CLASSIFICATION OF FETAL ABNORMALITIES USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Fetal heart diseases are the main source of fetal heart related deaths, and an immediate diagnosis may improve the fetus health condition. The state of the fetal heart can be studied based on Fetal Electrocardiogram (FECG) signal information. Various signal processing studies suggest that Artificial Neural Network (ANN) can be used as signal classifier. The abnormalities of FECG signal are classified based on a Pre-Ejection Period (PEP), left Ventricular Ejection Time (VET), Isovolumic Contraction Time (ICT), Isovolumic Relaxation Time (IVRT). The FECG signal has different time intervals to represent various peaks and these peaks contain useful information about the nature of disease affecting the heart. Based on the time intervals six abnormalities are classified. In this paper three back propagation algorithms, Levenberg-Marquardt, Scaled Conjugate Gradient and Bayesian Regularization are used to focus on to find out best neural network structure which classifies the abnormalities of fetal heart diseases. This technique also identifies the normal FECG and classifies the abnormalities; because of FECG waveform is varying from fetus to fetus at different condition. It is observed that Levenberg-Marquardt back propagation algorithm yields a regression value of 92 % approximately.

KEYWORDS: *Artificial neural network, Fetal Electrocardiogram, Back propagation, Levenberg-Marquardt and abnormalities.*

I. INTRODUCTION

The cardiovascular disease that occurs in the fetal heart are the main diseases that threaten the fetus, especially in developing the fetus at different stages. There are many ways to discover these cardiac arrhythmias by using FECG signal. Fetal Electrocardiography is an important device for recording FECG signals and variability of bioelectric potential with respect to time as fetal heartbeats. FECG is widely used for diagnosing heart activity among three features known as P, QRS and T waves. It also gives useful information about the functional aspect of the heart. The early detection of the cardiac arrhythmias can extend life and enhance the quality of living through appreciates treatment. Therefore, it needs to apply many techniques that can analyze the FECG signal to detect the heart diseases. The state of cardiac health is generally reflected in the shape of the FECG waveform, heart rate and contains important pointers to the nature of the disease attacking the heart [4,6,11].

FECG records can give the electronic activities of the heart, and has been widely adapted for diagnosing cardiac arrhythmia. Approaches have already been developed for classifying cardiac arrhythmias based on FECG signal, but still it is weak and have a poor accuracy because they depend on features extraction of FECG in order to classify cardiac arrhythmias. Various Machine learning and data mining methods have been applied to improve the accuracy for the detection of FECG arrhythmia [1,2].

FECG can be analysed automatically required for diagnosis and treatment of critical fetal heart conditions. FECG can be modeled and simulated under various conditions which may be very important in understanding the functioning of the cardiovascular system as well as in the diagnosis of heart diseases. Arrhythmias represent a serious threat to the fetus recovering from acute myocardial infarction, especially ventricular arrhythmias like ventricular tachycardia (VT) and ventricular

fibrillation (VF). Arrhythmia is defined as any sort of disorder that takes place in the normal rhythm of the heart. Some arrhythmias like ventricular fibrillation are fatal and also can cause death of fetal baby. The classification of arrhythmias is very important as some arrhythmias are severely fatal while others are not. The detection of arrhythmia is an important task in clinical reasons which can initiate lifesaving, some of them can be cured by medication and others with operation immediately after delivery [15].
In this paper, we have considered three different neural network models to classify arrhythmia cases into normal and abnormal. Three different ANN models designed are Levenberg-Marquardt, Scaled Conjugate gradient and Bayesian Regularization.

II. Artificial Neural Networks

An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes - or learns, in a sense - based on that input and output. ANNs are considered nonlinear statistical data modeling tools where the complex relationships between inputs and outputs are modeled or patterns are found. It is trained with training sample inputs and corresponding sample outputs to adjust the neuron weights.

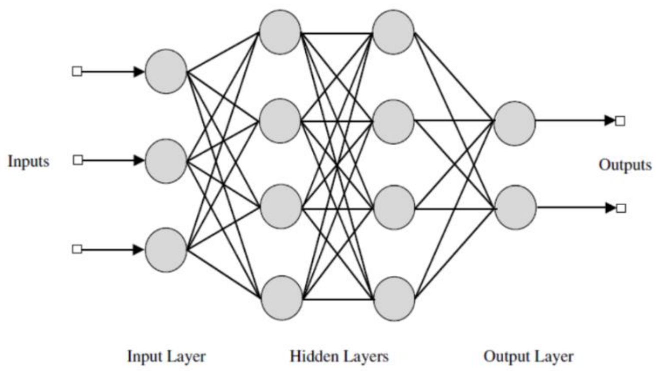


Figure 1: Artificial Neural Networks Structure

ANN has proven to be an efficient alternative to traditional methods of distance measures [3]. The back-propagation learning algorithm is used for training multi-layer perceptron's (MLP) as shown in figure 1. The MLP consists of a set of sensory units that constitute the input layer, one or more hidden layers followed by an output layer. The signal is applied at the input layer which propagates to the output through the hidden layer [5]. Input layer collects the inputs from the real world and presents a input pattern to the ANN. This process is known as excitation. The output layer presents a pattern to the external world after computing the inputs. Number of outputs depend on the type of problem. Hidden layer acts as an boundary layer between input and output. Hidden layers are not required for linearly separable problems. The complexity of the problem will decides the number of hidden layers. Underfitting is a condition when the number of hidden layers is less than the required number. Overfitting is a condition when the number of hidden layers is more than the required number. The number of hidden layer neurons is $2/3^{rd}$ the sum of input and output layers. The number of neurons in the first and second hidden layer should be almost same inorder to save the computation time. There are three algorithms used in this paper for training the neural network is Levenberg-Marquardt, Scaled Conjugate Gradient and Bayesian Regularization algorithm. The main focus of this training is to reduce the error as minimum as possible [14].

III. BACK PROPAGATION NEURAL NETWORK METHODS

There are various Back propagation algorithms, some of them are Gradient Descent (GD), Gradient Descent with Momentum (GDM), Variable Learning Rate with Momentum (GDX), Scaled Conjugate Gradient (SCG), Quasi-Newton (BFGS), Levenberg-Marquardt (LM), and Bayesian Regularization (BR) back propagation are used to adjust the weights of the Neural network.

In the gradient descent Back Propagation algorithm, bias weights and network weights are updated in the direction of negative gradient performance function. The parameter η is the learning rate parameter which has a direct influence on the training the network. G_k is the error gradient with respect to the weight vector. The updated weight vector is given in equation 1 [5]. Gradient Descent suffers from the shallow local minimum. GDM can skip such minimum values by updating the weight values equal to the sum of modified weight in Gradient descent and fraction of previous weight values as given in equation 2. The parameter μ is the coefficient of momentum and it varies between 0 and 1 [13].

$$W_{k+1} = W_k - \eta * G_k \quad (1)$$

$$W_{k+1} = W_k - \eta * G_k - \mu * W_{k-1} \quad (2)$$

The GD and GDM method suffers from the problem of low convergence rate. The learning rate parameter value has a direct relation to the convergence. As the learning rate increases convergence value increases. If η is too small, the algorithm takes a long time to converge and if it is too large the network becomes unstable. To overcome this problem, variable learning rate back propagation with momentum is used. In this algorithm, the value of η is large initially and in decreases as time progresses. The weight adjustment in GDX is given by equation 3.

$$W_{k+1} = W_k - \eta_{k+1} * g_k + \mu * W_{k-1} \quad (3)$$

The methods discussed till now uses a steepest descent method which works at the direction of the negative gradient for modifying the neuron weights. The convergence rate of these methods is very slow. In order to improve the convergence rate, conjugate direction of the search is preferred over steepest descent method. Conjugate gradient descent back-propagation algorithm (CGD-BP) is used for training purpose. In CGP search is performed along the conjugate gradient direction which will minimize the cost function along the line by adjusting the step size. The weight update is given in equation 4. Conjugate gradient search direction is given in equation 5. β_k is the ratio of norm squared of the current gradient to norm squared of the previous gradient as shown in equation in 6.

$$W_{k+1} = W_k + \eta * P_k \quad (4)$$

$$\text{Where } P_k = -g_k + \beta_k * P_{k-1} \quad (5)$$

$$\beta_k = \frac{\Delta g_{k-1}^T * g_k}{g_{k-1}^T * g_{k-1}} \quad (6)$$

Levenberg-Marquardt algorithm aimed at speeding up the training without computing the hessian matrix directly. The hessian matrix is computed using the jacobian matrix as shown in equation 7. The principal diagonal elements of Hessian matrix are larger than zero. The weight update rule in the Levenberg-Marquardt algorithm is presented in equation 8

$$H = J^T J + \mu I \quad (7)$$

$$W_{k+1} = W_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \quad (8)$$

The Levenberg-Marquardt switches between steepest descent algorithm and Gauss Newton algorithm during the training phase. The convergence rate of the Gauss Newton method is fast and unstable, whereas, Levenberg-Marquardt overcomes the problem instability by maintaining the convergence rate fast. Gauss Newton algorithm is used when the coefficient μ is very small. The Steepest Descent method is used when μ is very large. The relation between learning rate η and the combination coefficient μ is given by the following relation as shown in equation 9

$$\eta = 1/\mu \quad (9)$$

The activation function typically used in a multi-layer networks is a sigmoid transfer function. The primary role of activation function is to compress the infinite input range to a finite output range. For higher values of inputs, the slope of the activation function approximates zero. This creates a problem while training multi-layer networks since the gradients have small magnitude. To eliminate these effects, resilient back propagation training algorithm is used. Sign of the derivative plays a crucial role in the weight update rather than the magnitude of the derivative. If the derivative of the performance function for two successive iterations has same sign, then the weight update value and bias values will be increased otherwise it has decreasing pattern. If the derivative is zero, then weights will not update.

IV. METHODOLOGY

The causes for the Congenital Heart Diseases (CHD) can be based on environmental factors like drugs, chemicals or infections, some of them will be chromosome abnormalities, maternal diseases, genetic diseases and unknown factors. Most of the CHD has no proper reason for its cause. From the causes, nothing can be obtained for the heart defect. Some of the heart diseases may occur based on the family background, these heart defects may occur due to genetic syndrome. Some of the heart issues are probably going to happen if the mother had disease while pregnant and was taking some medications (like anti-seizure). However, in most of the cases, the is no identifiable reason to why the heart defects are occurred [7,15].

Heart diseases may vary from simple to complex. The CHD can be taken care by the baby physician and can be managed with medicines and some of them can undergo surgery, in case of emergency the surgery can be done immediately after couple of hours after delivery. For some babies the heart problems may grow with the baby, such as Atrial Septal Defect (ASD) or Patent Ductus Arteriosus (PDA) as shown in figure 2, these defects may close up on their own as the baby grows. For some babies, it may be a combination of the defects and require few operations for the duration of their life.

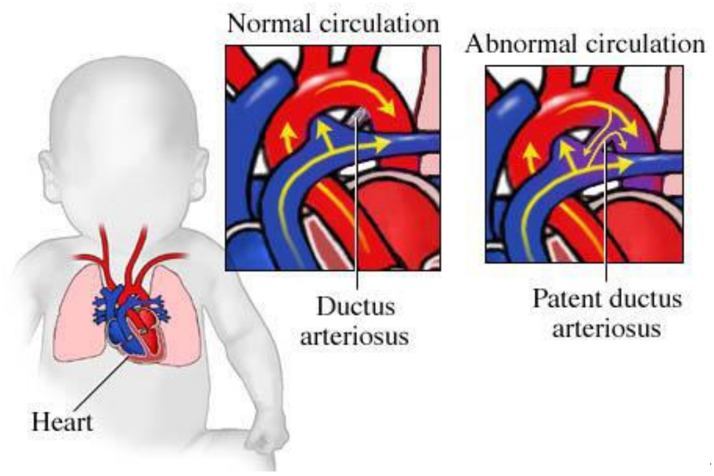


Figure 2: Normal and abnormal circulation system and heart position

Sometimes environmental factors can also find faults. Such as Fetal Alcohol Syndrome (FAS), which occur due to consumption of alcohol when the mother is pregnant and in case if the mother is suffering from German measles (rubella) while pregnant, the infection will impair the growth of the fetal heart and other organs [9,10].

Some of the common heart defects that are present before and after birth are [15]

- i. Atrial Septal Defect
- ii. Ventricular Septal Defect
- iii. Patent Ductus Arteriosus
- iv. Bicuspid Aortic Valve
- v. Tetralogy of Fallot
- vi. Transposition of the Great Vessels

Atrial Septal Defect (ASD):

An ASD is a group of CHDs that involves their inter-atrial septum of the heart. The left and right atria are separated by inter-atrial septum tissue.

Ventricular Septal Defect (VSD):

A VSD is caused when the opening in the ventricular septum, or separating the walls between the two lower chambers of the heart recognized as the left and right ventricles. During the early stages of pregnancy, smoothing may affect the heart development during the first 8 weeks of pregnancy, resulting in a VSD.

Patent Ductus Arteriosus (PDA):

PDA is a CHD where the child ductus arteriosus fails to close after birth. The symptoms may include breathing problem and cardiac arrhythmia, and may develop to congestive heart failure if it is left uncorrected. During the development of the fetus, the Ductus Arteriosus (DA) is a shunt linking the pulmonary artery to the aortic arch that allows much of the blood from the right ventricle to bypass the fetus' fluid-filled lungs.

Bicuspid Aortic Valve (BAV):

BAV is one of the most common type of aortic valve abnormality happening in about two percent of the population. Instead of the normal three leaflets or cusps, the bicuspid aortic valve has only two. This type of defect can be seen more common in males than females. This defect does not produce problems, although there is the possibility that in later life, it could begin to cause some symptoms of 'aortic stenosis'.

Tetralogy of Fallot (TF):

TF is also one of the common form of cyanotic CHD. Cyanosis is the abnormal bluish discoloration of the skin that occurs because of low levels of circulating oxygen in the blood.

Transposition of the great vessels (TGV)

TGV in which the aorta arises from the right ventricle and the pulmonary artery arises from the left ventricle, with an associated intracardiac shunt. In normal individuals, oxygen-depleted blood from the right ventricle goes through the pulmonary artery to the lung to get oxygenated. The oxygen-rich blood goes to the left ventricle, from which it gets ejected into the aorta to the rest of the body.

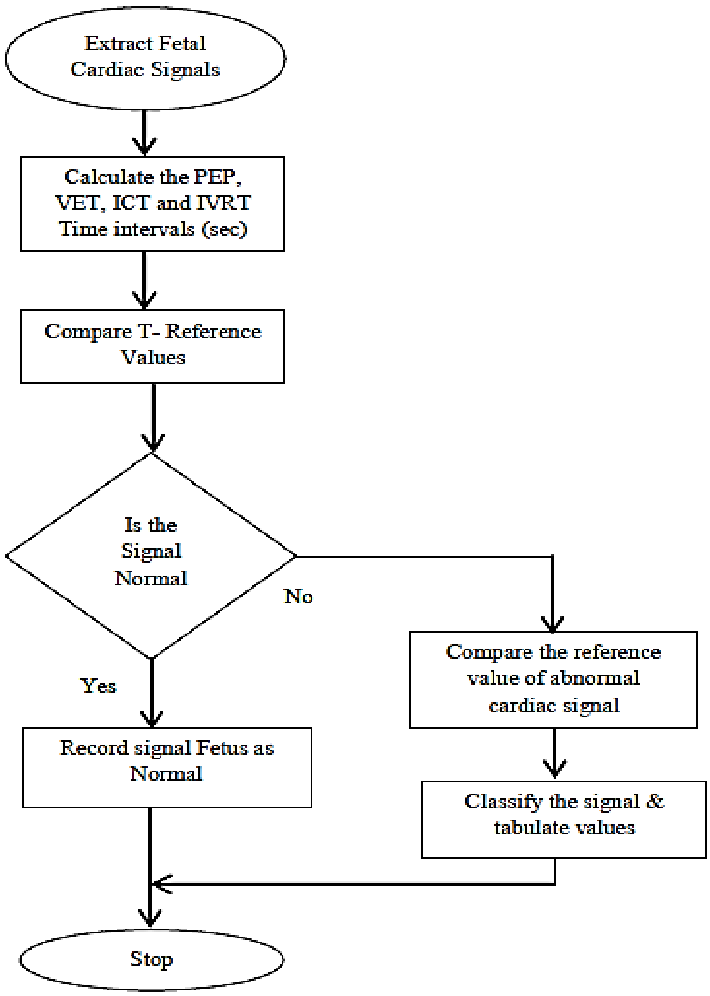


Figure 5: Flowchart showing classicisation of fetal cardiac arrhythmias [15]

Table 1: Reference values for Normal and abnormal fetal cardiac signal [9].

Fetal condition	PEP (m sec)	VET (m sec)	ICT (m sec)	IVRT (m sec)
Normal	75±11.9	152.3±18.9	50±15.9	69.6±9.7
Abnormal	89±10.3	168.6±25	52.2±17.2	51.6±13.7
Atrial septal defect	89±10.3	152.3±18.9	50±15.9	69.6±9.7
Ventricular septal defect	75±11.9	168.6±25	50±15.9	69.6±9.7
Patent ductus arteriosus	75±11.9	152.3±18.9	52.2±17.2	69.6±9.7
Bicuspid aortic valve	75±11.9	168.6±25	50±15.9	69.6±9.7
Tetralogy of Fallot	89±10.3	168.6±25	52.2±17.2	51.6±13.7
Transposition of the great vessels	75±11.9	152.3±18.9	52.2±17.2	51.6±13.7

V. RESULTS AND DISCUSSIONS

The FECG signal with time intervals which represents PEP, VET, ICT and IVRT are as shown in table 1. Test patterns were generated with 10% deviation in the time intervals. These patterns are used to train, validate and test the network [12]. The network has four inputs for which represents PEP, VET, ICT and IVRT values at certain time intervals are given as inputs. It has one output which is used to classify the 7 different reflectivity values. In order to save time and complexity, the number of hidden layers used in this model is ten. The block diagram of neural network model is shown in figure 3.

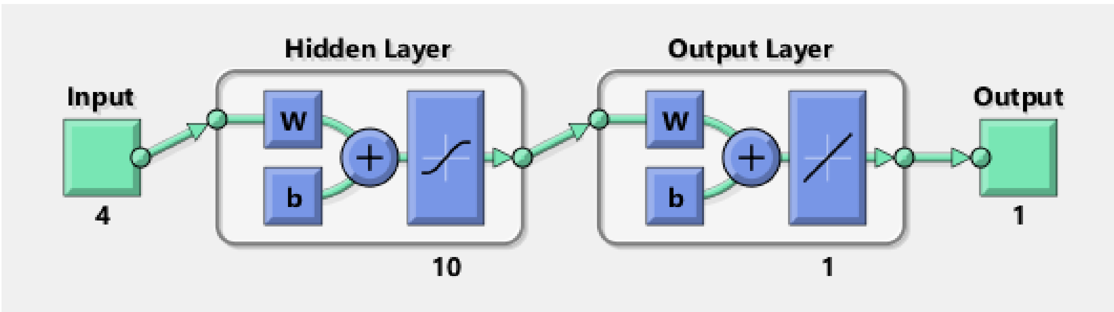
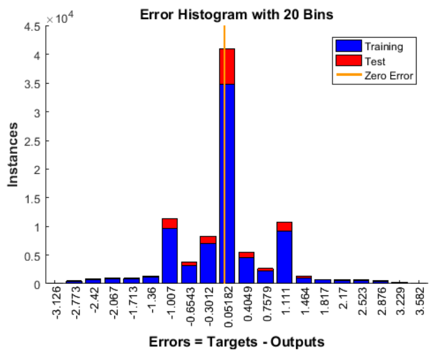


Figure 3: Block diagram of Neural network model

The neural network is trained with different types of back propagation algorithms such as LM, SCG and BR. Based on the flexibility in the timing constraints as shown in Table 1, 90,000 different combination of inputs are generated. The network is provided with 90,000 different samples for training, testing and validating. Out of which 70% of the samples is used for training, 15% for testing and 15% for validating the network. The error histogram is a plot between error value and the number of instances the error has occurred. The error histogram of 20 bins is plotted as shown in figure 4.The results of the work proposed is tabulated in Table2.
From the regression plots of LM, SCG and BR model as shown in figure 5, the dashed line gives the regression plots that indicate the outputs. The best fit between outputs and targets is indicated by the solid line in the regression plot. The relation between input and output is specified by the value of R. If the value of R is close to unity, the relation between input and output is closely related. If the value of R approaches zero indicated no relation between output and target**.** The regression values for the LM, SCG and BR are 0.91813, 0.91225 and 0.91174 respectively. LM back propagation algorithm shows better performance compared with the other three models.

Figure 6 shows the performance plot is a plot between Mean Square Error (MSE) and the number of epochs. MSE is defined as the average of the squared difference between outputs and targets. Zero MSE signifies that there is errors. If the MSE value keeps on reducing, as the training process continues. The training process stops when the MSE value reaches to a minimum value. Once the training process is complete, the system is validated with input samples. In the validation phase, if the network behaves properly, then the training stops and it is ready for testing.



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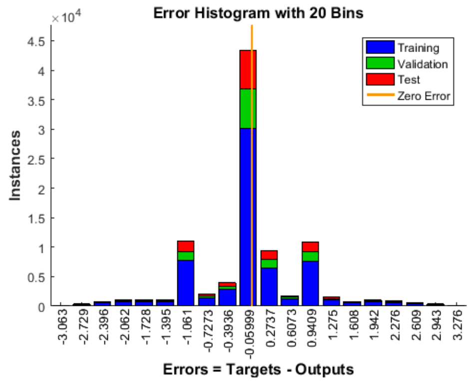

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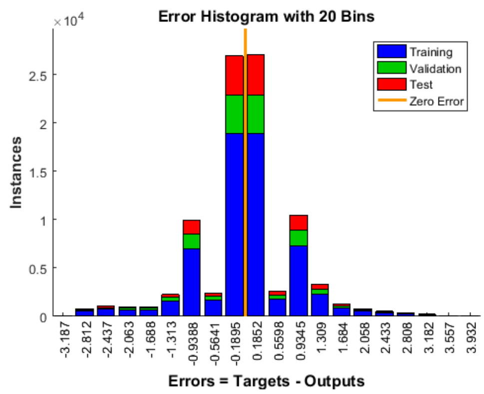
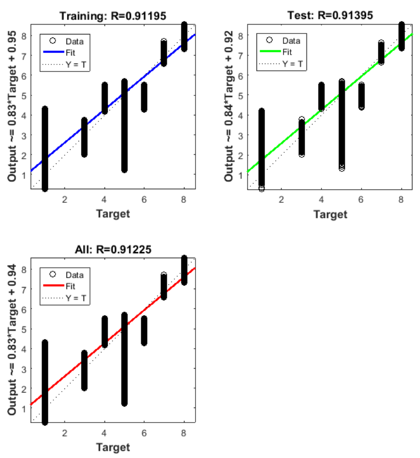


(c)

Figure 4: Error histogram plots (a) BR (b) LM (d) SCG



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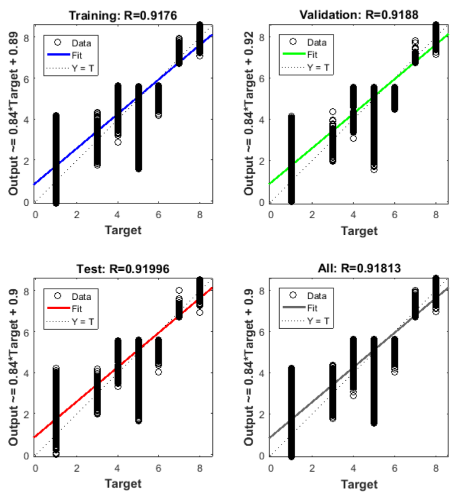

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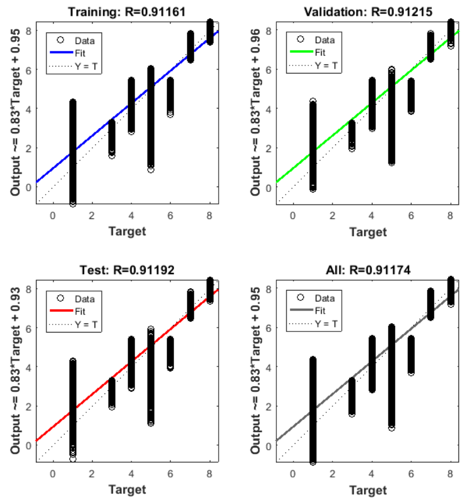

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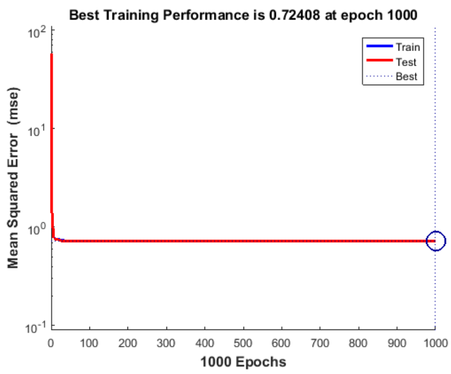
Figure 5: Regression plots (a) BR (b) LM (d) SCG



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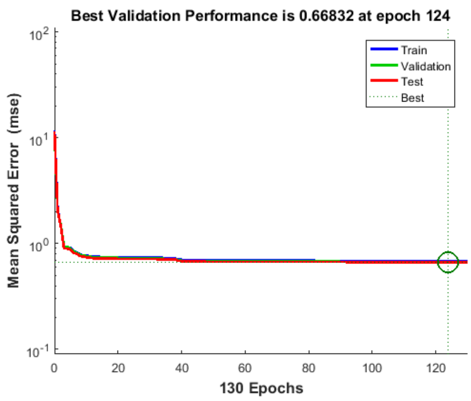

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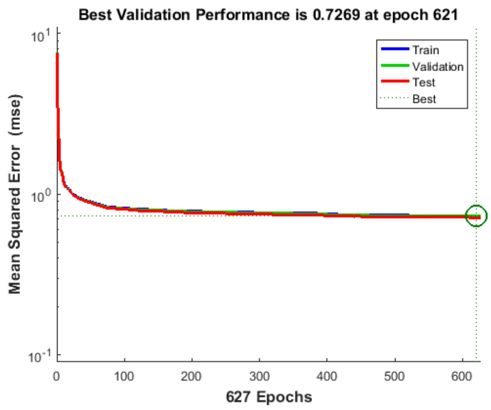

(c)

Figure 6: Performance Curves (a) BR (b) LM (d) SCG

Table 2: Performance Comparison table

Method	% of Accuracy
Analytical method	84.5
Scaled Conjugate Gradient	96.57
Bayesian Regularization	96.78
Levenberg-Marquardt	96.79

VI. CONCLUSION

This paper presents an effective time interval based arrhythmia classification based on artificial neural networks. Classification of Six arrhythmias using different time intervals is evaluated. The network is provided with 90,000 input samples to classify the 7 different target outputs. The network is trained with different types of back propagation algorithms such as BR, LM and SCG. It gives the normal and abnormal cases of the FECG signals obtained from 220 samples. In this, variations of the parameters used for classification are too small to differentiate from each arrhythmia. The network trained with LM gives better performance values as shown in table 2.

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