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RESEARCH ARTICLE

A New ANN, GRNN and RBF Neural Network for Heart Disease Diagnosis

Pramod Kumar Yadav¹

¹Research Scholar, Department of Computer Science, Govt. P. G. Science College Rewa (M.P.), India
yadav.pramod181@gmail.com

Dr. K.L.Jaiswal²

²Asst.Professor, Department of Physics, Govt. P. G. Science College Rewa (M.P.), India
drkanhaiyalajaiswal@gmail.com

Dr. Kamlesh Singh³

³Asst.Professor, Department of Physics, Govt. P. G. Science College Rewa (M.P.), India
Drkamleshsingh72@gmail.com

Satish Pandey⁴

⁴Research Scholar, Department of Computer Science, Govt. P. G. Science College Rewa (M.P.), India
Satishpandey189@rediffmail.com

Abstract -In this paper, two types of Artificial Neural Network (ANNs), Generalized Regression Neural Network (GRNN) and Radial Basis Function (RBF) have been used for heart disease to prescribe the medicine. Diagnosing the heart disease and prescribing the medicine on the basis of symptoms is a very challenging task to improve the ability of the physicians. The training capacity and medicines provided by these two techniques are compared with the original medicines provided by the heart specialist. About 300 patient's data are collected from S.G.M.Hospital Rewa under the supervision of doctor. This study includes the detailed information about patient and preprocessing was done. The GRNN and RBF have been applied over this patient data for the outcome the medicine. The result of these evaluation show that the overall performance of RBF can be applied successfully for prescribing the medicine for the heart disease patient.

Keywords: Generalized Regression Neural Network, Radial Basis Function, Heart Disease diagnosis, Symptoms, Medicine

1. INTRODUCTION

Statistics have consistently shown that heart disease is one of the leading causes of deaths in US and all over the world [1]. Significant life saving, however, can be achieved if an accurate diagnosis decision can be promptly made to patients suffering various types of heart diseases, after which an appropriate treatment can immediately follow. Unfortunately, accurate diagnosis of heart diseases has never been an easy task. As a matter of fact, many factors can complicate the diagnosis of heart diseases, often causing the delay of a correct diagnosis decision. For instance, the clinic symptoms, the functional and the pathologic manifestations of heart diseases are associated with many human organs other than the heart, and very often heart diseases may exhibit various syndromes. At the same time, different types of heart diseases may have similar symptoms. To reduce the diagnosis time and improve the diagnosis accuracy, it has become more of a demanding issue to develop reliable and powerful medical diagnosis system to support the yet and still increasingly complicated diagnosis decision process. The medical diagnosis by nature is a complex and fuzzy cognitive process, hence soft computing methods, such as neural networks, have shown great potential to be applied in the development of medical diagnosis of heart diseases. In [2], a probability network based heart failure program was developed to assist physicians in reasoning about patients, which produced appropriate diagnoses about 90% of the time on the training set. Azuaje *et al.* [3] employed artificial neural networks (ANN) to recognize Poincare-plot-encoded heart rate variability patterns related to the risk of the coronary heart disease. Tkacz *et al.* [4] demonstrates how wavelet neural networks (WNN) can be applied for disease classification useful to diagnose coronary artery disease at different levels. For the diagnosis of congenital heart diseases, Reategui *et al.* [5] proposed a model by integrating case-based reasoning with neural networks. In [6] fuzzy reasoning optimized by genetic algorithm was used for the classification of myocardial heart disease. All the above studies, with different types of soft computing methods being applied, deal with only one specific type of heart disease individually. In fact, of all the known heart diseases, hypertension, coronary heart disease, rheumatic alular heart disease, chronic cur pulmonale, and congenital heart disease have been identified as the five most common ones [7]. No study, however, has yet attempted to consider a system to differentiate the diagnosis of all these five major heart diseases simultaneously, which is essential to assist physicians for their diagnosis.

The proposed methodology uses neural network for classifier. The performance of proposed methodology was evaluated with two different neural network techniques. Moreover, we compared our result with Generalized Regression Neural Network and Radial Basis Function with original medicines provided by the doctor. The paper is organized as following, in Section 2, a brief overview on previous related works and in section 3, introduction of Generalized Regression Neural Network and Radial Basis Function is described. Section 4, the proposed methodology and preparing data for neural network. Section 5, Experimental analysis and coding of patients as well as medicine data is described. Section 6, discussion and result of first five patient's medicine given by the Generalized Regression Neural Network and Radial Basis Function is compared with the original medicine. Finally, we concluded this paper in Section 7.

2. A BRIEF BACKGROUND OF NEURAL NETWORK

Artificial neural networks (ANN) have emerged as a result of simulation of biological nervous system, such as the brain, on a computer. On the other hand, biological neural networks are much more complicated than the mathematical models used for ANNs. ANN was founded by McCulloch and co-workers beginning in the early 1940s [8]. They built simple neural networks to model simple logic functions. Since it is customary to drop the "A" or the "artificial", NN and ANN will be used interchangeably throughout the rest of the paper to refer to an artificial neural network. Nowadays, neural networks can be applied to problems that do not have algorithmic solutions or problems for which algorithmic solutions are too complex to be found. In other words, it is not easy to formulate a mathematical model that does not have a clear relationship between inputs and outputs for some systems. To overcome this problem, ANN uses the samples to obtain the models of such systems. Their ability to learn by example makes neural networks (NN) very flexible and powerful. Therefore, neural networks have been intensively used for solving regression and classification problems in many fields. In short, neural networks are nonlinear processes that perform learning and classification. Recently neural networks have been used in many areas that require computational techniques such as pattern recognition, optical character recognition, outcome prediction and problem classification. In materials science and engineering fields, the researchers have used neural network techniques to develop prediction models for mechanical properties of materials [9]. For instance, Hague and Sudhakar [9] published many papers for the prediction of fracture toughness in micro alloy steel, corrosion fatigue behavior and fatigue crack growth in dual-phase (DP) steel, mechanical behavior of powder metallurgy steel, dry sliding wear in Fe₂Ni based PM alloy and the effect of heat treatment on mechanical properties in MIM alloy. Artificial neural networks consist of a large number of interconnected processing elements known as neurons that

act as microprocessors. Each neuron accepts a weighted set of inputs and responds with an output. Fig. 1 depicts a single neuron model. Such a neuron first forms weighted sum of the inputs

$$n = (\sum_{i=1}^p w_i x_i) + b \tag{1}$$

Where P and w_i are the number of elements and the interconnection weight of the input vector x_i , respectively, and b is the bias for the neuron. Note that the knowledge is stored as a set of connection weights and biases. The sum of the weighted inputs with a bias is processed through an activation function, represented by f, and the output that it computes is

$$F(x) = f[(\sum_{i=1}^p w_i x_i) + b] \tag{2}$$

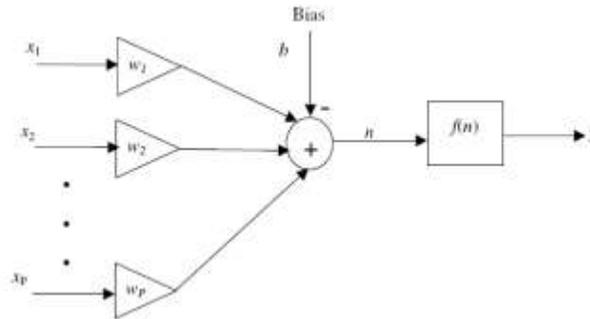


Figure 1. Single Neuron Model

Basically, the neuron model represents the biological neuron that fires when its inputs are significantly excited, i.e., n is big enough. There are many ways to define the activation function such as the threshold function, sigmoid function, and the hyperbolic tangent function. The type of activation function depends on the type of the neural network to be designed. For the threshold function, the output of the neuron is either 0, if the net input argument n is less than zero; or 1, if n is greater than or equal to 0. The sigmoid function takes the input, which may have any value between plus and minus infinity, and squashes the output into the range 0 and 1. The hyperbolic tangent function is one of the functions that take a sigmoid shape. By interconnecting neuron models, a neural network is formed. A neural network can be trained to perform a particular function by adjusting the values of connections, i.e., weighting coefficients, between the processing elements. In general, neural networks are adjusted/trained to reach from a particular input to a specific target output until the network output matches the target. Hence the neural network can learn the system. This type of learning is known as supervised learning. The learning ability of a neural network depends on its architecture and applied algorithmic method during the training. Training procedure can be ceased if the difference between the network output and desired/actual output is less than a certain tolerance value. Thereafter, the network is ready to produce outputs based on the new input parameters that are not used during the learning procedure. A neural network is usually divided into three parts: the input layer, the hidden layer and the output layer. The information contained in the input layer is mapped to the output layers through the hidden layers. Each unit can send its output to the units on the higher layer only and receive its input from the lower layer. This structure is known as multilayer perception and is shown in Fig. 2. This network is a three-layer perception since there are three stages of neural processing between the inputs and the outputs. More hidden layers can be added to obtain a quite powerful multilayer network.

3. Theory of Generalized Regression Neural Network and Radial Basis Function

3.1 Generalized Regression Neural Network

A GRNN is a variation of the radial basis neural networks, which is based on kernel regression networks [10–12]. A GRNN does not require an iterative training procedure as back propagation networks. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function [12].

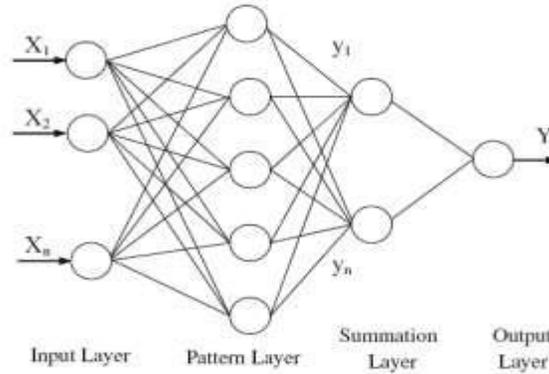


Figure2. General Structure of GRNN

A GRNN consists of four layers: input layer, pattern layer, summation layer and output layer as shown in Fig. 2. The number of input units in input layer depends on the total number of the observation parameters. The first layer is connected to the pattern layer and in this layer each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. The summation layer has two different types of summation, which are a single division unit and summation units. The summation and output layer together perform a normalization of output set. In training of network, radial basis and linear activation functions are used in hidden and output layers. Each pattern layer unit is connected to the two neurons in the summation layer, S and D summation neurons. S summation neuron computes the sum of weighted responses of the pattern layer. On the other hand, D summation neuron is used to calculate un-weighted outputs of pattern neurons. The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value Y_{0i} to an unknown input vector x as [13];

$$Y_i = \frac{\sum_{i=1}^n y_i \cdot \exp -D(x, x_i)}{\sum_{i=1}^n \exp -D(x, x_i)} \quad (3)$$

$$D(x, x_i) = \sum_{k=1}^m \left(\frac{x_k - x_{ik}}{\sigma} \right)^2 \quad (4)$$

Y_i is the weight connection between the i_{th} neuron in the pattern layer and the S-summation neuron, n is the number of the training patterns, D is the Gaussian function, m is the number of elements of an input vector, x_k and x_{ik} are the j_{th} element of x and x_i , respectively, r is the spread parameter, whose optimal value is determined experimentally.

3.2 Radial Basis Function (RBF)

RBFN is an alternative to the more widely used MLP network and is less computer time consuming for network training. RBFN consists of three layers: an input layer, a hidden (kernel) layer, and an output layer. The nodes within each layer are fully connected to the previous layer. The input variables are each assigned to the nodes in the input layer and they pass directly to the hidden layer without weights. The transfer functions of the hidden nodes are RBF. An RBF is symmetrical about a given mean or center point in a multidimensional space. In the RBFN, a number of hidden nodes with RBF activation functions are connected in a feed forward parallel architecture. The parameters associated with the RBFs are optimized during the network training. These parameter values are not necessarily the same throughout the network nor are they directly related to or constrained by the actual training vectors. When the training vectors are presumed to be accurate, i.e. no stochastic, and it is desirable to perform a smooth interpolation between them, then linear combinations of RBFs can be found which give no error at the training vectors. The method of fitting RBFs to data, for function approximation, is closely related to distance weighted regression. The RBF expansion for one hidden layer and a Gaussian RBF is represented by

$$Y_i(X) = \sum_{i=1}^H W_{ki} \exp \left(-\frac{\|X - u_i\|^2}{\sigma_i} \right) \quad (5)$$

An interpolation RBFN is characterized by equal number of basic functions with training points. However, each input training point serves as a center for the basis function. In order to ensure a smooth fit of the desired outputs, the width of each kernel has to incorporate the training points [25].

4. METHODOLOGY

4.1 Proposed methodology and implementation of with GRNN and RBF

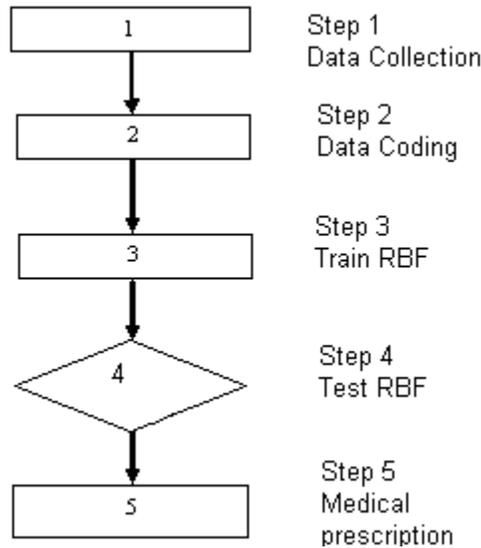


Figure 3. Flow chart of proposed methodology

4.2 Preparing Data to implement neural network techniques:

The data is collected from daily OPD session while doctor examining the patients. The symptoms and information about patients details like Previous History(p1), Present History(p2), Personnel History(p3), Physical Examination(p4), Cardio Vascular System(CVS), Respiratory Rate(RS), Per Abdomen(PA), Central Nervous system(CVS), ECG and Blood Investigation(BI). The main point is ECG from which the patient can easily diagnose whether the patient is having heart problem or not. All 300 patients data collected regarding heart disease and the data are prepared in different Excel Sheets which contains codes of each individual disease, history and symptoms. In one excel file 13 sub-sheets are taken for each field of information such as for Previous History (p1), for Present History the second sub-sheet and the name is given (P2), for Personnel History (P3) the third sub sheet is taken, like this the data collection has 13 different sub sheets for different fields. All the fields are taken under the supervision of the Cardiologist The code is given to each symptoms, physical examination parameter or diseases in each sub-sheet for experimental work. On this data some pre-processing i.e. normalization, coding and decoding methods are applied for the expected output. In table 1, the Previous History (P1) has represented with 1 to 18 different diseases of total 300 heart patients and it is defined by the codes respectively from 1 to 18. The code 1 which represents Hypertension, Code 2 represents Diabetes Mellitus like this it contains 18 different diseases. Some of them are as shown in table 1.

Table 1. Previous History of Patients

Code	Name of Disease
1	Hypertension
2	Diabetes Mellitus
3	TB
4	Bronchial Asthama
5	Hyperthyroidism

In table 2, Present History (P2) and the symptoms present in P2 are represented by Codes. The Code 1 which represents Chest Pain/Discomfort, Code 2 represents Retrosternal Pain like this it contains 29 different symptoms. Some of the symptoms are shown in table 2.

Table 2. Present History of patients

Code	Symptoms
1	Chest Pain/Discomfort
2	Retrosternal Pain
3	Palpitation
4	Breathlessness
5	sweating

In table 3, Personnel History (P3) and the information present in P3 are represented by codes for different bad habits. The Code 1 which represents Smoking, Code 2 represents Tobacco like this 4 different bad habits are taken and specified by 1 to 4 codes. Some of the personnel history parameters are given below.

Table 3. Personnel History

Code	Personnel History
1	Smoking
2	Tobacco
3	Alcohol
4	Nil

In table 4, Physical Examination (P4) and the information present in P4 are represented by codes for different physical parameters. The Code 1 which represents Consciousness, Code 2 represents Orientation like these 25 different physical parameters and specified by 1 to 25 codes for each parameter. Some are as shown below in table4.

Table 4. Physical Examination

Code	Physical Examination
1	Altered Consciousness
2	Orientation
3	Dyspnoea
4	Fever
5	Low Pulse Rate

In table 5, Cardio Vascular System (CVS) and the information present in CVS are represented by codes for different symptoms. The Code 1 which represents Heart Sound, Code 2 represents Normal Heart Rate like these 8 different symptoms and specified by 1 to 8 codes for each symptom. Some are as shown below in table 5.

Table 5. Cardio Vascular System

Code	Symptoms
1	Heart Sounds
2	Normal Heart Rate
3	Tachycardia
4	Bradycardia
5	Regular Heart Rhythm

In table 6, Respiratory System (RS) and the information present in RS are represented by codes for different symptoms. The Code 1 which represents Breath Sound preserved, Code 2 represents Breath Sound Reduced like this 5 different symptoms are found and specified as shown in table 6.

Table 6. Respiratory System

Code	Symptoms
1	Breath Sounds Preserved
2	Breath Sound Reduced
3	Basal Crepts
4	No Abnormality Detected (NAD)
5	Abnormality Detected (NAD) 5 Ranchi

In table 7, Per-Abdomen (PA) and the information present in PA are represented by codes for different symptoms. The Code 1 which represents Liver (Hepatomegaly), Code 2 represents Spleen (Splnomegaly) like these 6 different symptoms have found and specified by 1 to 6 codes for each symptom. Some are as shown below in table 7.

Table 7. Per Abdomen

Code	Symptoms
1	Liver(Hepatomegaly)
2	Spleen (Splnomegaly)
3	Free Fluid Present
4	Abdominal Distension
5	No Abnormality Detected (NAD)

In table 7, Central Nervous System (CNS) and the information present in CNS are represented by codes for different symptoms. The Code 1 which represents Consciousness, Code 2 represents Orientation like these 5 different symptoms are found and specified by 1 to 5 codes for each symptom. Some are as shown below in table 8.

Table 8. Central Nervous System

Code	Symptoms
1	Consciousness
2	Orientation
3	Focal Deficit
4	No Abnormality Detected (NAD)
5	Restlessness

In table 8, Electro Cardio Gram (ECG) and the information present in ECG are represented through codes for different finding which points to different problems of heart. The Code 1 which represents ST Elevation, Code 2 represents Anterior Wall like these 21 different heart findings are found and specified by 1 to 21 codes for each finding. Some are as shown below in table 9.

Table 9. Electro Cardio Gram (ECG)

Code	ECG Point
1	ST Elevation
2	Anterior Wall
3	Antero Septal
4	Inferior
5	Infero Posterior

In table 10, Blood Investigation (BI) and the information present in BI are represented through codes for blood investigation. The Code 1 which represents Cardiac Enzymes (High), Code 2 represents Blood Sugar Test like this 24 different investigations has found and specified by 1 to 24 codes for each investigation in all patient. Some are as shown below in table 10.

Table 10. Blood Investigation

Code	Symptoms
1	Lipid Profile normal
2	Lipid Profile Abnormal
3	Complete Blood Count Normal
4	Leucocytosis
5	Anemia

In table 11, all the medicines names along with their codes i.e. MID which are prescribed by the doctor to the patients. The medicine sheet contains 52 different medicines which are prescribed by the doctor in different 300 stages. Some are as shown below in table 11.

Table 11. Medicine Names

Code	Medicine Name
1	Alprazolam
2	Amlodopine
3	Aspirin
4	Atenolol
5	Atorvastatin

In table 12, all Patients information such as previous history(P1), P2(Present History), P3(personnel History), P4(Physical Examination), CVS(Cardio Vascular System), RS(Respiratory System), PA(Per Abdomen), CNS(Central Nervous System), ECG(Electrocardiography) and BI(Blood Investigation) which contains all the represented codes that are present in the individual patients.

Table 12. Collection of different details of the individual Heart Patients

Sr. No.	Patient Name	Symptoms and Findings										
		Age	P1	P2	P3	P4	CVS	RS	PA	CNS	ECG	BT
1	A	55M	2	1,2,5,13	4	7,10	8	4	5	4	1,3	14
2	B	58M	2	1,2,8	2	7,8,13,14	8	4	5	4	2	7
3	C	60M	8	5,7,13	4	1,6,12	8	4	5	4	9	14
4	D	60M	1,2	4,5	4	1,2,7,13,14	3,5	3	5	4	12	4
5	E	56F	1	15,16	4	6,9,12	8	4	5	4	10	2

In table 13, different 52 medicines were used by the doctor on total 300 patients. All the medicines are prescribed by the doctor. In this table the medicines codes are used as the description given in the table 11.

Sr. No.	Patient Name	MID 1	MID 2	MID 3	MID 4	MID 5	MID 6	MID 7	MID 8	MID 9	MID 10	MID 11	MID 12	MID 13
1	A	2	3	5	6	14	17	19	21	23	25	26	27,29	36
2	B	2	3	5	6	14	16	17	21	23	25	26	27	28
3	C	1	5	6	14	25								
4	D	3	5	7	10	11	13	14	17	19	30			
5	E	5	14	15	19									

5. Experimental Analysis

For further training of neural network process the proposed information is coded in binary form (0 or 1). If the symptom is present in the patients at particular position at that point it is defined by one (1) and if the symptoms or disease is not present at that position it is placed by Zero (0). Suppose for example in the field P2 (present history) there are total 29 symptoms present and the patient no 1 is having the symptom 1, 2,5 and 13 so these locations are defined by 1 (one) and all other symptoms are 0 (zero). In such a way all the fields are defined. All the parameter that we consider in medical prescription like Sr. No., ,age , P1, P2,P3,P4,CVS, RS, PA, CNS, ECG and BT are converted in binary number where this is used in neural network for train the neurons for achieving better result.

Table 14. The individual data of the patient 1 is defined in binary form

Sr. No	00000001
Age	0110111
P1	010000000000000000
P2	1100100000001000000000000000
P3	0001
P4	00000010010000000000000000
CVS	00000001
RS	00010
PA	000010

CNS	00010
ECG	10100000000000000000
BT	0000000000001000000000

Using this sequence of binary format we were not getting appropriate result. Therefore we have change the order of fields as per suggestion of the doctor because the doctors are prescribing the medicines on the basis of the ECG and blood investigation. So the order of ECG is changed from field no. 9 to field no. 1 and after ECG we have taken Blood Investigation and rest of the fields are same and at last age is placed. Due of reshuffling of the fields we got satisfactory result up to 97% by using Radial Basis Function. For this expert system total 52 different medicine are prescribed by the Doctor and if the medicine is present at that position it is defined by one (1) and if it is absent at that position it is defined by Zero(0). Similarly for patient one the prescribed medicine are defined as: 0 1 1 0 1 1 0 0 0 0 0 1 0 0 1 0 1 0 1 0 1 1 1 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0;

Figure 4 Medicine Coding of the patient 1

6. Discussion of First five patients results with doctor

5.2.1 Original Medicines given by doctor:

- A) 1,3,5,6,14,17,19,21,23,25,26,27,29,36
- B) 2,3,5,6,14,16,17,21,23,25,26,27,28
- C) 1,5,6,14,25
- D) 3, 5, 7, 10,11,13,14,17,19,30
- E) 3,14,15,19

4.2.1 Medicines given by GRNN

- A) 1, 3, 5,6,14, 16,17,21,23,25,26,27
- B) 1,3,5,6,11,14,16,17,21,22,23,24,25,26,27,36
- C) 1, 3, 5,6,11,17,21,25
- D) 1,3,5,6,11,13,14,17,21,25
- E) 3, 5,6,14.

4.2.3 Medicines given by RBF:

- A) 3,5,6,14,16,17,21,23,25,26,27,28,29
- B) 1,3,5,6,11,14,16,17,21,22,23,24,25,26,27,28,36
- C) 1,3,5,6,14,21,25
- D) 1,3,5,6,11,13,14,17,21,25,30
- E) 3,5,6,14,15

So Medicines given by the expert system using Generalized Regression Neural Network is not producing the appropriate result as compared with the RBF.

5.2.5 C. So we have taken doctors opinion on the result of RBF as:

Patient A is having major heart attack for which the expert system has provided the medicine no. 1 which is anxiolytic and is given in almost all patients. Medicine no. 16 is beneficial as it reduces the heart rate and thereby reduces workload and improves outcome. Medicine no. 26 can prove useful as it prevents stress erosions/ulcer. The medicine no. 28 is sedative (sleep inducing drug) and is beneficial and if given may help improve outcome.

Patient B Medicine no 1 is alprazolam which is anxiolytic and is given in almost all patients and won't affect the heart patient. Medicine no. 11 should not be prescribed as it is a diuretic and can cause fall in blood pressure/electrolyte imbalance. And is not appropriate and is wrongly given by the expert system. Medicine no 22 is Antioxidant and if given is useful. Medicine no. 24 is antibiotic and is given in presence of infection and does not affect the cardiac outcome.

Patient C, Medicine 21 is prescribed which has a cardiac remodeling effect and if given improves outcome.

Patient D, Medicine no 1 is alprazolam which is used for its anxiolytic effect is given in almost all patients and won't affect the heart patient. Medicine no. 6 has near to same action as medicine no. 3 which is already prescribed. Expert system has not given medicine no. 7 which is useful in this patient as patients clinical condition has poor heart pumping. Medicine no. 19 is a antipyretic drug (to reduce fever) or as analgesic an if given won't affect the cardiac outcome. Medicine no. 25 is ant clotting medicine which is wrongly given and it should be given in moderate to severe cases after assessing clinical condition of the patient.

Patient E . Medicine no. 5 is not given by the expert system which has cholesterol reducing agent and plays important role for positive outcome. Medicine no. 6 has the same action as medicine no. 3 and is already prescribed.

Medicines given by expert system in few patients are comparatively less and in few patients additional. The system has analyzed 125 sample data and is prescribing 97% accuracy in the medicines as prescribed by the doctor after his clinical assessment. In some cases it is justified but in some cases it depends on the Clinical condition. The additional medicines prescribed may prove beneficial or harmful and vice versa prescribing less medicines (which if essential) can affect the cardiac outcome.

7. CONCLUSION

The main purpose of this study is to investigate the applicability and capability of ANN methods, GRNN and RBF for prediction of medicine for the heart disease on the basis of symptoms. For this study, GRNN and RBF techniques are applied to existing experimental data of the heart disease patient. In this paper, around 300 patient's information is collected from SGM Hospital, under supervision of Dr. C.B.Singh,(MD Medicine) SGM Hospital, Rewa (M.P.). The collected information is coded, normalized and entered into 13 different excel sub-sheets. All the patients' data is trained by using SVM and RBF. Around 50 samples were tested with these two techniques. If the more data set is used for the training the NN model gives more robust results. The analysis model by using SVM and RBF of ANN gives better result for medical prescription for heart disease patient. However, there are several techniques that can improve the speed and performance of the back propagation algorithm, weight initialization, use of momentum and adaptive learning rate. It is found that the result of testing data by using SVM is not satisfactory but the medicines prescribed by the RBF are satisfactory as per the result verified by the doctor. The diagnosis performance of this study shows the advantage of this system. : it is rapid, easy to operate, noninvasive and not expensive. The working prototype model in the field of heart diagnosis can use the system. It also helps for training beginner's doctors and medical students who work in the field of heart diagnosis. In future, this work may be extend Using support vector machine.

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