# Diagnosis and Medical Prescription of Heart Disease Using FFBP, SVM and RBF

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***Abstract***: An Expert System is a problem solving and decision making system based on knowledge of its task and logical rules or procedures for using knowledge. Both the knowledge and the logic are obtained from the experience of a specialist in the area.  In the field of medicine, heart diseases have caused turbulence all over the world.  The use of neural network on different diseases has been used on large scale since last three decades.  The expert system has been innovated to bring out relief for the heart patients.

This paper includes details about patient's data, coding, normalization and tabulation.  The Feed Forward Back-propagation (FFBP), Support Vector Machine (SVM)  and Radial Basis Function (RBF) has been applied over the data for the experiment.  Sahara Hospital, Roshan gate, Aurangabad has played an encore role for collecting the information of 375 patients under the supervision of Dr. Abdul Jabbar (MD Medicine).  In order to obtain a correct diagnosis the expert system is precisely trained for giving the required medicine.  To make the system more authentic and reliable out of 375 patients 250 patients were used for training set and 125 for evaluation process.  This study includes the detailed information about patient and preprocessing was done. The FFBP, SVM  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. In conclusion, the experiments proved beneficial as it gave maximum positive result upto 90 to 95%.

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## 1. INTRODUCTION

Cardiovascular diseases (CVD), including coronary heart disease, stroke, and peripheral vascular diseases constitute major public health problems worldwide.[1] They are the leading cause of global morbidity and mortality. The World Health Organization (WHO) estimated that 17.5 million people died from CVDs in 2005, representing 30% of all global fatalities.[2] An estimated 7.6 million were due to coronary heart disease and 5.7 million due to stroke. By 2015, almost 20 million people will die from CVDs, mainly from heart disease and stroke. These are projected to remain the single leading cause of death.

Cardiovascular risk factors, including hypertension (HPT), diabetes mellitus (DM), hypercholesterolemia (HyCh), cigarette smoking, excess body weight, and sedentary lifestyle play a major role in the occurrence of CVD.[3] A report released by the Media and Health Awareness Information Center at the Ministry of Health (MOH) pointed out that the Cardiovascular diseases (CVDs), including heart attacks and strokes, are the number-one cause of deaths globally: they are the cause of 17.3 million deaths annually, and this number can be increased. By 2030, almost 23 million people will die from CVDs, mainly from heart disease and stroke, unless effective interventions are taken. [4]

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 [4], 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. [5] 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. [6] 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. [7] proposed a model by integrating case-based reasoning with neural networks. In [8] fuzzy reasoning optimized by genetic algorithm was used for the classification of myocardial heart disease.

The proposed methodology uses neural network for classifier. The performance of proposed methodology was evaluated with three different neural network techniques. Moreover, we compared our result with Feedforward Back propagation Neural Network, Support Vector Machine, 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 Feedforward Back propagation Neural Network, Support Vector Machine, 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 patients medicine given by the Feedforward Back propagation Neural Network, Support Vector Machine, 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 [9]. 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. For instance, Haque and Sudhakar [10] published many papers for the prediction of fracture toughness in microalloy steel, corrosion fatigue behavior and fatigue crack growth in dual-phase (DP) steel, mechanical behavior of powder metallurgy steel, dry sliding wear in Fe2%Ni 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

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

where P and wi are the number of elements and the interconnection weight of the input vector xi, 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

$$f(n) = f\left[\left(\sum_{i=1}^{P} w_i x_i\right) + b\right]$$

### BACKGROUND

#### 1. RELATED WORKS

Up to now, various classification algorithms have been employed on Turkoglu's valvular heart disease data set and high classification accuracies have been reported in the last decade [36-41]. Turkoglu's valvular heart disease data set was obtained from Firat Medical Center. A detailed description for the data set will be given in the next section.

The valvular heart disease data set was firstly utilized in [36] where Turkoglu et al. fulfilled an expert diagnosis system which uses backpropagation artificial neural networks (BP-ANN) classifier. The performance evaluation of the realized system was evaluated by classification accuracy and the correct classification rate was about 94% for normal subjects and 95.9% for abnormal subjects. Later, Turkoglu et al. suggested an intelligent system for detection of heart valve disease based on wavelet packet neural networks (WPNN) [37]. The reported correct classification rate was about 94% for abnormal and normal subjects. Recently, Comak et al. investigated the use of least-square support vector machines (LS-SVM) classifier for improving the performance of the Turkoglu's proposal [38]. They intended to realize a comparative study. Classification rates of the examined classifiers were evaluated by ROC curves based on the terms of sensitivity and specificity. The application results showed that according to the ROC curves, the LS-SVM classifier performance was comparable with ANN, but the training time of LS-SVM is shorter than that of the ANN and it can always converge the same solution while ANN cannot. According to these results, LS-SVM's training time is about 13 times shorter than ANN's training time. This is an important difference. Because, LS-SVMs are trained only depending on support vectors, not by whole training data set. In addition, LS-SVM can overcome the overfitting much successfully than ANN.

More recently, Uguz et al. performed a biomedical system based on Hidden Markov Model for clinical diagnosis and recognition of heart valve disorders [39]. The fulfilled methodology was also used the database of Turkoglu et al. In the presented study, continuous HMM (CHMM) classifier system was used. Single Gaussian model was preferred to determine emission probability. The methodology was composed of two stages. At the first stage, the initial values of average and standard deviation were calculated by separating observation symbols into equal segments according to the state number and using observation symbols appropriate to each segment. At the second stage, the initial values of average and standard deviation were calculated by separating observation symbols into the clusters (FCM or K-means algorithms) that have equal number of states and using observation symbols appropriate to the separated clusters. The implementations of the experimental studies were carried out on three different classification systems such as CHMM, FCM–K-means/CHMM and ANN. These experimental results were obtained for specificity and sensitivity rates 92% and 94% for

CHMM, 92% and 97.26% for FCM–K-means/CHMM), respectively. Finally, Sengur et al. investigated the use of principal component analysis (PCA), artificial immune system (AIS) and fuzzy $k$-NN to determine the normal and abnormal heart valves from the Doppler heart sounds [40].

For reducing the complexity, PCA was used. In the classification stage, AIS and fuzzy $k$-NN were used. To evaluate the performance of the methodology, a comparative study was realized by using a data set containing 215 samples. The validation of the method was measured by using the sensitivity and specificity parameters; 95.9% sensitivity and 96% specificity rate was obtained. Sengur et al. also investigated the use of Linear Discriminant Analysis (LDA) and Adaptive neuro-fuzzy inference system (ANFIS) for clinical diagnosis and recognition of heart valve disorders [41]. The validation of the method is measured by using the sensitivity and specificity parameters. 95.9% sensitivity and 94% specificity rate was obtained.

#### 2. INTRODUCTION TO NEURAL NETWORK TECHNIQUES

##### I) FEEDFORWARD BACKPROPAGATION (FFBP)

The Feedforward Backpropagation is one of the most studied neural network by the scientific community and the most common used in many medical applications. The feedforward, back-propagation architecture was developed in the early 1970's by several independent sources (Werbor; Parker; Rumelhart, Hinton and Williams) [11]. This independent co-development was the result of a proliferation of articles and talks at various conferences which stimulated the entire industry. Currently, this synergistically developed back-propagation architecture is the most popular, effective, and easy to earn model for complex, multi-layered networks[12]

This network is used more than all other combined. It is used in many different types of applications. This architecture has spawned a large class of network types with many different topologies and training methods. Its greatest strength is in non-linear solutions to ill-defined problems [13,14]. The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but typically there is just one or two [15].

Some work has been done which indicates that a minimum of four layers (three hidden layers plus an output layer) are required to solve problems of any complexity. Each layer is fully connected to the succeeding layer, as shown in Figure 1[16]
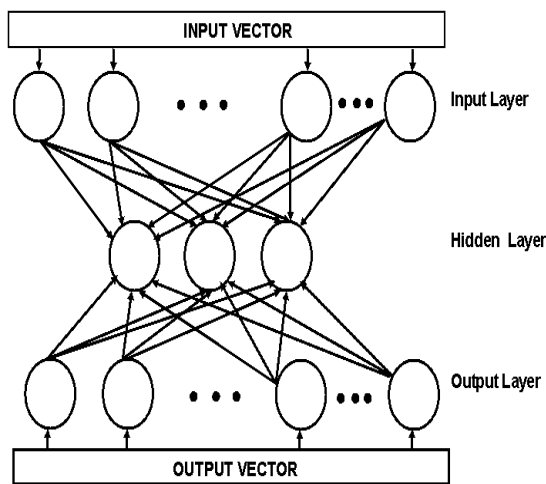
**Figure 1 An example of Feedforward Backpropagation Network**

The in and out layers indicate the flow of information during recall. Recall is the process of putting input data into a trained network and receiving the answer. Back- propagation is not used during recall, but only when the network is learning a training set. The number of layers and the number of processing element per layer are important decisions. These parameters to a feedforward, back -propagation topology are also the most ethereal. They are the art of the network designer. There is no quantifiable, best answer to the layout of the network for any particular application. There are only general rules picked up over time and followed by most researchers and engineers applying this architecture of their problems[18][19].

Typical feedforward, back-propagation applications include speech synthesis from text, robot arms, evaluation of bank loans, image processing, knowledge representation, forecasting and prediction, and multi-target tracking. Each month more back- propagation solutions are announced in the trade journals[17].

## II) SUPPORT VECTOR MACHINE :

Support Vector Machines(SVMs) are a state of the art pattern recognition techniques whose foundation stem from statistical learning theory. However, the scope of SVMs goes beyond pattern recognition because they can also handle two more learning problems i.e. regression estimation and density estimation. An SVM is a general algorithm based on guaranteed risk bounds of statistical learning theory i.e. the so called structural risk minimization principle. It is a learning machine capable of implementing s set of functions that approximate best the supervisor's response with an expected risk bounded by the sum of the empirical risk and Vapnik – Chevonenkis (VC) confidence. Recent advances in statistics, generalization theory, computational learning theory, machine learning and complexity have provided new guidelines and deep insights into the general characteristics and nature of the model building/learning/fitting process [20]. Some researchers have pointed out that statistical and machine learning models are not all that different conceptually [21,22]. Many of the new computational and machine learning methods generalize the

idea of parameter estimation in statistics. Among these new methods, Support Vector Machines have attracted most interest in the last few years.

Support vector machine (SVM) is a novel learning machine introduced first by Vapnik [23]. It is based on the Structural Risk Minimization principle from computational learning theory. Hearst et al. [24] positioned the SVM algorithm at the intersection of learning theory and practice: ''it contains a large class of neural nets, radial basis function (RBF) nets, and polynomial classifiers as special cases. Yet it is simple enough to be analyzed mathematically, because it can be shown to correspond to a linear method in a high dimensional feature space nonlinearly related to input space.'' In this sense, support vector machines can be a good candidate for combining the strengths of more theory-driven and easy to be analyzed conventional statistical methods and more data-driven, distribution free and robust machine learning methods.

In the last few years, there have been substantial developments in different aspects of support vector machine. These aspects include theoretical understanding, algorithmic strategies for implementation and reallife applications. S VM has yielded excellent generalization performance on a wide range of problems including bioinformatics [25, 26, 27], text categorization [28], image detection [29], etc. These application domains typically have involved high-dimensional input space, and the good performance is also related to the fact that SVM's learning ability can be independent of the dimensionality of the feature space.

The SVM approach has been applied in several financial applications recently, mainly in the area of time series prediction and classification [30,31]. A recent study closely related to our work investigated the use of the SVM approach to select bankruptcy predictors. They reported that SVM was competitive and outperformed other classifiers (including neural networks and linear discriminant classifier) in terms of generalization performance [32]. In this study, we are interested in evaluating the performance of the SVM approach in the domain of heart disease in comparison with that of Radial Basis Function in neural networks.

### iii) Radial Basis Function (RBF)

Radial basis function (RBF) networks were introduced into the neural network literature by Broomhead and Lowe [33]. The RBF network is similar to a general feed-forward neural network trained using the back-propagation scheme . It has three layers of neurons, namely input, hidden and output. However it uses only one hidden layer, each neuron in which operates as the Gaussian transfer function, as against the sigmoid function.

The idea of Radial Basis Function (RBF) Networks derives from the theory of function approximation. We have already seen how Multi-Layer Perceptron (MLP) networks with a hidden layer of sigmoidal units can learn to approximate functions. RBF Networks take a slightly different approach.

Mathematically, the output $y$ of an RBF network corresponding to input $x$ is computed by the equation;

$$y = f(x) = \sum_{i=1}^{n} w_i \varphi \parallel x - c_i \parallel + w_0 \qquad \text{(Eq.A.1)}$$

where $w_i$ is the connection weight between the $i$th hidden neuron and output neuron; $w_0$ the bias. $\varphi \parallel x\text{-}c_i \parallel$ indicates a RBF which is normally Gaussian having following expression;

$$\varphi \parallel x - c_i \parallel = -\exp(-\sum_{i=1}^{n} \frac{\parallel x_i - c_i \parallel^2}{2\sigma_i^2}) \qquad \text{(Eq. A.2)}$$

where $c_i$ are centers of the receptive field; and $\sigma_i$ the widths of the Gaussian function which indicates the selectivity of a neuron.
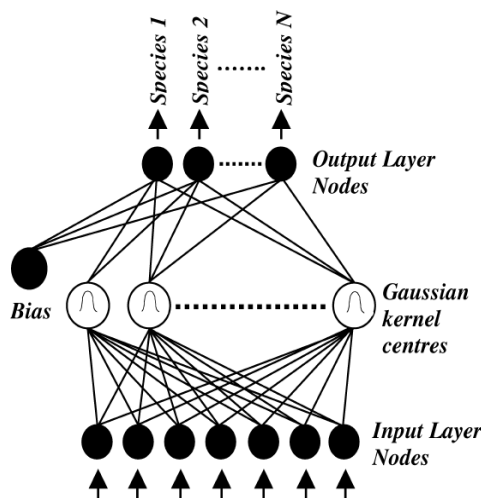


**Figure 2. Schematic diagram of RBF**

The major task of RBF network design is to determine centers. The easiest way to do so is to choose the centers randomly from the training set. Another approach is to use the k-means technique consisting of clustering the input training set into groups and choose the mean of each group as the center. Also, the centers can be treated as a network parameter along with $w_i$ and adjusted through error-correction training. After the center is determined, the connection weights $w_i$ between the hidden layer and output layer can be obtained through ordinary back-propagation-based training [34,35].

Chaitanya Roygaga et.al.[42] has developed intelligent system, which can diagnose whether a patient is suffering from a heart disease or not. The dataset is acquired from the UCI Machine Learning Repository. The training dataset was fed into the network. Error Back Propagation algorithm is the learning network used in the analysis. This system has given the best accuracy (at 80.27%) of diagnosing heart disease when the neurons in the hidden layer are kept at four, with high sensitivity and specificity value. This paper[43] does a comparative study of commonly used machine learning algorithms in predicting the prevalence of heart diseases. It uses the publicly available Cleveland Dataset and models the classification techniques on it. They used F1 score and ROC curves as evaluative measures. Through this effort, they aim to provide a benchmark and improve earlier ones in the field of

heart disease diagnostics using machine learning classification techniques.

This paper [44] is twofold, first provides the classification of Artificial Neural Networks (ANNs) and second present the techniques of medical science which comprehensively enables the ANNs techniques to the prediction of medical diseases. This paper [45] proposes a diagnostic system for predicting heart disease. For diagnosis of heart disease 14 significant attributes are used in proposed system as per the medical literature. The results tabulated evidently prove that the designed diagnostic system is capable of predicting the risk level of heart disease effectively when compared to other approaches.

## 3. PROPOSED METHODOLOGY AND IMPLEMENTATION OF WITH FFBP, SVM AND RBF
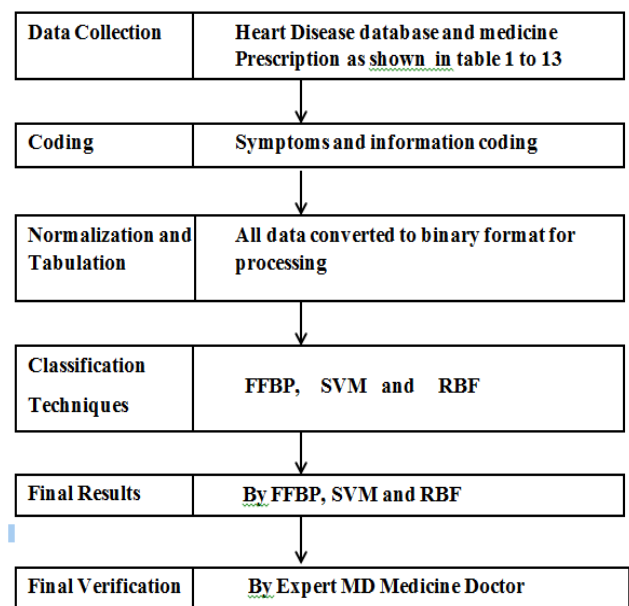


*I) PREPARING DATA FOR UNDERLYING NEURAL NETWORK:*

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 375 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 375 heart patients and represents the codes respectively from 1 to 18. The code 1 which represents Hypertension, Code 2 represents Diabetes Mallitus like this it contains 18 different diseases. Some of them are as shown in Table 1.

| Code | Name of Disease |
|------|-----------------|
| 1 | Hypertension |
| 2 | Diabetes Mallitus |
| 3 | TB |
| 4 | Bronchial Asthama |
| 5 | Hyperthyroidism |

**Table 1: Previous History of Patients**

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.

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

**Table 2: Present History of patients**

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.

| Code | Personnel History |
|------|-------------------|
| 1 | Smoking |
| 2 | Tobacco |
| 3 | Alcohol |
| 4 | Nil |

**Table 3 : Personnel History**

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 table 4.

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

**Table 4 : Physical Examination**

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 this 8 different symptoms and specified by 1 to 8 codes for each symptom. Some are as shown below in table 5.

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

**Table 5: Cardio Vascular System**

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.

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

**Table 6: Respiratory System**

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 (Splenomegaly) 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.

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

**Table 7: Per Abdomen**

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 this 5 different symptoms are found and specified by 1 to 5 codes for each symptom. Some are as shown below in table 8.

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

**Table 8: Central Nervous System**

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 this 21 different heart findings are found and specified by 1 to 21 codes for each finding. Some are as shown below in table 9.

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

**Table 9 : Electro Cardio Gram (ECG)**

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.

| Code | Symptoms |
|------|----------|
| 6 | Lipid Profile normal |
| 7 | Lipid Profile Abnormal |

| 8 | Complete Blood Count Normal |
|------|-----------|
| 9 | Leucocytosis |
| 10 | Anaemia |

**Table 10 : Blood Investigation**

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.

| Code | Medicine Name |
|------|---------------|
| 1 | Alprazolam |
| 2 | Amlodepine |
| 3 | Aspirin |
| 4 | Atenolol |
| 5 | Atorvastatin |

**Table 11 : Medicine Names**

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.

| 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 | 58 M | 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 |

**Table 12 : collection of different details of the individual Heart Patients**

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 | | | | | | | | | |

**Table 13 : All the Medicine codes provided by the doctor to the individual patients.**

## 4. 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 III
THE INDIVIDUAL DATA OF THE PATIENT NO 1 IS DEFINED IN BINARY FORM

| Sr. No | 00000001 |
|--------|----------|
| Age | 0110111 |
| P1 | 010000000000000000 |
| P2 | 11001000000010000000000000000 |
| P3 | 0001 |
| P4 | 000000100100000000000000000 |
| CVS | 00000001 |
| RS | 00010 |
| PA | 000010 |
| CNS | 00010 |
| ECG | 101000000000000000000 |
| BT | 00000000000010000000000 |

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 upto 97%.

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 0 0 1 0 0 1 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;

*MEDICINE CODING OF THE PATIENT 1.*

*V. DISCUSSION OF FIRST FIVE PATIENTS RESULTS WITH DOCTOR:*

**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

**Medicines given by the Expert system using FFBP**

A) 1,3,5,6, 14, 16, 17,21,23,25,26,27,28
B) 1,3,5,6,14,25
C) 1,3,5,6,14,25
D) 1,3,5,6,14,25
E) 1,3,5,6,14,25

**Medicines given by the Expert system using SVM**

A) 1,3,5,6, 16,1718,21,23,25,26,27,28,29
B) 1,3,5,6,16,17,18,21,23,25,26,27,28,29
C) 1,3,5,6,11,14,21,22,23,24,25,26,27
D) 1,3,5,6,13,14,17,2122,23,25,26,27,28
E) 1,2,3,5,14.

**Medicines given by Expert System 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

## 5. CONCLUSION

The main purpose of this study is to investigate the applicability and capability of ANN methods, FFBP, SVM and RBF for prediction of medicine for the heart disease on the basis of symptoms. For this study, FFBP, SVM and RBF techniques are applied to existing experimental data of the heart disease patient. In this paper, around 375 patient's information is collected from Sahara Hospital, under supervision of Dr. Abdul Jabbar, (MD Medicine) Sahara Hospital, Roushan Gate, Aurangabad. The collected information is coded, normalized and entered into 13 different excel sub-sheets. All the patients data is trained by using FFBP, SVM and RBF. Around 125 samples were tested with these three techniques. It is found that the result of testing data by using FFBP and SVM is not satisfactory but the medicines prescribed by the RBF are satisfactory as per the result verified by the doctor. The diagnosis performances of this study shows the advantage of this system. : it is rapid, easy to operate, non-invasive 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 regression technique.

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