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Design and Analysis of a Back Propagation Neural Network in Estimating Risk of Coronary Artery Disease

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Abstract: Detailed reports in hospitals show a high degree of prevalence in Coronary Artery Disease in a number of people all over the world. The number of people suffering from the same assumes significant proportions especially in the age group of fifty and above. Although advances in medical science have effected a considerable reduction in the number of cases, a wide amount of research is still prevalent. Taking this view point into consideration a system has been developed that focuses on estimation of risk levels for the disease in consideration. A neural network model has been designed taking into account a wide variety of factors and providing a suitable estimate of risk factor. This analysis is expected to supplement the work of the doctor in providing reliable results.

Key words: Artificial Neural Network · Learning · Coronary Artery Disease · Regression · Risk factor

INTRODUCTION

Technology has been improving at a rapid pace. Although it has said to improve the levels of comfort of an average human being, the adverse impact it creates in the life of a person is extremely severe. A sizable increase in incidences of health related problems pertaining to every organ of the body has been observed over the years. Heart is no exception. Although doctors have a reasonable degree of success in treating patients, the new histrionics created by technology has increased the risk levels of patients. In earlier days, the causes were limited and the symptoms were very few. But this is no longer the case. The exposure of people to vast amount of radiation from mobiles and laptops has created a void in day to day life. With increase in number of causes, identifying the effect of one cause on another can play a pivotal role in tracking the problems of patients. This work aims at identifying and finding the relationships between various causes and their effects in undermining the risk of a heart disease. With a large number of doctors with varying degrees of expertise and experience, this work is expected to aid the doctor in analyzing a patient much better which in turn could provide the right treatment.

Literature Survey: Although soft computing techniques have made rapid progress in recent times, the first computational model for neural network was developed way back in 1940's. In 1943, Mc Culloh and Pitts developed a computational model for neural networks. In early 1940's and 1950's several hypothesis on neural network models have been created. However, usage of neural networks has been in vogue ever since. In the 1990's neural networks were overtaken in popularity in machine learning by support vector machines and other much simpler methods such as linear classifiers. Renewed interest in neural nets was sparked in the 2000's by the advent of deep learning.

Recent developments have been observed in artificial neural networks field. For instance, in the year 2005, Karimi, M. and Amirfattahi, R. Sadri S. and Marvasti S.A. [1] made an analysis on Noninvasive detection and classification of coronary artery occlusions using wavelet analysis of heart sounds with neural networks. A further improvement was made in the year 2007, when Kochurani, O.G. Aji, S. and Kaimal, M.R.[2] developed a Neuro Fuzzy Decision Tree Model for Predicting the Risk in Coronary Artery Disease. The diagnosis results have been published at the IEEE 22nd International Symposium. A similar experiment had been carried out made by Zand,

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M.D. Ansari, A.H. Lucas, C.; Zoroofi and R.A.Z. [3] in the year 2010, based on Neuro-Fuzzy Classifiers. In the same year, a fuzzy-evidential hybrid inference engine was developed for the Risk Assessment of Coronary Artery Disease (CAD) by Vahid Khatibi and Gholam Ali Montazer. In the year 2011, automated diagnosis of coronary heart disease using neuro-fuzzy integrated system has been carried out by Ansari, A.Q. and Gupta, N.K. [4] In the year 2012, another diagnosis related to CAD is made with the inclusion of genetic polymorphisms and clinical parameters by Oleg Yu. Atkov, Svetlana G. Gorokhova, Alexandr G. Sboev,Eduard V. Generozov, Elena V. Muraseyeva, Svetlana Y. Moroshkina and Nadezhda N. Cherniy. In the year 2013, a journal on Automated diagnosis of Coronary Artery Disease using LDA, PCA, ICA and Discrete Wavelet Transform was published by Donna Giria, U. Rajendra Acharyab, Roshan Joy Martisb, S. Vinitha Sreed, Teik-Cheng Lima, Thajudin Ahamed VIe and Jasjit S. Surif [5].

However, despite the extensive research being conducted in this area, the results have been far from satisfactory. It is hence proposed to design a feasible network that could supplement the doctor with far better information pertaining to diagnosis.

About Cardiac: The CAD is caused by plaque building up along the inner walls of the arteries of the heart, which narrows the arteries and restricts blood flow to the heart.CAD is the most common type of heart disease in the United States and it is the main cause of death for both men and women. The most common symptom of coronary artery disease is angina (chest pain).Other symptoms include Shortness of breath, Palpitations (irregular heartbeats), faster heartbeat, Dizziness, Nausea, Extreme weakness, Sweating. Diagnosis of coronary artery disease is performed by talking to patients about their symptoms, reviewing their medical history and risk factors and performing a physical exam. Diagnostic tests like blood tests, electrocardiogram (ECG or EKG), exercise stress tests or cardiac catheterization may be required to appropriately diagnose and treat coronary artery disease. These tests help the doctor evaluate the extent of CAD. However it has been observed that the performance of tests followed by diagnosis by the doctor is highly time-consuming. Besides, it has also been inferred over the years a variation in the results of diagnosis followed by recommendation of treatment based on the expertise levels and skill of the various doctors.

This work is intended to assist the doctor in helping with the diagnosis through the design of a suitable soft computing technique. The soft computing techniques have led to various developments in the field of cardiology. Recently, neural networks have been used to a very large extent in the diagnosis and treatment of various cardiac diseases. It can be easily inferred from the reports of various patients that the various parameters affecting the risk level of the disease have definite values. For such cases, designing a neural network will be the ideal choice.

Choice of Neural Network: Artificial neural networks have been designed for a wide variety of applications. The ability of a neural network to find relationships between a set of inputs and outputs deserve no special mention. In this competitive world of technology, the need of the hour is to find reasonably accurate relationships as fast as possible.

With this perspective in mind, different types of neural networks have been taken into consideration. As the numbers of parameters have been found to be exceedingly large, two subsystems have been designed based on observation of relationships between them.

Studies have shown that probabilistic neural network and generalized regression technique are fast and easy to train. However, they are suitable only for linear models.

Both subsystems deal with estimation of risk based on a specific set of factors like cholesterol, age, systolic pressure, diastolic pressure, body mass index, parathyroid hormone, lipoproteins, fat content and sugar level. It has been observed that the relations are non linear. Hence, the usage of generalized regression and probabilistic techniques has been ruled out.

Experimentation has been carried out using perceptron technique. The chief advantage of perceptron technique is that it is capable of separating any linearly separable set of training data.

With considerable amount of non linearity, it could be observed that the level of convergence is not achieved even after one lakh iterations. The results of the same have been shown in Fig. 1 and Fig. 2

Experimentation results clearly highlight the fact that back propagation with feed forward neural network is the ideal choice for the given problem.

Design of Neural Network: Two subsystems have been designed using Back propagation neural network with feed forward connections.

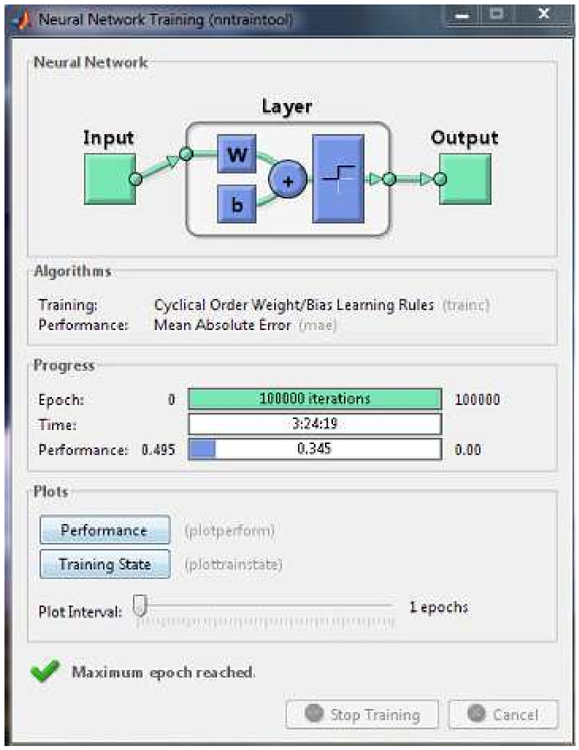

Fig. 1: Perceptron Neural Network Training (subsystem1)

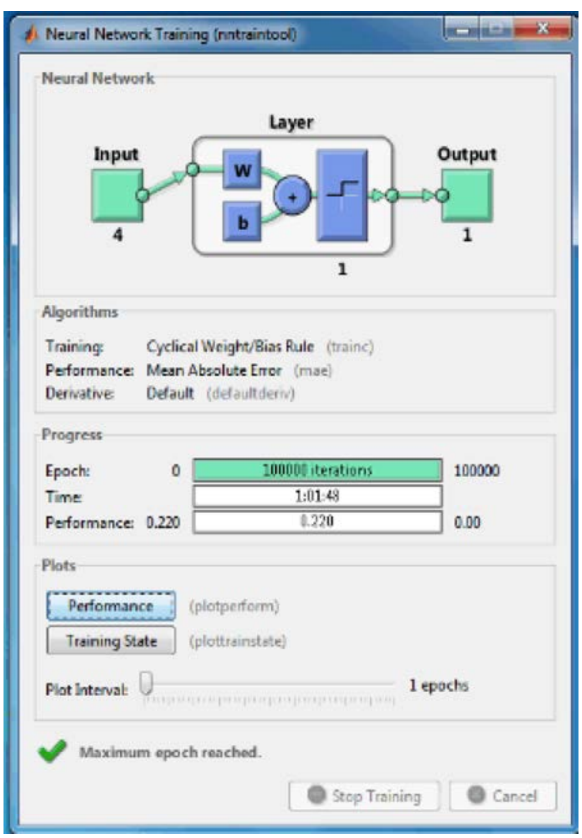

Fig. 2: Perceptron Neural Network Training (subsystem2)

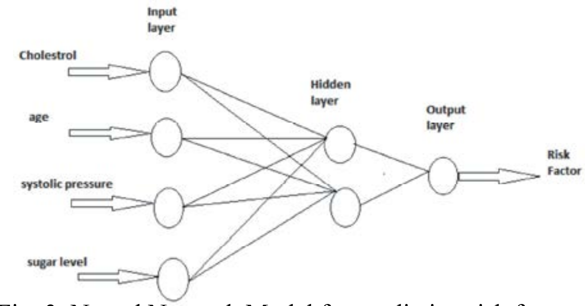

Fig. 3: Neural Network Model for predicting risk factor

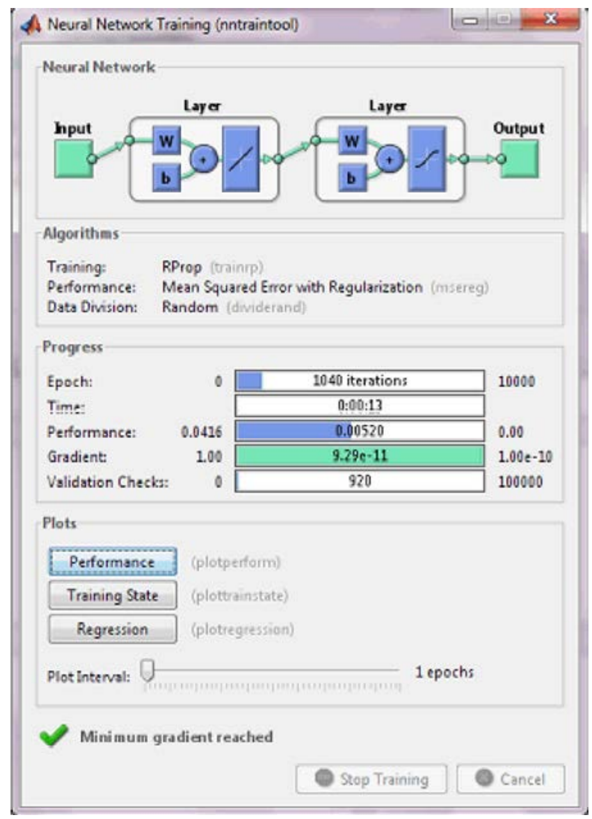

Fig. 4: Neural Network Training

In the subsystem shown in Fig. 3, the risk factor is estimated based on cholesterol, age, systolic pressure and sugar level. The structure of the network is shown in Fig. 3.

The subsystem is expected to find the relationship between the given set of inputs and the risk factor.

Different training and learning functions have been taken into consideration. For the subsystem taken into consideration, a good regression value of 0.95657 is obtained when training function is TRAINRP, learning function is LEARNGDM, performance function is MSEREG and transfer function is LOGSIG. It could be clearly inferred from Fig.4 that the system is able to learn

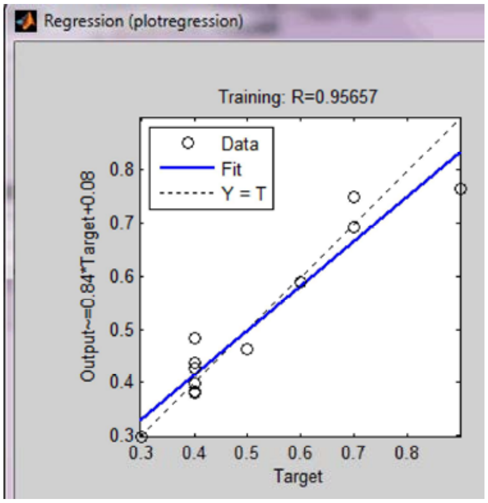

Fig. 5: Regression plot

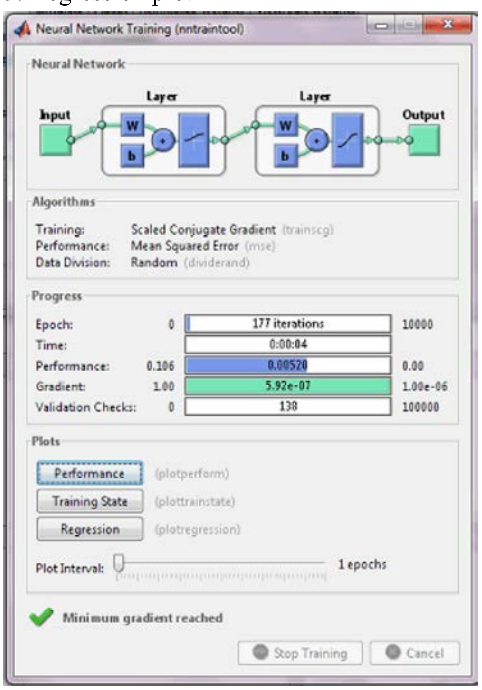

Fig. 6: Neural Network Training

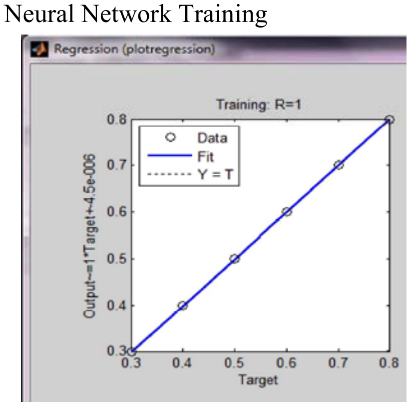

Fig. 7: Regression plot

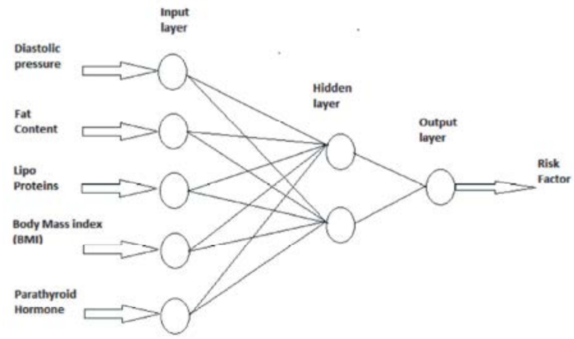

Fig. 8: Neural Network Model for predicting risk factor

the relationship between parameters in 1040 iterations. The regression plot has been shown in Fig. 5. It could be observed that the points are scattered close to the straight line.

This system is now trained again by modifying the various training function parameters without modifying the learning function. A LOGSIG transfer function has been used in place of PURELIN. Results are found to be significant. It has been observed that a maximum regression value of 1 has been obtained. Besides, the network has been able to estimate the same in much lesser amount of time.

As inferred from Fig. 6 the network is able to estimate in 177 iterations with training function as TRAINSCG and performance function as MSE. The regression plot has been shown in Fig. 7. It could be clearly observed that the various points fall exactly on the straight line.

In the subsystem shown in the Fig. 8, the risk factor is estimated based on diastolic pressure, fat content, lipoproteins, body mass index and parathyroid hormone. The structure of the network is shown in Fig. 4.

The subsystem is expected to find the relationship between the given set of inputs and the risk factor.

For the subsystem is taken into consideration, a good regression value of 0.99945 is obtained when training function is TRAINRP, learning function is LEARNGDM, performance function is MSE and transfer function is LOGSIG. It could be clearly inferred from Fig. 9 that the system is able to learn the relationship between parameters in 715 iterations. A regression value very close to 1 is obtained. The plot for the same is shown in Fig. 10.

This system is now trained again by modifying the various training function parameters without modifying the performance function. Results are found to be significant. It has been observed that a maximum

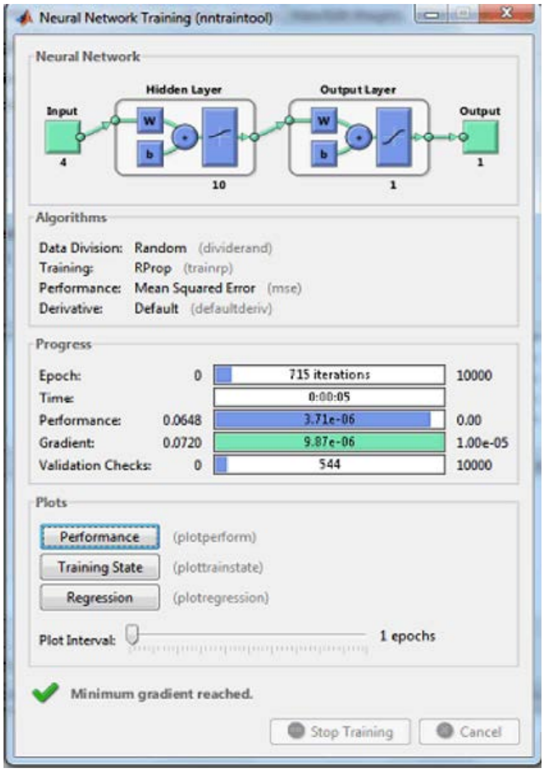

Fig. 9: Neural Network Training

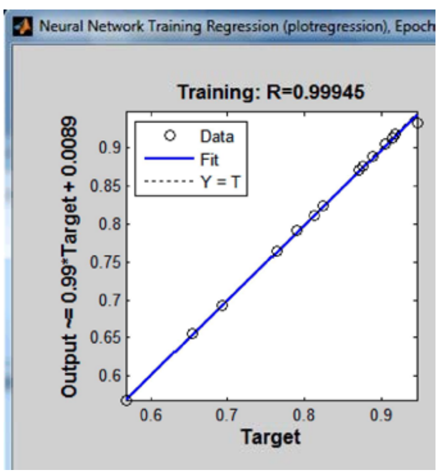

Fig. 10: Regression Plot

regression value of 1 has been obtained. Besides, the network has been able to estimate the same in much lesser amount of time.

As inferred from Fig. 11, the network is able to estimate in 194 iterations with training function as TRAINCGB, learning function as LEARNGD and transfer function is TANSIG. The regression plot has been shown in the Fig. 12, It could be clearly observed that the various points fall exactly on the straight line.

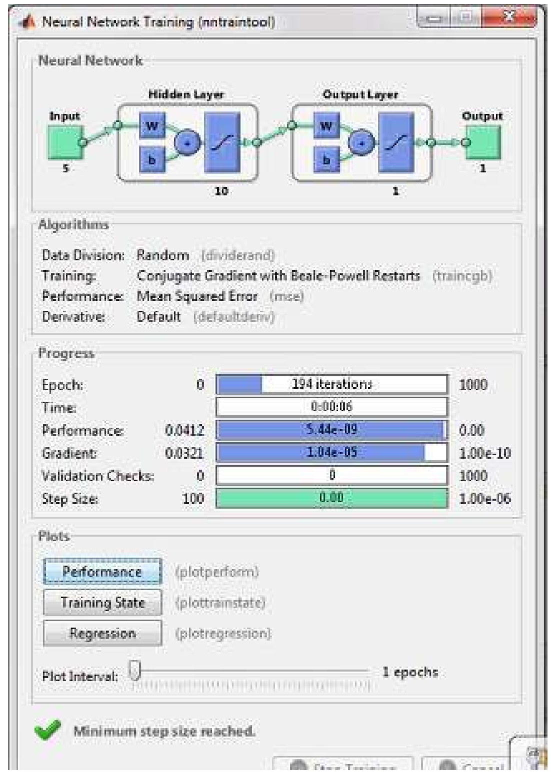

Fig. 11: Neural Network Training

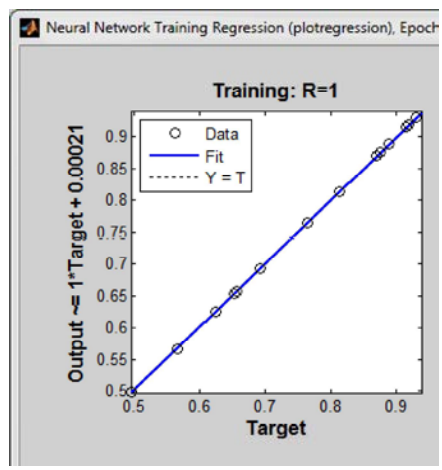

Fig.12: Regression plot

Diagnosis of Neural Network: With the availability of a wide range of choices, it becomes necessary to choose the most appropriate training function. The choice of the learning rate also plays an important role during the estimation.

With increase in value of learning rate, convergence is expected to be much faster. However, the chances of convergence significantly reduce with higher values of learning rate. With smaller values of learning rate, chances

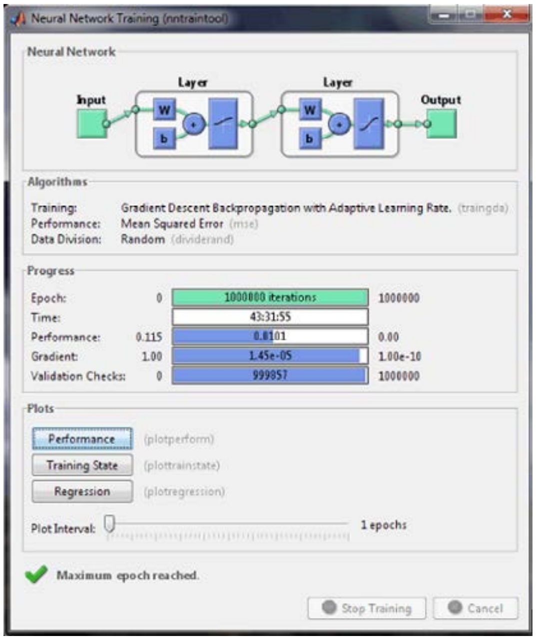

Fig. 13: Neural Network Training

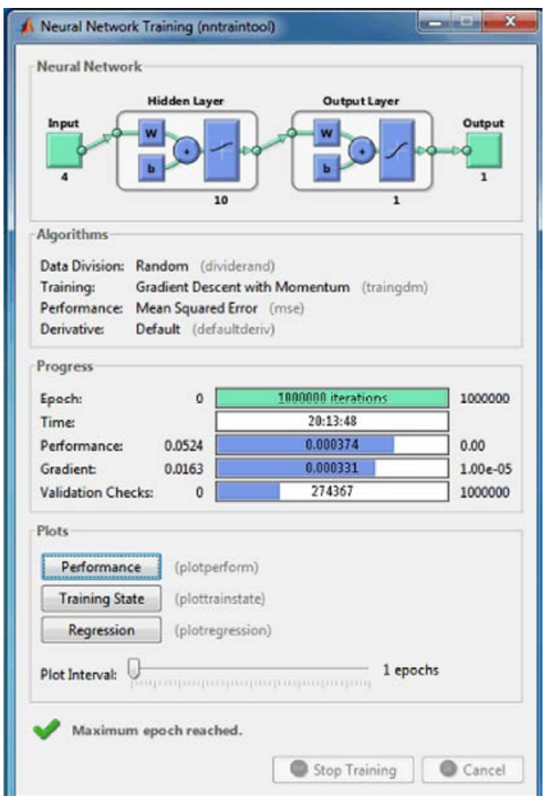

Fig. 14: Neural Network Training

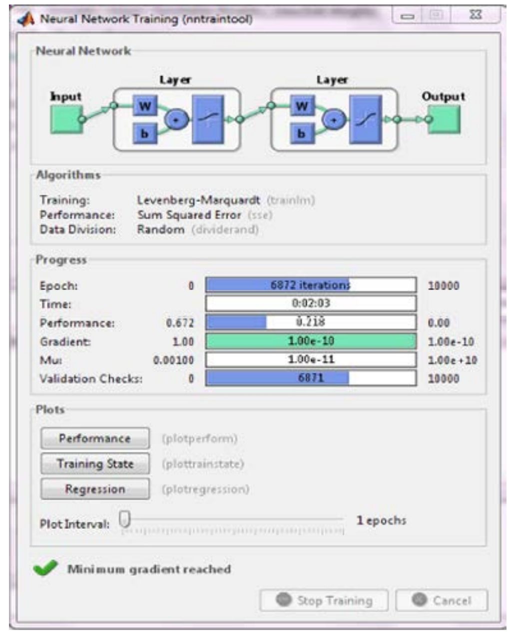

Fig. 15: Neural Network Training

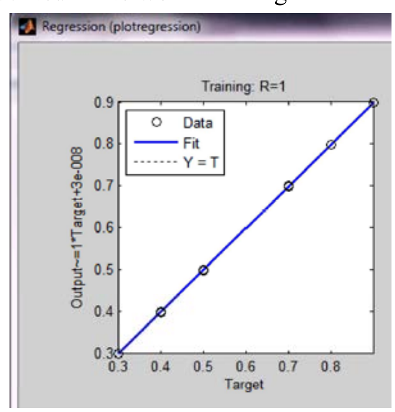

Fig. 16: Regression plot

of convergence are much higher. However, the process is too slow for comfort. Hence, ideally the values chosen for the same are neither too high nor too low.

Further experimentation led to the choice of different gradient descent functions. In both the subsystems it has been observed that there is no convergence even after ten lakh iterations. This has been highlighted in Fig.13 and Fig. 14.

For the subsystem shown in Fig. 3, experimental results clearly show that usage of training function trainlm, performance function sse, transfer function logsig, learning function learngd with momentum is faster than usage of above similar functions without momentum.

This is clearly highlighted in Fig. 15 and Fig.17 where the results are obtained in 1108 iterations as compared to 6872 iterations. The regression plots have been shown in Fig. 16 and Fig. 18. It could be observed that in both plots the various points fall exactly on the straight line.

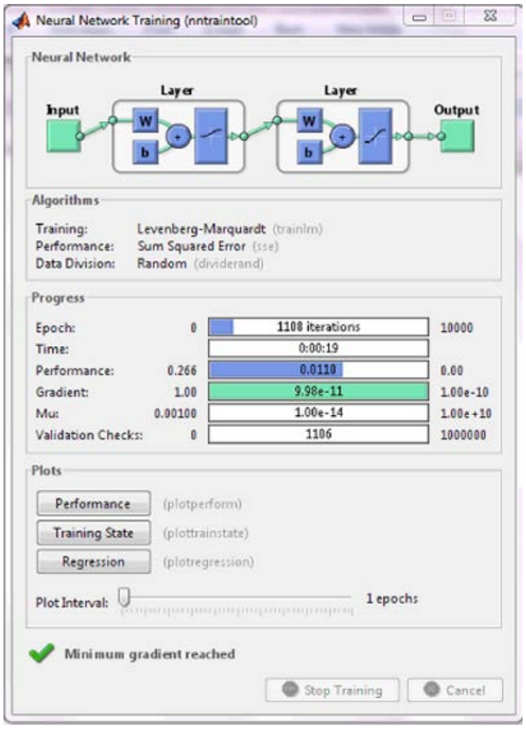

Fig. 17: Neural Network Training

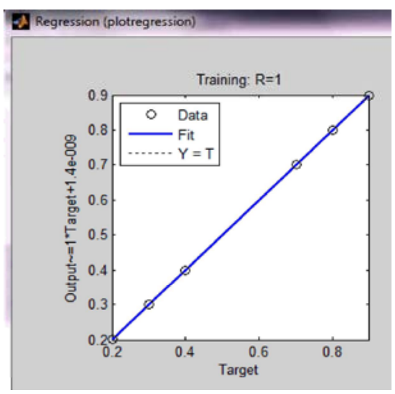

Fig. 18: Regression plot

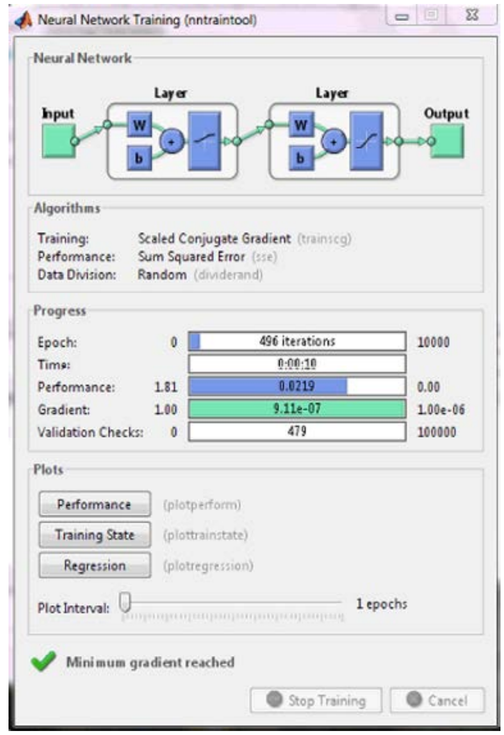

Fig. 19: Neural Network Training

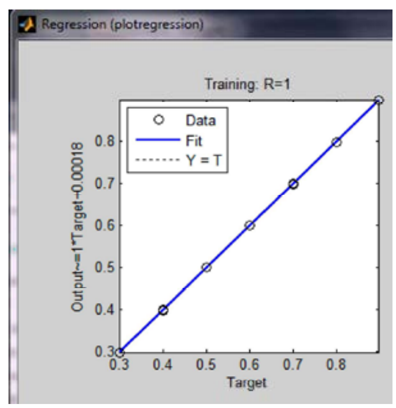

Fig. 20: Regression plot

Studies have shown that usage of training function trainscg, performance function sse, transfer function logsig, learning function learngd without momentum is faster than usage of above similar functions without momentum [6-9]. The experimental results agree with the same as clearly highlighted in Fig. 19 and Fig. 21. However, the degree of variation is much lesser as the results are obtained in 441 iterations as compared to 496 iterations [10-14]. The regression plots have been shown in Fig. 20 and Fig. 22. In both the plots, the variation shows a good degree of linearity as the various points fall exactly on a straight line [15-17].

For the subsystem shown in Fig. 8, when TRAINSCG training function is used, regression obtained is below 9.0 (less accurate) for all combinations of learning, performance and transfer functions [18-20]. The neural network training for two instances are shown in Fig. 23 and Fig. 25.

From the regression plots shown in Fig. 24 and Fig. 26 it can be clearly inferred that TRAINSCG training function is not suitable for considered subsystem.

Accurate risk factor for CAD disease can be detected using the network with training function TRAINCGB, learning function involving gradient descent algorithm

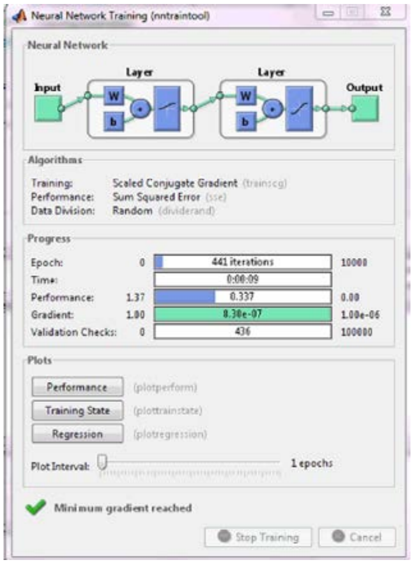

Fig. 21: Neural Network Training

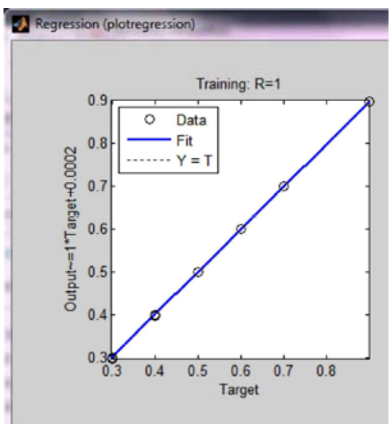

Fig. 22: Regression plot

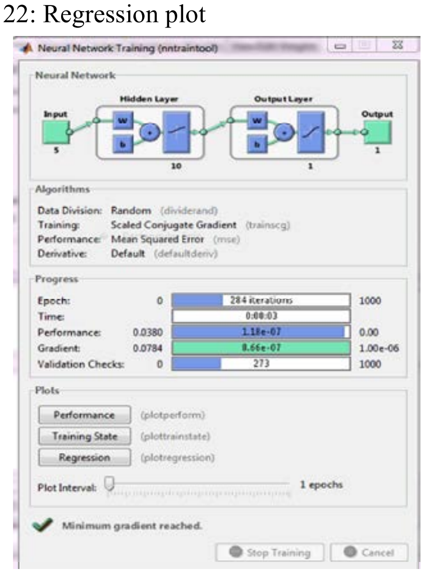

Fig. 23: Neural Network Training

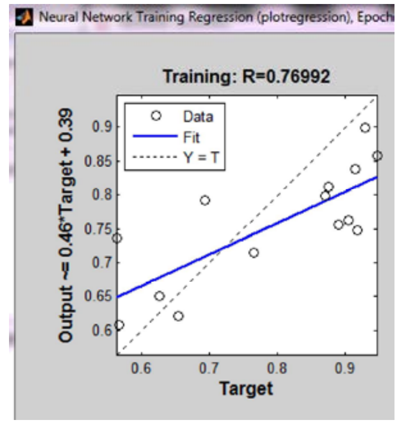

Fig. 24: Regression plot

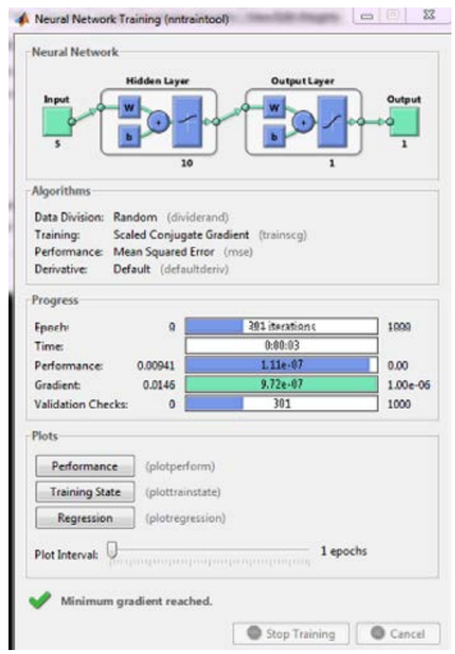

Fig. 25: Neural Network Training

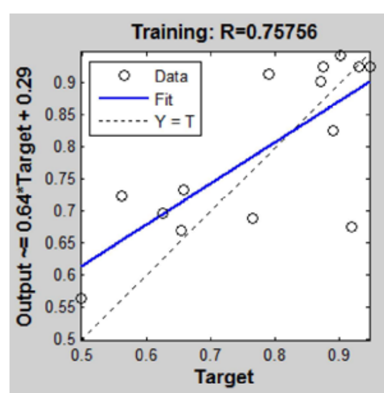

Fig. 26: Regression plot

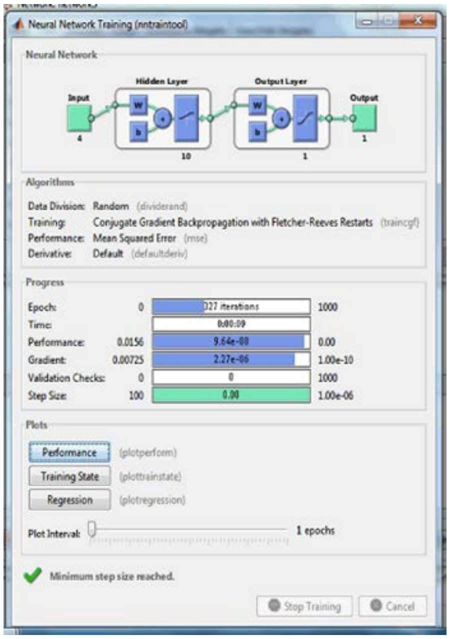

Fig. 27: Neural Network Training

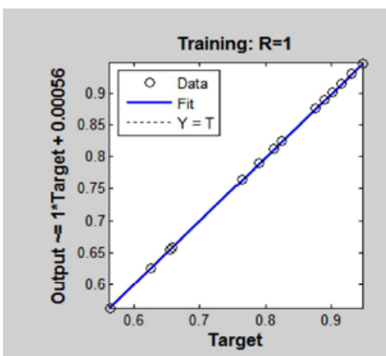

Fig. 28: Regression plot

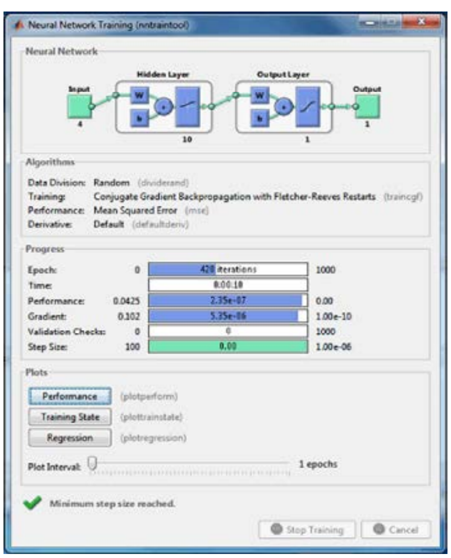

Fig. 29: Neural Network Training

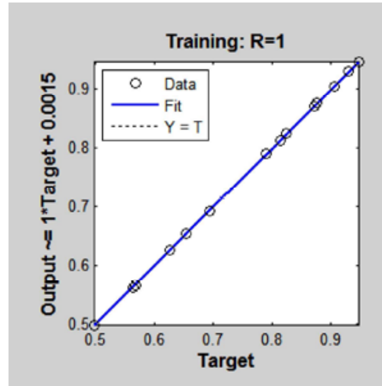

Fig. 30: Regression plot

with and without momentum, with transfer function TANSIG and performance function MSE. The neural network training for two instances are shown in Fig. 27 and Fig. 29.

Regression plots obtained for above analysis are shown in Fig. 28 and Fig. 30.

CONCLUSIONS

An efficient backpropogation neural network has been designed to access the level of risk associated with Coronary Artery Disease. The speciality of this network is that it caters to all possible characteristic behavioral aspects associated with a patient.

The feed forward nature of this network is able to provide a more accurate relationship between the parameters.

It has been observed that all the factors that have been taken into consideration play a significant role in estimation of risk. In addition, the results show that the level of cholesterol and blood pressure levels are more sensitive as compared to the other parameters. This result is in tune with the estimation carried out by doctors in the hospital.

Although the network designed helps save the doctor valuable amount of time, the level of prediction accuracies could be much higher when a much larger dataset from a wider variety of hospitals across the globe can be considered.

It has been observed that some factors that are not measured on a time to time basis have been pruned out. This work could be even more realistic with the inclusion of factors like level of smoking, physical inactivity, C-reactive protein, homocysteine and fibrinogen.

However, despite the minor shortfalls, the system is still found to be efficient in making reliable assessments of risk.

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