ranging from 10 to 100. Once the learning rate is satisfied, it is further tested with increased hidden neurons to get the lowest MSE result. Six (6) target outputs are set as in the Table III. This is represented by 6x1 matrix of each category of normal and five heart diseases.

TABLE III
. THE TARGET OUTPUT OF NORMAL AND ABNORMAL HEART DISEASES

ASD	**PS**	**PDA**	**VSD**	**MR**	**NORMAL**
1	0	0	0	0	0
0	1	0	0	0	0
0	0	1	0	0	0
0	0	0	1	0	0
0	0	0	0	1	0
0	0	0	0	0	1

The network is trained to output a "1" result at the position where maximum vector is generated between each row and fill the rest of the output vectors with "0"s. As such, a "1" is targeted at row one for ASD, row two for PS, row three for PDA, row four for VSD, row five for MR and row six for Normal. To easily identify the disease, the number is assigned to the disease such that "1" for ASD, "2" for PS, "3" for PDA, "4" for VSD, "5" for MR and "6" for Normal.

The test set is used for validation of the patterns. The network with the highest accuracy is then used for the calculation of sensitivity, specificity, Positive Predictive Value (PPV) and Negative Predictive Value (NPV) of the diseases based on their categories. Then, the overall system testing is performed. This test allows the heart sound signals to be modeled by six NARX model. The performance of the system is tested again to check its accuracy in classifying normal and abnormal heart sounds. The process of overall testing is illustrated in the Fig. 3.

The test started by acquiring the heart sound signal. The heart sound signal is either original or added with the background noise of SNR ranging from 1 to 20 dB. This signal is modeled through six NARX networks which are represented as ASD, PS, PDA, VSD, MR and Normal. Once the feature of the modeled signal is extracted and selected, the frequency component patterns are fed into the FFNN and each output response would be checked and compared. Each MLP network will have ten patterns at the input. Thus ten outputs will be responded at the output. The "Check Pattern" box is used to compare and select only one output response. There are two comparison steps; the first compares the output response amongst the patterns. The output response or assigned number which occurs more than four times is selected. The second compares these results amongst the networks. The output response which occurs more than two times is selected. The final result will be one classified disease at the output. Detailed block diagram of the "Classifier" and "Check Pattern" box is shown in Fig. 4.

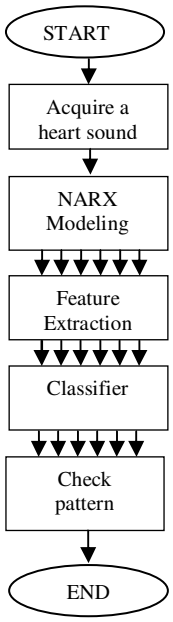


Fig. 3. Overall Testing flowchart

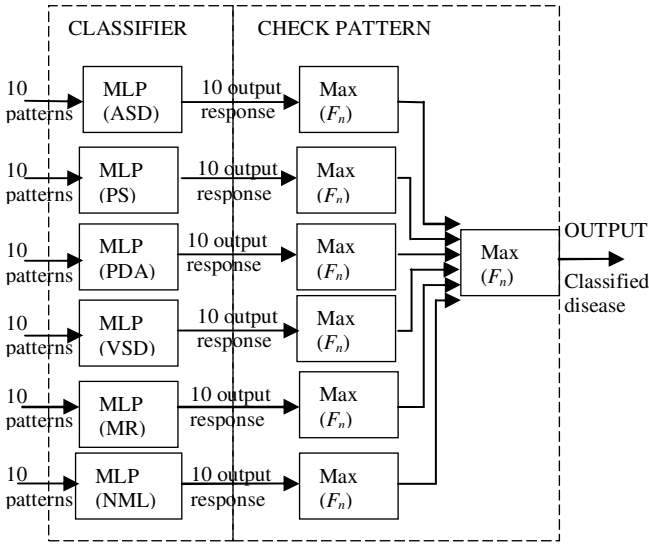


Fig. 4. Detailed block diagram of the "Classifier" and "Check pattern" box

VII. RESULTS

Fig. 5 shows the spectrum of background noise of level 20dB (VSD_n20), 15dB (VSD_n15), 10dB (VSD_n10) and 5db (VSD_n5) injected to the modeled VSD signal. The pattern of all signals

remains the same but at different amplitude. The higher the SNR level, the higher the amplitude.

By using STFT, the absolute value of energy density of each heart sound is plotted against frequency (y-axis) and time (x-axis) domain or spectrogram as shown in Fig. 6.

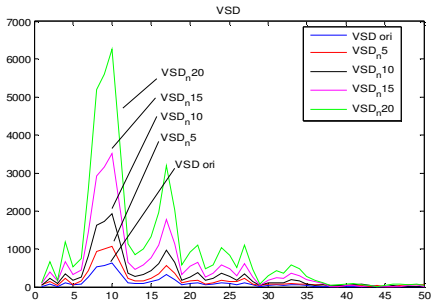
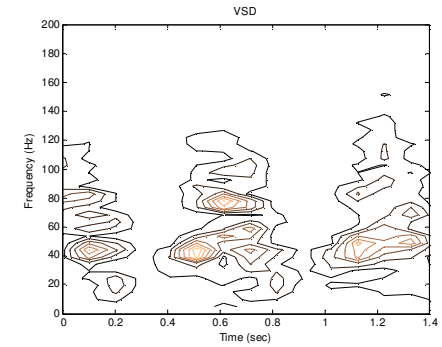
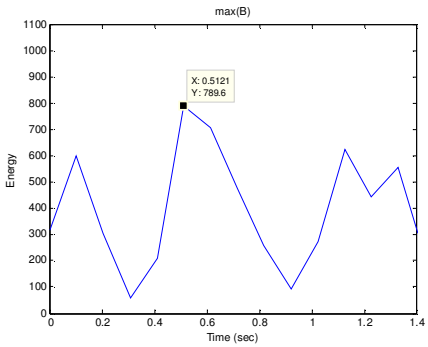


Fig. 5. The spectrum of background noise added to the modeled VSD



(a)



(b)

Fig. 6. (a) The spectrogram of VSD signal and (b) its corresponding local maximum energy values

The red color of the plot showed that the energy value is at high density. This energy represents either S_1 or S_2 and occurs approximately at 50 Hz. Other frequencies occurred around it are murmur signals which represent the heart disease. The frequency of murmur signal can go up to 150Hz. The other graph showed the local maximum energy of each segment occurred at that particular time. From this graph, the approximate time at which S_1, S_2 and murmur signal occurred is checked with the spectrogram. The energy for each disease is varied depending on the amplitude and frequency of heart sounds at one particular time. For VSD signal, the energy is high at approximately 0.1s, 0.5s, 06s, 1.1s and 1.3s. Murmurs happen in between 0 to 0.2s, 0.4 to 0.8s and 1 to 1.4s. Ten highest local maximum points are selected from this graph.

Fig.7 shows detail frequency component pattern of one of these points from 0 to 300 Hz. This pattern has 50 index elements. As the frequency is increased up to 43.9Hz, the energy has reached at its maximum point. This happens at time equal to approximately 0.5s (refer Fig. 6(b)). As frequency is increased further, energy is decreased and started to die off above 150Hz. At this point, the pattern is trimmed. Consequently, only 32 (2^5) index elements are chosen as input to the neural network. This is to make sure that the CPU of a computer can process the neural network faster since it is represented in binary data [18].

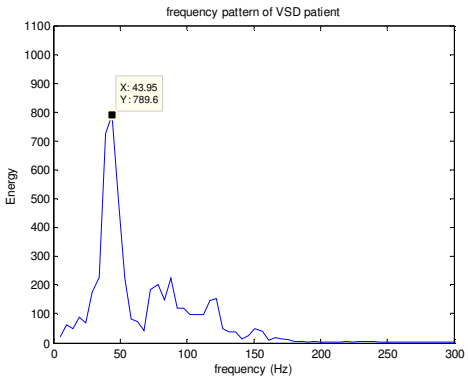


Fig. 7. Frequency component pattern of selected VSD patient

Fig. 8 shows the MSE plot against hidden neurons for various learning rates. Based on trial and error, for each hidden neurons, the network is reinitialized and retrained for five times in order to generalize well with the smallest MSE value. Only the lowest MSE result is taken for this plot.

Each learning rate has approximately generated the same of MSE value against various hidden neurons. As the hidden neurons increased, the MSE value of various learning rates is decreased. The MSE is ranged from 0.2 to 0.42. The learning

rate of 0.07 gave the lowest MSE of approximately 0.2 and thus it is used to optimize the hidden neurons. As seen from the graph, the hidden neurons need to be increased further in order to produce stabilized and accurate network. For this purpose, it is further increased to 300. Fig. 9 showed the MSE plot against various hidden neurons. There are four knee points where the MSE starts to stabilize before it is decreasing again. These points are at hidden neuron equals to 60, 100, 220 and 260. Thus the architecture of the network is 32-60-6, 32-100-6, 32-220-6 or 32-260-6.

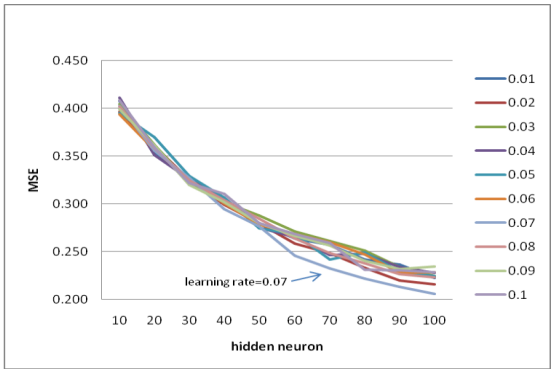


Fig. 8. The network MSE against hidden neurons for various learning rates

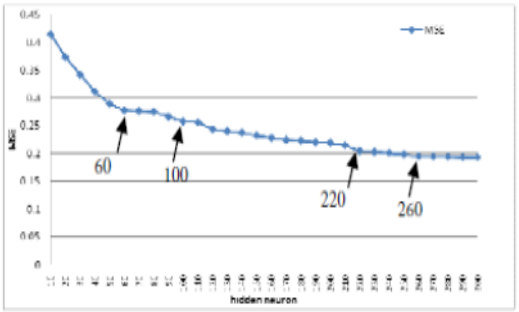


Fig. 9. The network MSE against hidden neurons from 10 to 300

Validation of the training and test set of these architectures are compared and only one is selected to be used in the system. Table IV showed the accuracy of each network by calculating the correct classified disease over the whole samples. The accuracy of the network is increased as the hidden neuron increases for the training patterns. However, for test patterns, the accuracy is decreased with increased hidden neurons. Net220 has correctly classified 5353 (92.9%) and 1345 (93.4%) patterns for training and test data set respectively. This is a True positive (TP) result where each disease is correctly detected as itself. Net220 is selected for the Diagnostic Test calculation since it has highest accuracy as compared to other networks.

Table V shows the detail of the test result. There are 240 patterns classified as ASD disease when tested with net220. Out of that, only 219 patterns are True Positive (TP). The rest of 21 patterns are wrongly classified ASD or False Positive (FP). These patterns are actually PS, PDA, VSD, MR and Normal disease. Out of 239 ASD true target, there are 20 ASD patterns classified as PS, PDA, VSD, MR and Normal disease or False Negative (FN) accordingly.

With network net220, it is concluded that PDA and PS disease is the highest wrongly classified for FN and FP respectively whereas Normal is the highest correctly classified as True Positive (96.2%).

TABLE IV
ACCURACY OF SELECTED NETWORK FOR TRAINING AND TEST PATTERN SET

Correct classified disease	Training patterns				Test patterns			
	Net 60	**Net 100**	**Net 220**	**Net 260**	**Net 60**	**Net 100**	**Net 220**	**Net 260**
	4652	4947	5353	5421	1161	1259	1345	1288
Total patterns	5760				1440			
Accuracy (%)	80.8	85.9	92.9	94.1	80.6	87.4	93.4	89.4

TABLE V
DETAIL TEST RESULT OF NET220 FOR TEST DATA

Target		TEST RESULT OF NET220 FOR TEST DATA						TRUE TARGET	DISEASE PRESENT, TEST NEGATIVE (FN)
		ASD	**PS**	**PDA**	**VSD**	**MR**	**NML**		
ASD	1	**219**	6	3	9	0	2	239	20
PS	2	4	**227**	0	1	3	5	240	13
PDA	3	4	10	**234**	4	0	3	255	21
VSD	4	5	4	2	**239**	2	4	256	17
MR	5	5	4	6	1	**224**	0	240	16
NML	6	3	2	3	0	0	**202**	210	8
TESTED		240	253	248	254	229	216	**1440**	
DISEASE ABSENT, TEST POSITIVE (FP)		21	26	14	15	5	14		**95**

To calculate sensitivity, specificity, positive predictive value (PPV), negative predictive value

(NPV) and accuracy of net220, the test result of each disease is summarized as in the Table VI.

TABLE VI
THE DIAGNOSTIC TEST RESULT OF NET220 FOR TEST DATA

NET220	TP	FP	FN	TN	Sensitivity TP/(TP+FN)	Specificity TN/(FP+TN)	PPV TP/(TP+FP)	NPV TN/(FN+TN)	Accuracy (TP+TN)/ 1440
ASD	219	21	20	1180	91.6%	98.3%	91.3%	98.3%	97.2%
PS	227	26	13	1174	94.6%	97.8%	89.7%	98.9%	97.3%
PDA	234	14	21	1171	91.8%	98.8%	94.4%	98.2%	97.6%
VSD	239	15	17	1169	93.4%	98.7%	94.1%	98.6%	97.8%
MR	224	5	16	1195	93.3%	99.6%	97.8%	98.7%	98.5%
Normal	202	14	8	1216	96.2%	98.9%	93.5%	99.3%	98.5%

Table VI shows the validation result of 1440 test patterns. The highest number of disease being test positive (sensitivity) is Normal of 96.2%. The highest number of disease being test negative (specificity) when disease is absent is MR of 99.6%. The PPV and NPV value for net220 is more than 89% and 98% respectively. Therefore, the accuracy of the network in detecting each disease is more than 97% which suggests that the network performs well and is doing as 'gold standard'.

For the overall test, a simple program is written to automate the classification result. A known heart sound signal such as PDA is selected. This signal is modeled by 6 NARX models, features extracted and the patterns are fed into six net220 networks according to Normal and abnormal diseases. The output response of this signal is shown at the Table VII.

TABLE VII
.THE OUTPUT RESPONSE OF EACH CLASSIFIER FOR PDA SIGNAL.

pattern	ASD	PS	PDA	VSD	MR	Normal
1	3	3	3	3	3	3
2	4	4	4	4	4	4
3	3	3	3	3	3	3
4	1	1	1	1	1	1
5	3	3	3	3	3	3
6	3	3	3	3	3	3
7	3	3	3	3	3	3
8	3	3	3	3	3	3
9	3	3	3	3	3	3
10	3	3	3	3	3	3
Most no. occurred	3	3	3	3	3	3

VIII. CONCLUSIONS

This study successfully classifies Normal and several abnormal heart sound signals such as ASD, PS, PDA, VSD and MR. The system used FFNN to recognize the frequency pattern features of the modeled heart sound signals. With hidden neurons of 220, the accuracy of all diseases is above 97% when validated with the Diagnostic Test and further improved to 100% when overall testing is performed. The final architecture network for the classification is 32-220-6.

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