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Effective Diagnosis of Heart Disease Using Multilayer Feed Forward Neural Network using Back Propagation Algorithm and Associative Neural Network.

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ABSTRACT

Cardiovascular disease is common and prevalent in most human community and is vital reasons of morbidity and mortality. It still remains a dreadful disease, hence speedy and accurate diagnosis of Heart Disease (HD) is essential. Artificial neural network provides a powerful tool to help the medical professionals to clinically analyze the disease and get the best solutions. The aim of this paper is to make best use of Multilayer Feed Forward Neural Network (MLFFNN) using Back Propagation (BP) algorithm and Associative Neural Network (ASNN) for the effective diagnosis of Heart Disease. The MLFFNN is configured with 13, 20 and 1 neurons in the input, hidden and output layer. The ASNN is configured with 13, 10 and 1 neurons in the input, hidden and output layer. 270 datasets are used for training. The performance of both Neural Networks is analyzed in training and predicting the heart diseases. MLFFNN predicts heart disease with the excellent correlation co-efficient (R^2) = 0.9410 and 0.9999 for training and testing. ASSN provides satisfactory results with the correlation co-efficient (R^2) = 0.9999 for training and 0.9460 for testing. The results are cross validated by Leave-One-Out (LOO) procedure. The performance of MLFFNN is compared with ASNN. MLFFNN predict heart disease with better accuracy than ASNN for test dataset. The results so obtained have proved that the intricate and significant task of heart disease prediction can be carried out precisely and effectively using this automated medical diagnosis system.

Keywords: Heart Disease, Multilayer Feed Forward Neural Network using Back Propagation, Associative Neural Network, Cross validation.

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INTRODUCTION

Heart disease is known as Coronary Artery disease (CAD) and a Cardiovascular Disease (CVD) [1]. When the supply of blood to coronary arteries is blocked either due to blood clot or some other reason or when there is less supply of blood to myocardium (heart muscle), myocardial infarction occurs which in turn results in either death of a patient or some grave disability to the patient. Physical activity is vital in order to strengthen the heart muscle and also for enhancing the circulation of blood in the entire body. The other reasons for heart disease are high or low BP, Diabetes, Obesity and Cholesterol. Heart disease was a killer disease during 2007 in the United States of America, United Kingdom and Canada [2]. The pathetic report of the World Health Organization (WHO) is that 12 million people die of heart attack every year in the global level and out of 10 deaths in India 8 occurs due to non-communicable diseases (NCD'S) heart attack and diabetes. [3]. unless a very strong medical remedial measure is invented the entire human community will be put into the fear of death due to HD. A system of automated medical diagnosis is essential for speed and exact treatment on heart disease [4].

The major apprehension of all the health care institution is to provide efficacious treatment at reasonable cost and qualitative prophecy of clinical data to challenging a more quantitative evaluation of information and accord immediate treatment [5]. Wu, et al suggested that incorporation of clinical decision support with computer-based patient records could eliminate medical errors and false assumptions, improve patient safety, decrease redundant practice variation, and improve patient outcome [6]. Clinical decisions are mostly based on the physician's personal knowledge and expertise rather than the strong and accurate data base. Hence to assist medical experts in the diagnostic process, developing a medical diagnostic decision system is vitally required. The need for such an export system to efficiently diagnose the heart disease motivated this study.

Artificial Neural Network (ANN) is one of the best suitable techniques in practice for complex system of diagnosis with priorities of decision making and risk analysis. ANN was employed for effective diagnosis and prediction of many diseases such as Hepatitis, Diabetes, Heart diseases, Cancer, etc. Numerous authors have proposed various approaches for diagnosis of heart diseases [7]. Several algorithms were used on heart disease database in last decades and the classification accuracies reported found to be high. Polot et al (2005) employed a method with Artificial Immune System (AIS) and reached 84.5% classification accuracy [8]. Ozsen and Gunes used similar method and accuracy of 87% was reported [9]. Latha and Subramanian (2008) have utilized an efficient Coactive Neuro-Fuzzy Inference System (CANFIS) to diagnose HD [5]. Heon Gyu Lee ct at proposed a novel technique using three layered feed forward neural networks to diagnose stroke diseases has been proved by experimental results [10]. Niti Guru et al predicted Blood Pressure, Heart disease and Sugar utilising neural networks [11]. Shanthi et al. (2008) had employed neuro genetic approach to feature selection in stroke disease classification [12]. Sellappan Palaniappan et al (2008) developed prototype intelligent heart disease prediction system [13]. The aim of this study is to implement an efficient model for predicting heart disease by applying MLFFNN and ASNN which attempts to provide medical professionals an efficient automated tool to clinically analyse the heart disease precisely.

METHODS

The parameters used in this research work are taken from Statlog database [14]. Two types of Neural networks MLFFNN and ASNN are implemented for developing a dependable and robust system to recognize the presence of heart disease using the nonlinear relationship between the 13 input attributes and one output attribute. For Training 270 data set which contains 13 attributes (input) and 1 attribute as output are used. The Testing set consists of 50 data. The software for MLFFNN is used from dit.ipg.pt/MBP [15] and for ASNN from www.vcclab.org/asnn [16].

Neural Network

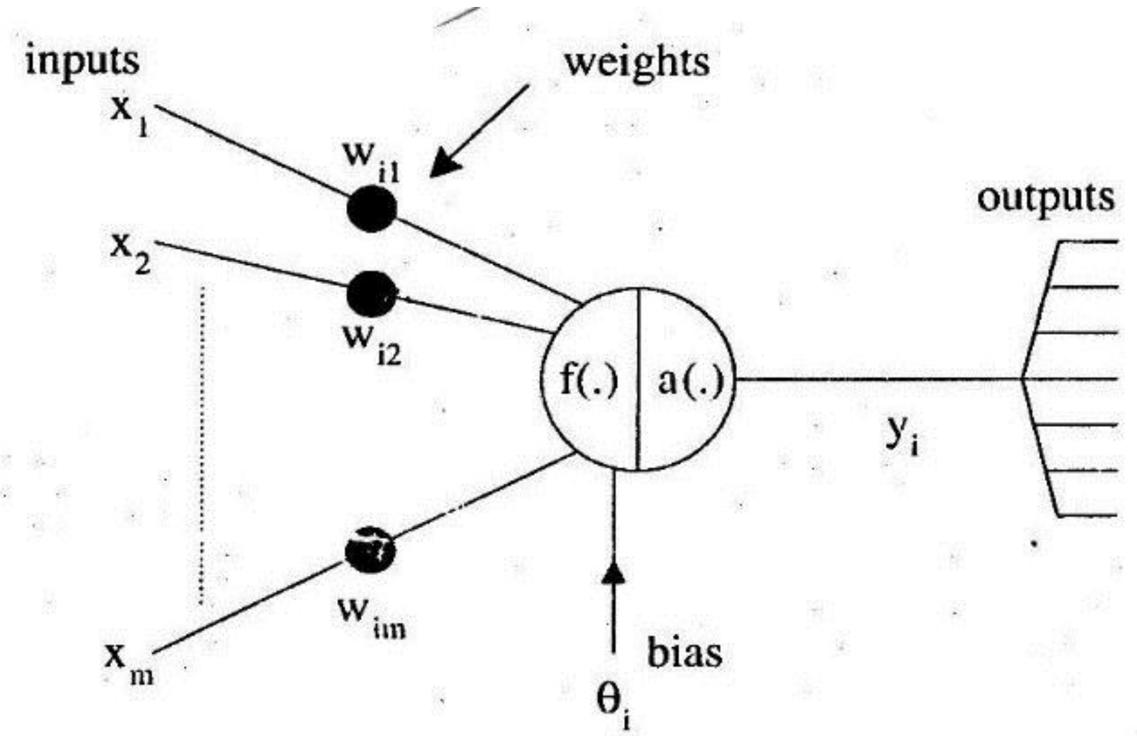

Figure 1: Artificial neuron model

Artificial Neural network(ANN) is a parallel, distributed computing system consisting of multiple number simple, highly interconnected computing elements (PE) called neurons that process information responding to external inputs through their dynamic state. These elements are inspired by biological nervous system. ANN like human brain performs (intelligent) task [17]. The Figure-1 shows Artificial neuron model. ANN structure consist of inputs(neurons), which are multiplied by strength of the respective signals (weights), and then computed by a mathematical function which finds the activation of the neuron and one more function executes the output of the neuron (sometimes depending upon a certain threshold). The process of adjusting weights on input connections to compute desired output is executed in the process of learning or training. Number of hidden layers and number of neurons in each layer strongly depends on the complexity of system studied. Neural network is an iterative learning process in which input data are given to the network one at a time and weights associated with input interconnections are adjusted each time. Once the neural network is modeled, and then it is ready to be trained for a given specific application. [18]. ANN is trained based on two training methods, Supervised Training - for supervised learning external teacher is available which provide the neural network input data and actual desired output. 2. Unsupervised Training-Input data and computation function is given to the network and output is calculated. It does not require the desired output.

Multilayer Feed Forward Neural Networks using Back Propagation

Multilayer Feed Forward Neural Networks (MLFFNN) is a class of flexible nonlinear regression, discriminate and data reduction models. It consists of three layers namely one input layer, one output layer and one or more hidden layers it is referred as multilayer. In the Feed Forward Neural Networks, the neurons at first layer forward their output to the second layer neurons in forward direction and there is no feedback [19]**.** The function of the input layer neurons is the division of the input signal x_i among neurons in the hidden layer among neurons in the hidden layer. Each neurons j in the hidden layer sum up its input signals x_i once it weights them with the strengths of the relevant connections w_{ji} from the input layer and to find out its output y_j as a function f of the sum which is given as

$$y_j = f \sum (w_{ji}\, x_i)$$

At this instant it is possible for f to be a simple threshold function such as a hyperbolic tangent function or sigmoid function. The output of neuron in the output layer is computed in an identical manner [20]. Figure 2 gives Multilayer Feed Forward Neural Network using Back Propagation.

The back propagation algorithm is utilized to train neural networks. The BP algorithm will change the network weights and bias values to decrease the square sum of the difference(SSE) between the desired output (*x11*) and an output values computed by the net (*x11'*) using gradient decent method which is given in the following formula:

$$SSE = 1/2\, N' \sum (x11 - x11')^2$$

Where N' represents the number of experimental data points used for the training.

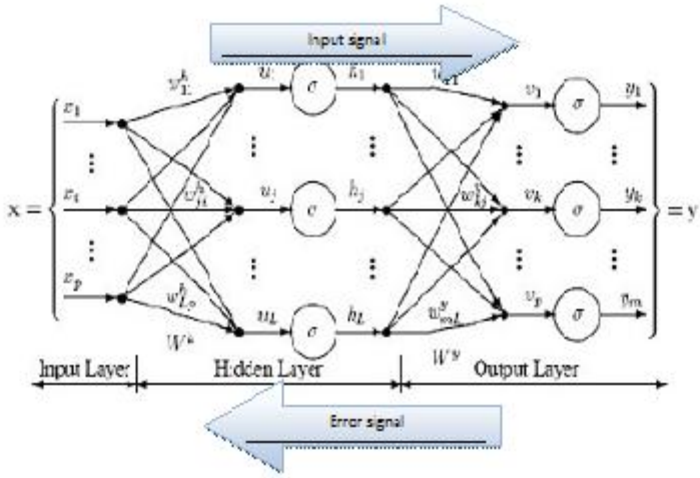

Figure 2: Multilayer Feed Forward Neural Network using Back Propagation

The steps involved in Back propagation algorithm are as follows:

1. Provide training data to network.
2. Compare the actual and desired output.
3. Compute the error in each neuron.
4. Calculate output for each neuron and how much

Output must be adjusted for required output.

5. Then adjust the weights.

The cycle for back propagation training is given in the figure 3

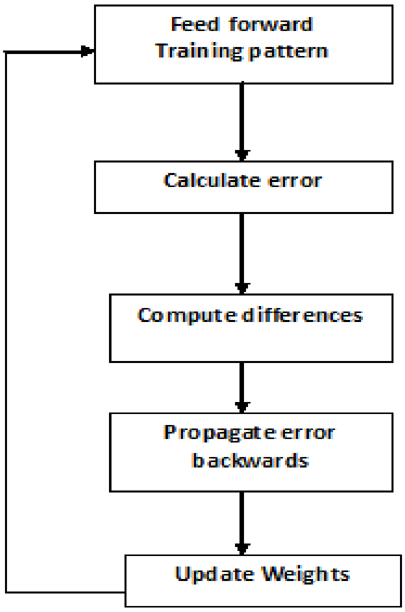

Figure 3: Flow of Back propagation neural network

Associative Neural Network

Associative neural network plays a very important role to ascertain non-linear relationship between input (attributes) and output (class attributes). The conventional artificial feed forward neural network has no memory. It is to state that, once the training is completed, all data about the input patterns is stored in the neural network weights and no input data is necessary. i.e., there is no specific storage of any example presented in the system. Quite opposed to it, Associative Neural Network (ASNN) is a group of memory-based and memory-less methods [21]. The Associative neural network (ASNN) offers an innovative approach to integrate "on the fly" the user's data. ASNN uses the association in between ensemble responses as a determination of distance among the cases analyzed for the closest neighbor method. By this correction or adjustment of the ensemble of neural network we arrive at a definite forecast and prediction. It is very much clear that ASNN holds a memory as synchronized with its training set of neurons. Whenever there is an available new data the network is provided with a possibility of increasing its capacity towards prediction. This feature of the network is very much significant as compared to conventional neural networks. ASNN has a special capacity to interrupt the results of the network by means of analysis on correspondence between the case data [22]. The network is trained with ESE (Early Stopping Ensemble) method. In ESE equal sets of training and evaluation ensembles were constructed. The network's weight is adjusted through the training or learning sets. When there is a minimum error the training or learning process is stopped (Early stopping point) and the set of evaluation or validation is calculated

RESULTS AND DISCUSSION

The purpose of the study is to evaluate and compare the performance of two neural networks MLFFNN and ASNN in diagnosing the Heart Disease (CAD/CVD). The database used in this study consists of 13 input parameters and one output which are given in table 1. Table 2 displays a part of training set with input parameters and output computed by networks. The output parameter consists of two diagnosis classes, Class 1: Normal, Class 2: Abnormal (Presence of Heart disease).

Table 1: Attribute description

Sl.No	Attribute	Description	Values
1	age	Age in years	Continuous
2	sex	Male or female	1 = male 0 = female
3	cp	Chest pain type	1 = typical type 1 2 = typical type angina 3 = non-angina pain 4 = asymptomatic
4	thestbps	Resting blood pressure	Continuous value in mm hg
5	chol	Serum cholesterol	Continuous value in mm/dl
6	Restecg	Resting electrographic results	0 = normal 1 = having ST_T wave abnormal 2 = left ventricular hypertrophy
7	fbs	Fasting blood sugar	1 ≥ 120 mg/dl 0 < 120 mg/dl
8	thalach	Maximum heart rate achieved	Continuous value
9	exang	Exercise induced angina	0= no 1 = yes
10	oldpeak	ST depression induced by exercise relative to rest	Continuous value
11	slope	Slope of the peak exercise ST segment	1 = up sloping 2 = flat 3 = down sloping
12	ca	Number of major vessels colored by fluoroscopy	0-3 value
13	thal	Defect type	3 = normal 6 = fixed
14	output	Output	1 = Normal (Absence of CAD) 2 = Abnormal (Presence of CAD)

Table 2: A Part of Training set with input and output parameters for ASNN and MLFFNN

Age	Sex	Cp	Trestbps	Chol	Fbs	Restecg	Thalach	Exang	Old peak	Slope	Ca	Thal	desired o/p	O/p ASNN	o/p MLFFNN
70	1	4	130	322	0	2	109	0	2.4	2	3	3	2	2.0000	2.0000
67	0	3	115	564	0	2	160	0	1.6	2	0	7	1	1.0000	1.0001
57	1	2	124	261	0	0	141	0	0.3	1	0	7	2	2.0000	1.9981
64	1	4	128	263	0	0	105	1	0.2	2	1	7	1	1.0000	1.0010
74	0	2	120	269	0	2	121	1	0.2	1	1	3	1	1.0000	1.0001
65	1	4	120	177	0	0	140	0	0.4	1	0	7	1	1.0000	1.0000
56	1	3	130	256	1	2	142	1	0.6	2	1	6	2	2.0000	1.9996
59	1	4	110	239	0	2	142	1	1.2	2	1	7	2	2.0000	2.0000
60	1	4	140	293	0	2	170	0	1.2	2	2	7	2	2.0000	2.0000
63	0	4	150	407	0	2	154	0	4	2	3	7	2	2.0000	1.9992
59	1	4	135	234	0	0	161	0	0.5	2	0	7	1	1.0000	1.0008
53	1	4	142	226	0	2	111	1	0	1	0	7	1	1.0000	1.0008
44	1	3	140	235	0	2	180	0	0	1	0	3	1	1.0000	1.0000
61	1	1	134	234	0	0	145	0	2.6	2	2	3	2	2.0000	1.9998
57	0	4	128	303	0	2	159	0	0	1	1	3	1	1.0000	1.0000
71	0	4	112	149	0	0	125	0	1.6	2	0	3	1	1.0000	1.0004
46	1	4	140	311	0	0	120	1	1.8	2	2	7	2	2.0000	2.0000
53	1	4	140	203	1	2	155	1	3.1	3	0	7	2	2.0000	1.9996
64	1	1	110	211	0	2	144	1	1.8	2	0	3	1	1.0000	1.0001
40	1	1	140	199	0	0	178	1	1.4	1	0	7	1	1.0000	1.0006
67	1	4	120	229	0	2	129	1	2.6	2	2	7	2	2.0000	2.0000
48	1	2	130	245	0	2	180	0	0.2	2	0	3	1	1.0000	1.0005
43	1	4	115	303	0	0	181	0	1.2	2	0	3	1	1.0000	1.0005
47	1	4	112	204	0	0	143	0	0.1	1	0	3	1	1.0000	1.0009
54	0	2	132	288	1	2	159	1	0	1	1	3	1	1.0000	1.0000
48	0	3	130	275	0	0	139	0	0.2	1	0	3	1	1.0000	1.0000
46	0	4	138	243	0	2	152	1	0	2	0	3	1	1.0000	1.0000
51	0	3	120	295	0	2	157	0	0.6	1	0	3	1	1.0000	1.0000
58	1	3	112	230	0	2	165	0	2.5	2	1	7	2	2.0000	2.0000
71	0	3	110	265	1	2	130	0	0	1	1	3	1	1.0000	1.0000
57	1	3	128	229	0	2	150	0	0.4	2	1	7	2	2.0000	2.0000
66	1	4	160	228	0	2	138	0	2.3	1	0	6	1	0.9999	1.0005
37	0	3	120	215	0	0	170	0	0	1	0	3	1	1.0000	1.0000
59	1	4	170	326	0	2	140	1	3.4	3	0	7	2	2.0000	2.0000
50	1	4	144	200	0	2	126	1	0.9	2	0	7	2	2.0000	1.9998
48	1	4	130	256	1	2	150	1	0	1	2	7	2	2.0000	2.0000
61	1	4	140	207	0	2	138	1	1.9	1	1	7	2	2.0000	2.0000
59	1	1	160	273	0	2	125	0	0	1	0	3	2	2.0000	1.9992
42	1	3	130	180	0	0	150	0	0	1	0	3	1	0.9991	1.0006
48	1	4	122	222	0	2	186	0	0	1	0	3	1	1.0000	1.0000

Performance Evaluation of MLFFNN using BP algorithm

The **MLFFNN** using back propagation algorithm consists of 13, 20 and 1 neurons in the input, hidden and output layer respectively. For Training 270 data set is used. The Testing set consists of 50 data. The numbers of hidden layers are varied accordingly in order to choose the optimum no. of hidden layers in the network that is having better performance. During data analysis, the last column is realized as output and other columns will be considered as input. The main function of neurons in the input layer is the division of the input signal among the neurons in the hidden layer. Out of different configurations tested, it is observed that best results for the diagnosis of heart disease are arrived with 20 neurons in its hidden layer. The topology of MLFFNN is given in figure 4.

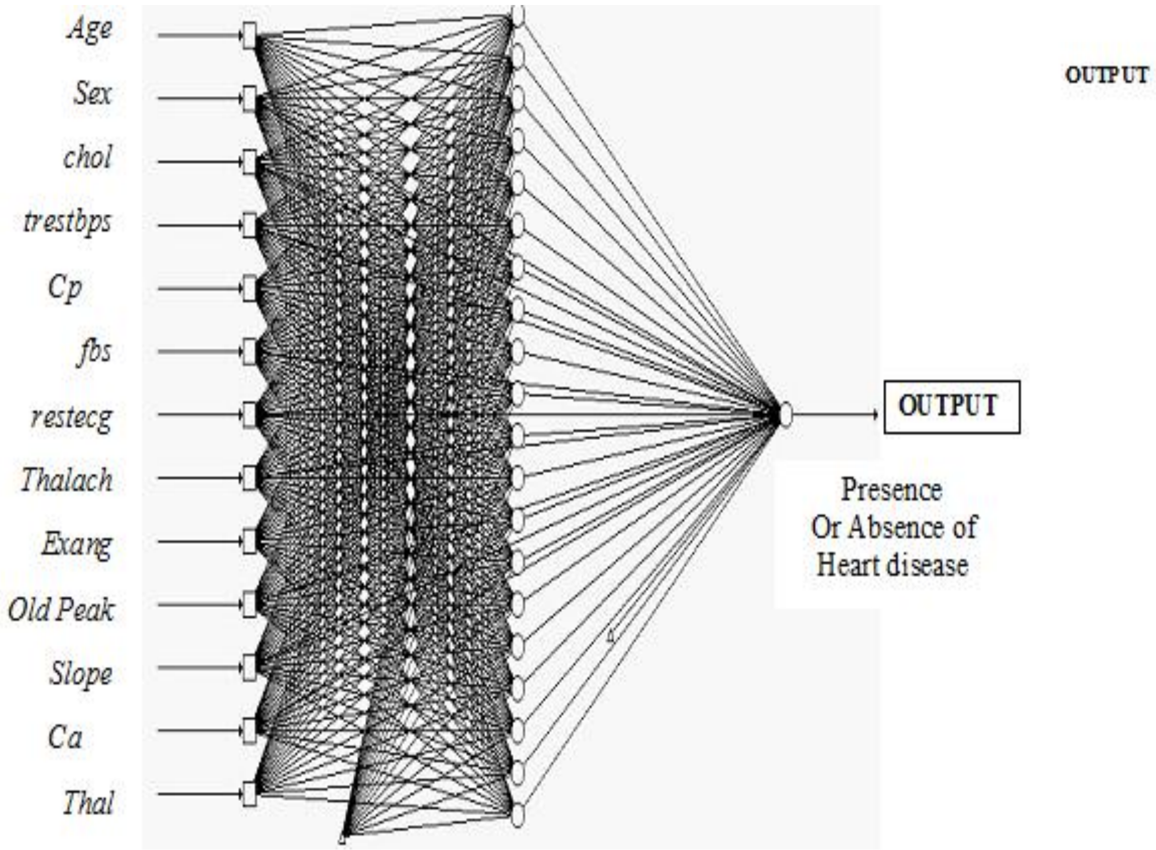

Figure 4: Topology of Multilayer Feed Forward Neural Network with Back Propagation

BP algorithm adjust weights and bias values to reduce the square sum of difference between the given output and output values computed by the network with the help of gradient decent method. During the training process, error is calculated in terms of percentage error of output from desired output (1 or 2.) On an average it took about 17966 iterations to converge to the result with learning rate of 0.7 and momentum of 0.7 which was found out to be an optimal value for binary sigmoid function. The architecture of MLFFNN is given in table 3. After successful training using database with desired output, the NN are able to diagnose the heart disease and make predictions for unknown cases. The number of classes is two: 1– Normal person (no heart disease), 2-represents presence of heart disease. The output layer has one neuron to represent these classes.

Table 3: The architecture of MLFFNN

Parameter	Value
Number of Neurons in Input layer	13
Number of Neurons in Hidden layer	20
Number of Neurons in output layer	1
Epoch	17966
Momentum	0.7
Learning rate	0.7

Table 4: Statistical results of MLFFNN

Mode	RMSE	R^2
Training	0.0680	0.941
Testing	0.0030	0.999

For testing the performance of the net, the test data is supplied as the input to the trained network and the output of the net is calculated with the adjusted weights. The learning ability of the network is realised by comparing computed output with desired output for classifying the heart disease data. The graph plotted for input data set vs. desired and network output is displayed in figure 5 and 6 for training and testing (MLFFNN). The accuracy of MLFFNN is determined by plotting a graph between desired output and network output given in figure 7 and 8. Table 4 displays the statistical analysis of MLFFNN. The correlation coefficient (R^2) is 0.9410 with RMS error of 0.0680 for training. For testing the correlation coefficient (R^2) = 0.999 with RMS error of 0.0030 was obtained. [23].

Figure 5: Input dataset vs. desired output and network output for training MLFFNN

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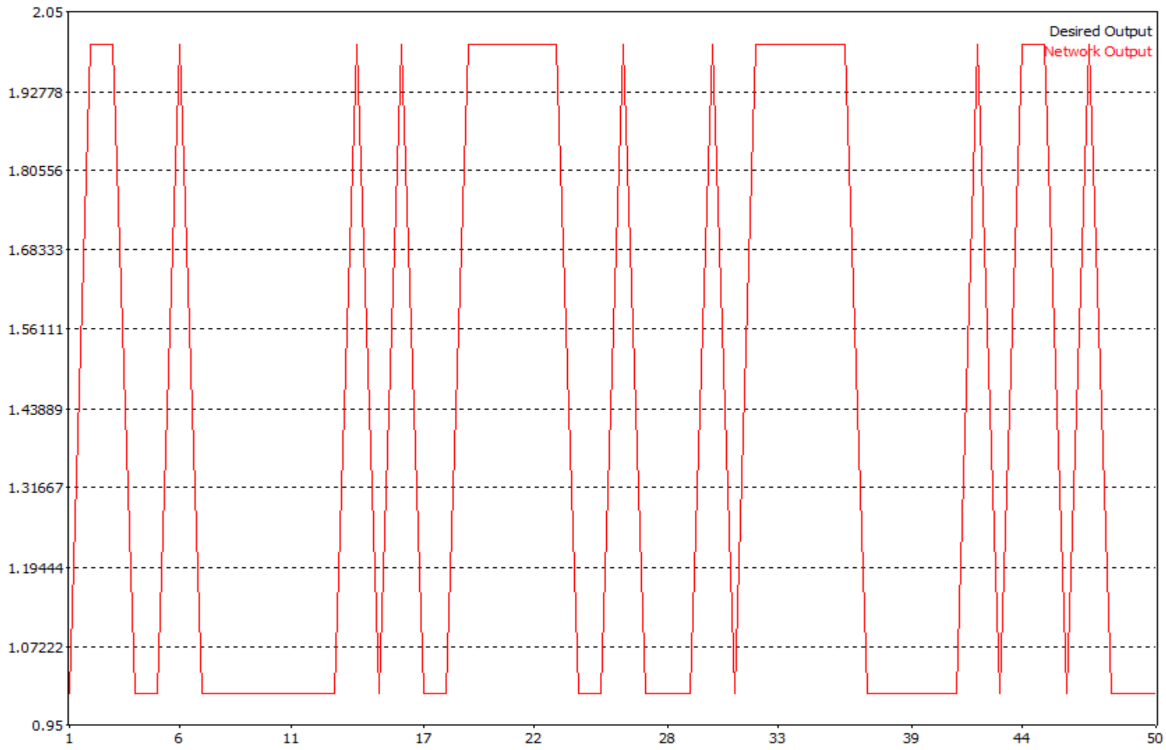

Figure 6: Input dataset vs. desired output and network output for testing MLFFNN

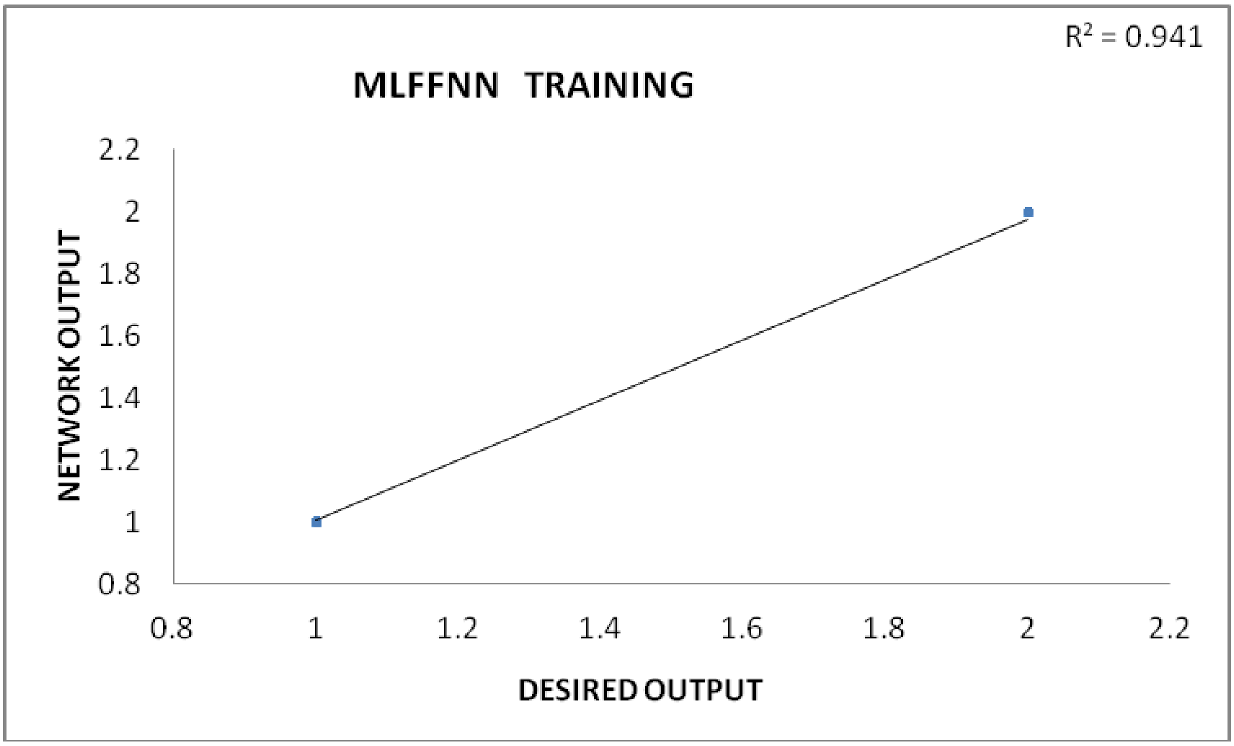

Figure 7: Desired output vs. network output for training using MLFFNN

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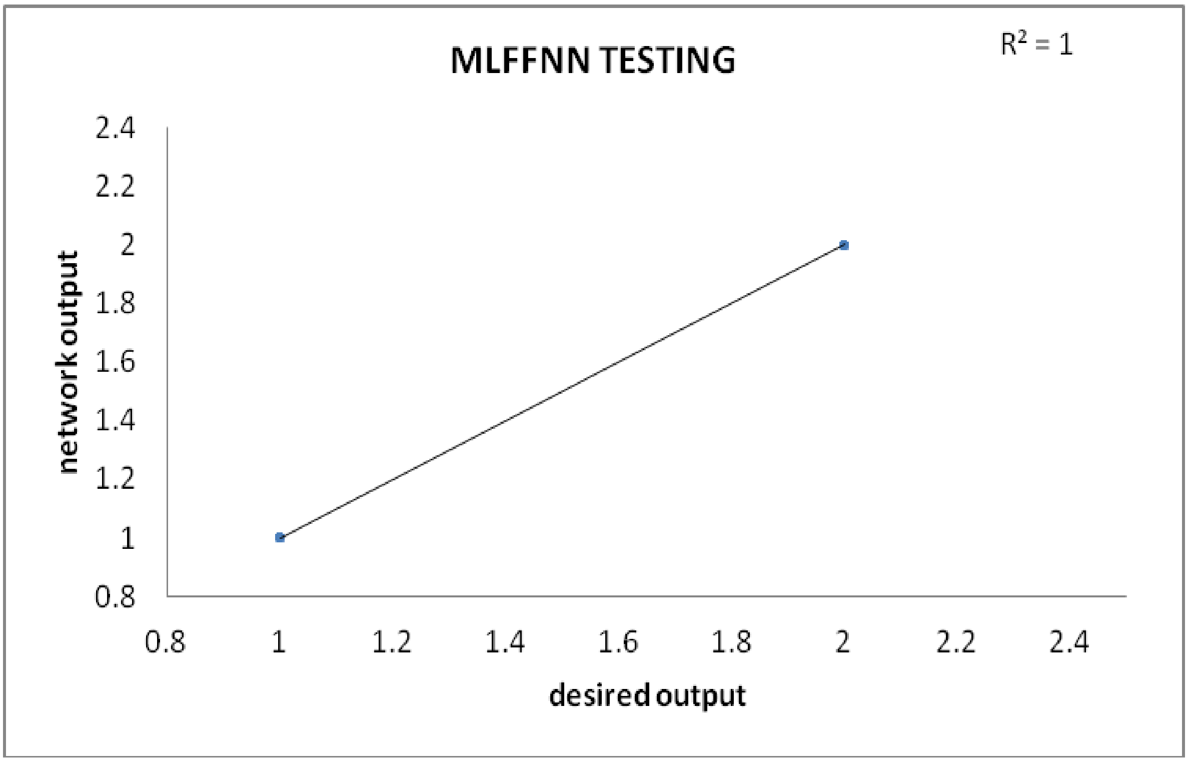

Figure 8: Desired output vs. network output for testing using MLFFNN

Performance Evaluation of ASNN

In the ASNN neural net work training 13, 10 and 1 attributes (Neurons) are involved in input, hidden and output layers respectively for 270 data sets. For Testing 50 data set are used .The number of hidden layers is optimized in order the ASNN to have the better performance. Out of different configurations tested, it is observed that best results for the diagnosis and prediction of heart disease is achieved with 10 neurons in its hidden layer. Seed number (100) is used in to start sequence of random numbers for initialization of neural network weights and partition of initial training set data on training/test sets. The activation function suitable for this work is Logistic 1/ (1+exp (-x)). The architecture of ASNN is shown in Table 5.

Table 5: Architecture and Specification of the generated ASNN

No. of nodes in the input layer	13
No. of nodes in the hidden layer	10
No. of nodes in the output layer	1
Seed value	100
Activation function	Logistic 1/(1+exp(-x))

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Table 6. Testing set with input parameters and output predicted by ASNN and MLFFNN

Age	sex	Cp	Tre	Cho	Fbs	Res	Tha	Exa	Old	Slo	Ca	Thal	Desired o/p	o/p by ASNN	O/p by MLFFNN
71	0	4	112	149	0	0	125	0	1.6	2	0	3	1	1.116	1.000
46	1	4	140	311	0	0	120	1	1.8	2	2	7	2	1.975	2.000
53	1	4	140	203	1	2	155	1	3.1	3	0	7	2	1.909	2.000
64	1	1	110	211	0	2	144	1	1.8	2	0	3	1	1.146	1.000
40	1	1	140	199	0	0	178	1	1.4	1	0	7	1	1.247	1.001
67	1	4	120	229	0	2	129	1	2.6	2	2	7	2	1.961	2.000
48	1	2	130	245	0	2	180	0	0.2	2	0	3	1	1.107	1.000
43	1	4	115	303	0	0	181	0	1.2	2	0	3	1	1.204	1.000
47	1	4	112	204	0	0	143	0	0.1	1	0	3	1	1.214	1.001
54	0	2	132	288	1	2	159	1	0	1	1	3	1	1.201	1.000
48	0	3	130	275	0	0	139	0	0.2	1	0	3	1	1.064	1.000
46	0	4	138	243	0	2	152	1	0	2	0	3	1	1.13	1.000
51	0	3	120	295	0	2	157	0	0.6	1	0	3	1	1.085	1.000
58	1	3	112	230	0	2	165	0	2.5	2	1	7	2	1.919	2.000
71	0	3	110	265	1	2	130	0	0	1	1	3	1	1.164	1.000
57	1	3	128	229	0	2	150	0	0.4	2	1	7	2	1.919	2.000
66	1	4	160	228	0	2	138	0	2.3	1	0	6	1	1.284	1.000
37	0	3	120	215	0	0	170	0	0	1	0	3	1	1.055	1.000
59	1	4	170	326	0	2	140	1	3.4	3	0	7	2	1.934	2.000
50	1	4	144	200	0	2	126	1	0.9	2	0	7	2	1.89	2.000
48	1	4	130	256	1	2	150	1	0	1	2	7	2	1.931	2.000
61	1	4	140	207	0	2	138	1	1.9	1	1	7	2	1.947	2.000
59	1	1	160	273	0	2	125	0	0	1	0	3	2	1.602	1.999
42	1	3	130	180	0	0	150	0	0	1	0	3	1	1.034	1.001
48	1	4	122	222	0	2	186	0	0	1	0	3	1	1.03	1.000
40	1	4	152	223	0	0	181	0	0	1	0	7	2	1.702	1.999
62	0	4	124	209	0	0	163	0	0	1	0	3	1	1.056	1.000
44	1	3	130	233	0	0	179	1	0.4	1	0	3	1	1.145	1.000
46	1	2	101	197	1	0	156	0	0	1	0	7	1	1.098	1.000
59	1	3	126	218	1	0	134	0	2.2	2	1	6	2	1.787	1.999
58	1	3	140	211	1	2	165	0	0	1	0	3	1	1.096	1.000
49	1	3	118	149	0	2	126	0	0.8	1	3	3	2	1.784	2.000
44	1	4	110	197	0	2	177	0	0	1	1	3	2	1.724	1.999
66	1	2	160	246	0	0	120	1	0	2	3	6	2	1.756	2.000
65	0	4	150	225	0	2	114	0	1	2	3	7	2	1.854	2.000
42	1	4	136	315	0	0	125	1	1.8	2	0	6	2	1.916	2.000
52	1	2	128	205	1	0	184	0	0	1	0	3	1	1.053	1.000
65	0	3	140	417	1	2	157	0	0.8	1	1	3	1	1.259	1.000
63	0	2	140	195	0	0	179	0	0	1	2	3	1	1.075	1.000
45	0	2	130	234	0	2	175	0	0.6	2	0	3	1	1.053	1.000
41	0	2	105	198	0	0	168	0	0	1	1	3	1	1.089	1.000
61	1	4	138	166	0	2	125	1	3.6	2	1	3	2	1.926	2.000
60	0	3	120	178	1	0	96	0	0	1	0	3	1	1.073	1.000
59	0	4	174	249	0	0	143	1	0	2	0	3	2	1.742	1.999
62	1	2	120	281	0	2	103	0	1.4	2	1	7	2	1.87	2.000
57	1	3	150	126	1	0	173	0	0.2	1	1	7	1	1.159	1.000
51	0	4	130	305	0	0	142	1	1.2	2	0	7	2	1.862	2.000
44	1	3	120	226	0	0	169	0	0	1	0	3	1	1.073	1.000
60	0	1	150	240	0	0	171	0	0.9	1	0	3	1	1.047	1.000
63	1	1	145	233	1	2	150	0	2.3	3	0	6	1	1.272	1.000

After the training process the ability of classifications(HD diagnosis) of the model is estimated from test data. The test data contains 50 instances. The output of the trained neural network is computed from the input test data. The output of ASNN consists of 2 classes. (Class-1) the output is 1 which indicates the patient is normal without heart disease. (Class-2) output is 2 Abnormal which represent the presence of heart disease. Table 6 gives testing set with input parameters and output values predicted by the networks.

The External Validation of ASNN

The accuracy of diagnosis is evaluated by using four parameters squared correlation co-efficient (R^2), Mean Square Error, root mean square errors (MSE and RMSE) and diagnosing accuracy. MSE is the average of the square of the variation between the output and targets. Lower the value, better the results and a zero value indicates no error. The squared correlation co-efficient (R^2) measures how well the predicted values from the output of the network “fit" with the actual data. The value of R^2 lies between 0 and 1. A correlation co-efficient greater than 0.9, is generally described as strong model, whereas a correlation co-efficient less than 0.5, is generally described as weak model. High value of R^2 and low value of RMSE or MSE indicated a more stable model.

Table 7: Statistical results of ASNN with classification accuracy.

Mode	RMSE	MSE	R^2	q^2
Training	0.0003	0.0009	0.999	0.999
Testing	0.1614	0.134	0.9460	0.895

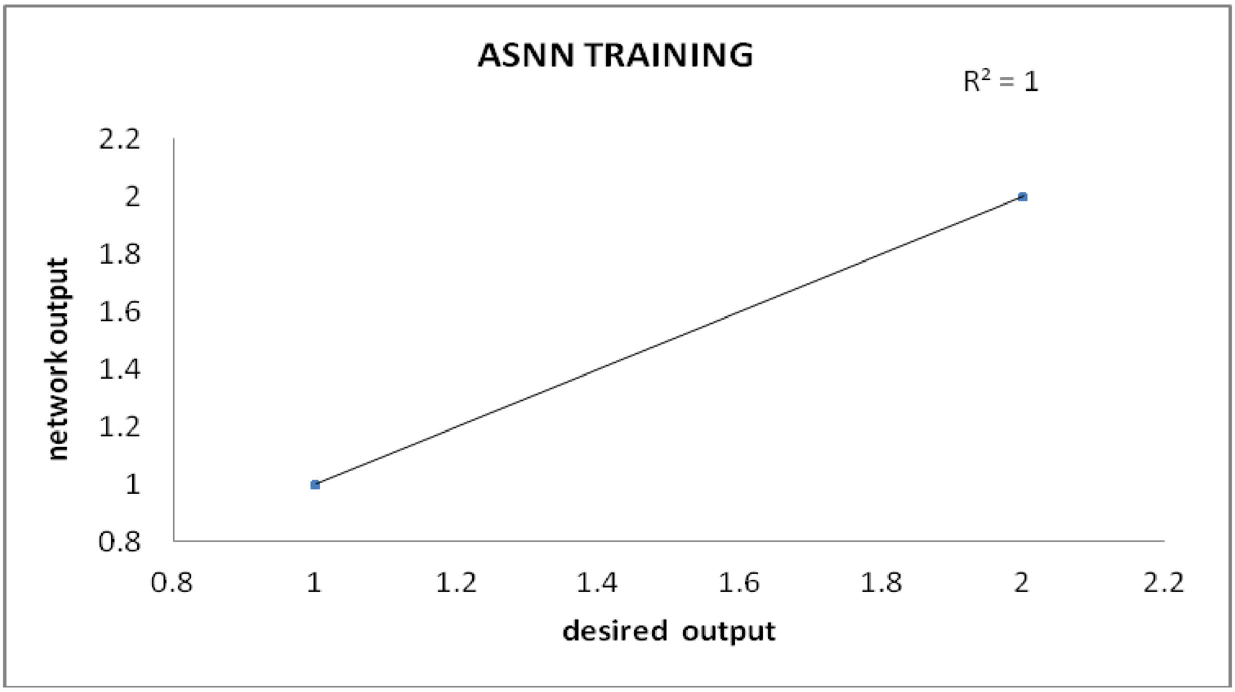

Figure 9: Desired output vs. network output for training using ASNN

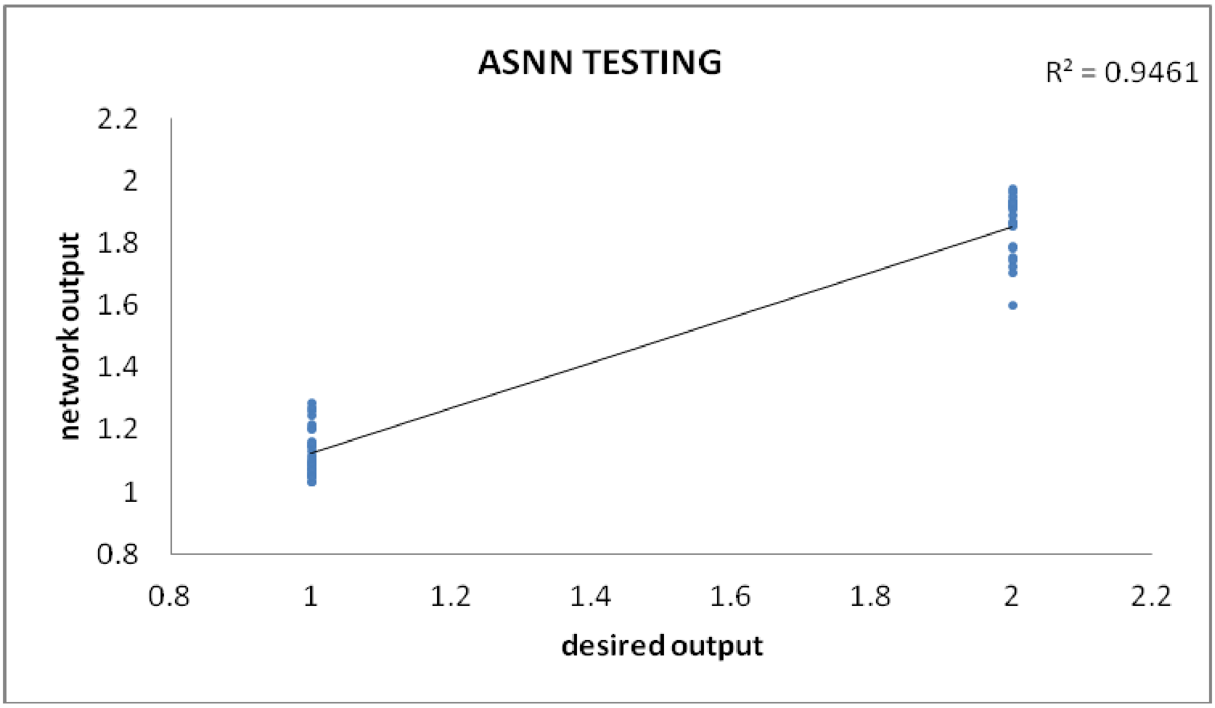

Figure 10: Desired output vs. network output for testing using ASNN

The developed model is evaluated for its stability using leave one out cross validation method of statistical analysis. A good correlation is obtained with LOO correlation co-efficient R^2 = 0.990 for training and 0.9460 for testing. The statistical performance of the Associative Neural Network is summarized in Table 7. The Root mean square errors of ASNN model for training and testing are 0.0003 and 0.1614 respectively. Figure 9 and 10 show scatter plot of the ASNN actual versus Predicted output for training and test set. So the predictive power of the ASNN model is very significant.

Heart disease even though is dreadful, it is curable when the patient is admitted with proper diagnosis whenever the patient suffers from indications of heart attack biz, low BP, diminishing pulse rate, excess sweating, discomfort, mild chest pain the patient has to be immediately administer drugs such as Aspirin, Clopidogrel etc… When the ECG reports ST elevation possibility of Heart disease is confirmed. The medical experts on confirmation of heart disease using this model may suggest nitro-glycerine to treat the heart patients. The implementation of this model is to provide the doctors with speedy remedial measures within a very short span of time by using this model. As an outcome of the study it is observed that the patient suffering from characteristic diabetics and prolonged hyper tension and cholesterol suffer from heart disease more certainly and also reveals that the risk factor is more prevalent in men than women. The remedial measure is extensive physical activities, fewer intakes of cholesterol and fat substances, and the regularly monitored and controlled diabetes, maintaining a normal BP.

CONCLUSION

This study explains a proficient prediction system for reliable diagnosis of heart disease (CVD/CAD) utilizing two neural networks MLFFNN using BP algorithm and ASNN. The MLFFNN with 13-20-1 architecture produces correlation coefficient of 0.9410 for training and 0.999 for testing. The ASNN with 13-10-1 architecture produces low error. The ASNN model is having the correlation coefficient (R^2) = 0.999 for training and 0.9460 for testing in HD diagnosis. Out of this two neural network MLFFNN is found to be efficient than ASNN in diagnosing the Coronary Artery disease a type of heart disease. The experimental results have demonstrated the effectiveness of this model in HD diagnosis to give treatment accordingly. It is also proved that the diagnosis using the ASNN and MLFFNN are more ideal, dependable and trustworthy to the medical experts by comparing the computer aided prediction results with pathologic findings for getting clinical clues and ideas regarding the therapy and medications according to the severity of suffered patients.

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