Prediction of Heart Disease Using Multi-Layer Perceptron Neural Network and Support Vector Machine

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***Abstract*— In recent years, heart disease is one of the major causes of death. So it is necessary to design a system that correctly diagnoses heart disease. In this study, we have proposed two classifiers. One is a Multi-Layer Perceptron neural network (MLP) and another is Support Vector Machine (SVM). Our work is to classify two-class of heart disease and five class of heart disease. Here we have used the Cleveland heart disease online database which consists of 303 instances with 5 classes and 13 attributes. For two-class classification problem, SVM has 92.45% accuracy while the accuracy of MLP is 90.57%. For five-class classification problem, MLP has an accuracy 68.86% while SVM is 59.01%.**

Keywords—heart disease, classification, Cleveland database, multi-layer perceptron (MLP), support vector machine (SVM).

I. INTRODUCTION

A human heart is one of the important parts of the body that pumps blood throughout the body via the circulatory system, supplying oxygen and nutrients to the tissues and removing carbon dioxide and other wastes [1]. Usually, heart disease is a disorder of blood vessels in the heart which can lead someone towards death [2].

Ischemic heart disease is the world's biggest killer, accounting for 8.76 million deaths in 2015 [3]. So it is necessary to design a decision support system that can help the medical physicians to correctly classify the heart disease and reducing the cost.

It is hard to predict heart disease correctly because the real world heart disease data is more complex. For reducing this complexity, we present two approaches for heart disease classification using multi-layer perceptron (MLP) and support vector machine (SVM). The Cleveland database was taken from the UCI machine learning repository [4]. The dataset contains five classes where 0 means normal patient and 1,2,3,4 corresponding to coronary heart disease, angina pectoris, congestive heart failure, and arrhythmias respectively. For two-class classification problem, 0 means normal patient and we convert 1,2,3,4 to 1 which corresponding to the abnormal patient. In our work, first, we normalize the data so that we can convert the values of numeric columns in the dataset to use a common scale [5] and increase the accuracy of the classification problem. Then we use MLP and SVM for classification.

The rest of the paper is organized as follows: Next section we give some knowledge about the previous works on heart disease. Section III describes the methodology. Section IV describes the proposed system. Section V describes the experimental results. Section VI describes the performance comparison between our work and the previous work. At last, section VII is the conclusion.

II. RELATED WORKS

In recent years, the prediction of heart disease using many machine learning techniques have been introduced by many researchers.

Sumit Bhatia et al., 2008 described an SVM based decision support system that was used for heart disease classification. They have used Cleveland database where 250 data were used for learning and 53 data were used for testing. They have selected important feature using an integer-coded genetic algorithm and they achieved 72.55% accuracy for five class classification while they achieved 90.57% accuracy for two-class classification [6].

M. Gudadhe et al., 2010 described SVM and artificial neural network (ANN) for heart disease prediction. They have used 200 data for training and 103 used for testing and achieved 80.41% accuracy for two-class classification [7].

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A. Khemphilia et al., 2011 described MLP with Back-Propagation (BP) for heart disease classification. They have used 182 data for training and 121 data for testing and achieved an accuracy of 13 features is 80.17% for two-class classification [8]. They also extracted feature and got accuracy 80.99% for 8 features.

M. A. M. Abusharian et al., 2014 proposed ANN and Neuro-Fuzzy system for heart disease classification. They have used Cleveland dataset where 80% data were used training and 20 % data were used for testing and they have achieved 87.04% accuracy for two-class classification problem [9].

S. Roostaee et al., 2016 suggested Meta-Heuristic algorithms and they have used binary cuckoo optimization algorithm and SVM. They have partitioned the data into 5 parts for training and testing and achieved 84.44% accuracy for two-class classification [10].

S. Pouriyeh et al., 2017 compared many machine learning technique. They have used 10 fold cross-validation. They have achieved 84.15% accuracy when they have combined SVM with MLP [11].

III. Methodology

There are many approaches to the prediction of heart disease. In this study, we explain multi-layer perceptron with backpropagation algorithm and support vector machine.

A. Multi-layer Perceptron (MLP)

MLP is a feed-forward artificial neural network which consists of, at least, three layers of nodes: an input layer, a hidden layer and an output layer [12]. For training, MLP uses a supervised learning approach called backpropagation (BP). Fig. 1 shows a multilayer feed-forward neural network [13].

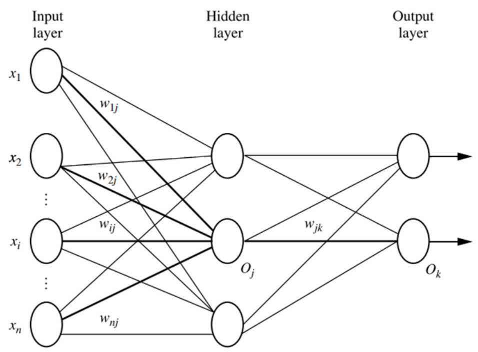

Fig. 1. Multilayer feed-forward neural network.

The algorithm for MLP with BP is described as follows [13]:

At first, initialize the weights to small random numbers and each unit associated with a bias.

Then the input data is fed to the network's input layer and the inputs pass through the input units without any modification. For an input unit,j its corresponding output, O_j. Each input is connected to a hidden unit and each connection has a weight. The total input I_j is computed by multiplying each input to its corresponding weight and calculating the summed. Hence for a unit j the net input I_j is

$$I_j = \sum_i w_{ij} O_i + \theta_j \quad (1)$$

Where w_{ij} is the connection weight from node i to node j and O_i is the output of node i and θ_j is the bias of node j. Here we used a sigmoid or logistic function which maps a large range input onto a smaller range of normally 0 to 1. The output of node j, O_j is calculated as

$$O_j = \frac{1}{1+e^{-I_j}} \quad (2)$$

Finally, the weights are adapted using the back propagation algorithm. The error Err_j of node j , is determined as

$$Err_j = O_j(1 - O_j)(T_j - O_j) \quad (3)$$

Where O_j = Actual output of node j
T_j = Target output of node j

Then the hidden layer error is calculated as

$$Err_j = O_j(1 - O_j)\sum_k Err_k w_{jk} \quad (4)$$

Where w_{jk} = Connection weight from node j to a node k

The weights are adapted as follows

$$\Delta w_{ij} = (l)Err_j O_i \quad (5)$$

$$w_{ij} = w_{ij} + \Delta w_{ij} \quad (6)$$

Where l = Learning rate

The bias is adapted as follows

$$\Delta\theta_j = (l)Err_j \quad (7)$$

$$\theta_j = \theta_j + \Delta\theta_j \quad (8)$$

B. Support Vector Machine (SVM)

The simple mechanism of SVM as described as follows [7], [13]:

For two-class classification problem, let the data set D to be given as $(X_i,\ y_i)$ where X_i is the set of training tuples and y_i is the class labels which can be +1 or -1 and linearly separable. Hence the equation of the hyperplane is

$$W^T X + b = 0 \quad (9)$$

Where W = Weight Vector
X = Input Vector
b = A bias

Hence any tuple that lies on or above the hyper plan (H_1) can be written as

$$H_1: W^T X_i + b \geq 0 \quad For\ y_i = +1 \quad (10)$$

And any tuple that lies below the hyper plan (H_2) can be written as

$$H_2: W^T X_i + b < 0 \quad For\ y_i = -1 \quad (11)$$

The discriminant function is written as [14]:

$$g(x) = W_0^T X + b_0 \qquad (12)$$

Fig. 2 shows separating hyperplane and the margin [7].

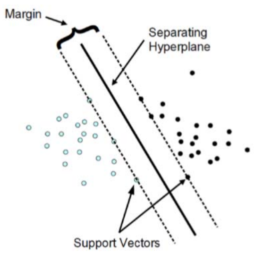

Fig. 2. Margin and hyperplane.

If the tuples are not linearly separable then a kernel function is used to transforms the tuples into a higher dimensional space where it is linearly separable [7]. Their various kernel functions are used such as [13]:
Polynomial kernel of degree$h$:

$$K(X_i, X_j) = (X_i.X_j + 1)^h \qquad (13)$$

Gaussian radial basis function:

$$K(X_i, X_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}} \qquad (14)$$

IV. The Proposed System

To predict heart disease we proposed two systems: MLP and SVM. First, the Cleveland dataset is divided into two parts. One part is used for training and another part is used for testing. Before training and testing, we need to standardize the data as data preprocessing. It is also known as feature scaling. Standardization is better than normalization in the case when the data includes outliers so we need to perform standardization. Since the Cleveland database consists of various features and range of values of data varies widely, in our algorithms, objectives function will not work properly without standardization. If one of the features has a broad range of values, the distance will be governed by this particular feature. For this reason, the range of all features should be standardized so that each feature contributes approximately proportionately to the final distance [15]. Then the resulting data are fed to our algorithm for heart disease classification.

Fig. 3 shows our proposed system.

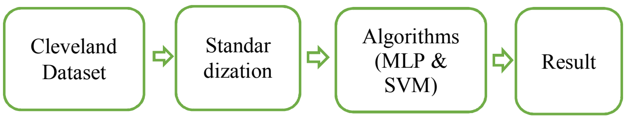

Fig. 3. Proposed System.

A. Prediction of heart disease based on MLP

In our model, MLP consists of an inactive input layer and two active layers: a hidden layer and an output layer. The input layer consists of 13 nodes since there are 13 features and the hidden layer consists of 50 nodes. For two-class classification, the output layer consists of two nodes where 0 means normal patient and 1 means the abnormal patient. Fig. 4 shows the model for two-class classification.

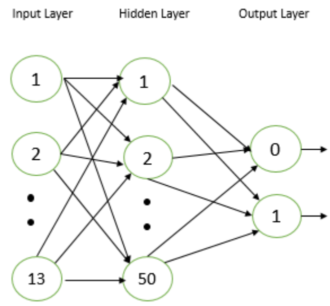

Fig. 4. MLP for two-class classification.

For five class classification, the output layer consists of five nodes where the classes vary from 0 to 4. Fig. 5 shows the model for 5 class classification. For updating the weight we used the backpropagation algorithm. Rectified Linear Unit (ReLU) is used for activation function.

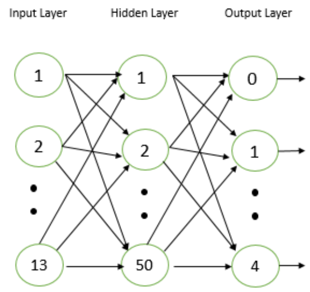

Fig. 5. MLP for five class classification.

B. Prediction of heart disease based on SVM

For two-class classification, we used SVM to get the separating hyperplane of both normal patient and heart disease patient. For multiclass classification, there are two popular methods: one against one (OVO) and one against all (OVA). We used OVA for five class classification problem.

V. Experimental Results

The proposed heart disease prediction using MLP and SVM were developed in python 3.

A. Data Source

The Cleveland database is used as a standard for heart disease diagnosis system which is taken from the UCI machine learning repository [4]. There are 303 tuples and 76 attributes in the database. But researchers only used 14 attributes for heart disease diagnosis. The class labels consist of five values such as 0 for the normal patient, 1 represented to Coronary heart disease, 2 represented to Angina pectoris, 3 represented to Congestive heart failure, and 4 represented to Arrhythmias. There some missing values in the dataset which were filled using interpolation values. Table II shows the clinical features and their description of Cleveland database [16].

The dataset was divided into two parts. One part is used for training and building the model. Another part is used for testing for finding the accuracy of the model.

TABLE I. DESCRIPTIONS OF CLEVELAND DATABASE

Attribute	Description	Data type
age	years	Continuous
sex	1:male, 0:female	Binary
Chest Pain	1:typical angina, 2:atypical angina, 3:non-anginal pain, 4:asymptomatic	$1-4$
Rbp	Resting blood pressure in $mmHg$	Continuous
Chol	Serum cholestoral in mg/dl	Binary
Fbs	fasting blood sugar $> 120mg/dl$	Binary
Resteeg	Resting electrocardiographic results, 0:normal, 1:having ST-T wave abnormality, 2:showing probable or definite left ventricular hypertrophy by Estes' criteria	$0-2$
Thalach	Maximum heart rate achieved	Continuous
Exang	Exercise induced angina	Binary
Oldpeak	ST depression induced by exercise relative to rest	Continuous
Slop	Slope of the peak exercise ST segment 1:upsloping, 2:flat, 3:downsloping	1-3
Ca	Number of Major Vessels $(0-3)$ colored by flourosopy	Continuous
Thal	3: ormal, 6:fixed defect, 7: reversible defect	3, 6, 7
Output	Class Target the predicted attribute	$0-4$

B. Performance Evaluation

In this section, we measured the accuracy, precision, recall, and f1-score of our models. We also considered the confusion matrix.

Accuracy can be defined as the fraction of predictions our model got right. Accuracy can be written as [17]:

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{15}$$

Where T_p = True positives refer to tuples that are abnormal and predicted correctly. T_N = True negatives refer to tuples that are normal and predicted correctly. F_P = False positives refer to tuples that are normal and predicted incorrectly. F_N= False negatives refer to tuples that are abnormal and predicted incorrectly.

Precision can be considered as a proportion of the tuples that are diagnosed as the abnormal patient exactly have heart disease. Precision can be calculated as [13]:

$$precision = \frac{T_P}{T_P + F_P} \tag{16}$$

Recall can be calculated as a ratio of the tuples that are actually the abnormal patient are diagnosed as having heart disease. Recall can be calculated as [13]:

$$recall = \frac{T_P}{T_P + F_N} \tag{17}$$

F1-score can be defined as the harmonic mean of precision and recall. F1-score can be calculated as [13]:

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \tag{18}$$

A confusion matrix can be defined as a summary of prediction results on a classification problem [18]. Table III shows a confusion matrix.

TABLE II. CONFUSION MATRIX

	Class 0 Predicted	Class 1 Predicted
Class 0 Actual	T_P	F_N
Class 1 Actual	F_P	T_N

a) Performance of two-class diagnosis system: For two-class classification 0 means normal patient and 1 means the abnormal patient. First, we divided the data into two parts: one part used for training and other part used for testing. Table III shows the performance of MLP without using standardization technique.

TABLE III. PERFORMANCE OF TWO-CLASS DIAGNOSIS SYSTEM BASED ON MLP WITHOUT STANDARDIZATION

Testing Data	T_P / F_P	F_N / T_N	Precision	Recall	F1-Score	Accuracy %
122	56 / 59	4 / 3	0.46	0.48	0.36	48.36
104	50 / 44	1 / 9	0.72	0.57	0.48	56.73
82	0 / 0	41 / 41	0.25	0.50	0.33	50.00
53	30 / 20	0 / 3	0.77	0.62	0.52	**62.26**

To improve the performance we performed standardization by standardization. Table IV shows the performance of MLP with standardization technique.

TABLE IV. PERFORMANCE OF TWO-CLASS DIAGNOSIS SYSTEM BASED ON MLP WITH STANDARDIZATION

Testing Data	T_P / F_P	F_N / T_N	Precision	Recall	F1-Score	Accuracy %
122	48 / 9	12 / 53	0.83	0.83	0.83	82.78
104	47 / 12	4 / 41	0.85	0.85	0.85	84.62
82	39 / 9	2 / 32	0.88	0.87	0.86	86.58
53	29 / 4	1 / 19	0.91	0.91	0.90	**90.57**

From table III and table IV it is seen that without standardization the best accuracy archived 62.26% using MLP while with standardization the accuracy reached to 90.57%. For two-class classification problem MLP achieved an accuracy of 82.78%, 84.62%, 86.58%, and 90.57% for 122, 104, 82, 53 data for testing respectively while using standardization.

Table V shows the performance of SVM without using standardization technique and table VI shows the performance of SVM with using standardization technique.

TABLE V. PERFORMANCE OF TWO-CLASS DIAGNOSIS SYSTEM BASED ON SVM WITHOUT STANDARDIZATION

Testing Data	T_P / F_P	F_N / T_N	Precision	Recall	F1-Score	Accuracy %
122	60 / 62	0 / 0	0.24	0.49	0.32	49.18
104	51 / 53	0 / 0	0.24	0.49	0.32	49.03
82	41 / 41	0 / 0	0.25	0.50	0.33	50.00
53	30 / 23	0 / 0	0.32	0.57	0.41	**56.67**

To improve the performance we performed standardization by standardization.

TABLE VI. PERFORMANCE OF TWO-CLASS DIAGNOSIS SYSTEM BASED ON SVM WITH STANDARDIZATION

Testing Data	T_P / F_p	F_N / T_N	Precision	Recall	F1-Score	Accuracy %
122	52	8	0.85	0.85	0.85	85.25
	10	52				
104	49	2	0.89	0.88	0.88	88.46
	10	43				
82	40	1	0.90	0.89	0.89	89.02
	8	33				
53	30	0	0.93	0.92	0.92	**92.45**
	4	19				

From table V and VI, it is seen that without standardization the best accuracy archived 56.67% using SVM while with standardization the accuracy reached to 92.45%.

From table IV and VI, it is seen that the accuracy of SVM is 92.45% which is better than the accuracy of MLP is 90.45%. Hence prediction of heart disease for two-class classification, SVM is quite good enough than MLP.

Fig. 6 shows the line plot of ROC curve for MLP while we have used 53 data for testing.

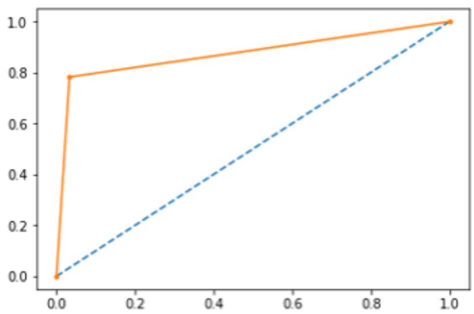

Fig. 6. Line plot of ROC curve for MLP.

Fig. 7 shows the line plot of ROC curve for SVM while we have used 53 data for testing.

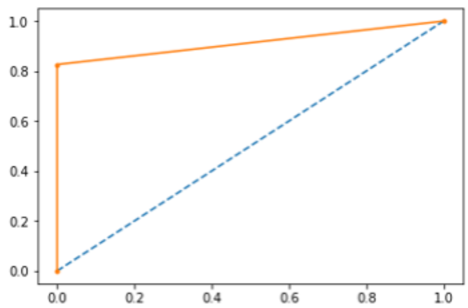

Fig. 7. Line plot of ROC curve for SVM.

From fig. 6 and fig. 7, it is seen that for two class classification the ROC curve for SVM is better than MLP.

b) Performance of five class diagnosis system: For five class classification, 0 means normal patient and 1 to 4 means various label of the abnormal patient. Table VII shows the performance of MLP with standardization technique.

TABLE VII. PERFORMANCE OF FIVE-CLASS DIAGNOSIS SYSTEM BASED ON MLP WITH STANDARDIZATION

Testing Data	Precision	Recall	F1-Score	Accuracy%
91	0.55	0.58	0.57	58.24
61	0.66	0.67	0.65	**68.86**

Table VIII shows the performance of SVM with using standardization technique for five class classification problem.

TABLE VIII. PERFORMANCE OF FIVE-CLASS DIAGNOSIS SYSTEM BASED ON SVM WITH STANDARDIZATION

Testing Data	Precision	Recall	F1-Score	Accuracy%
91	0.49	0.57	0.52	57.24
61	0.45	0.59	0.50	**59.01**

From table VII and VII, it is seen that the accuracy of MLP is 68.86% which is better than the accuracy of SVM is 59.01%. Hence prediction of heart disease for five class classification, MLP is performed well than SVM.

Fig. 8 shows the line plot of ROC curve for MLP while we have used 61 data for testing.

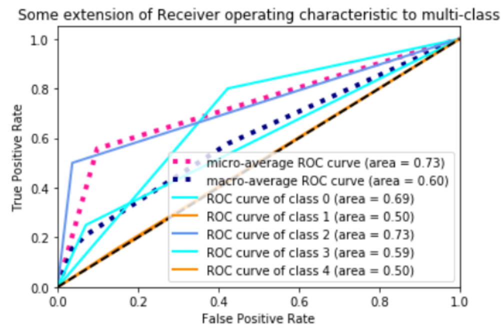

Fig. 8. Line plot of ROC curve for MLP.

Fig. 9 shows the line plot of ROC curve for SVM while we have used 61 data for testing.

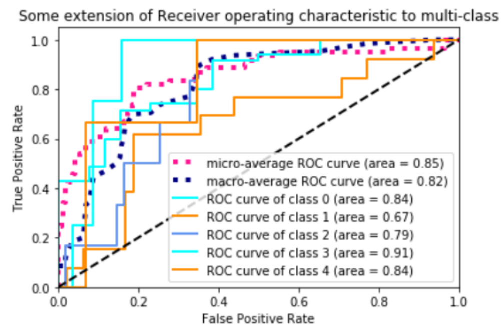

Fig. 9. Line plot of ROC curve for SVM.

VI. PERFORMANCE COMPARISON WITH PREVIOUS WORK

In this section, we compared the performance of our algorithms for heart disease classification with the previous work.

S. Bhatia et al., 2008 achieved accuracy 90.57% using SVM and GA while they have used 53 data for testing. We achieved an accuracy of 92.45% and 90.57% using SVM and MLP respectively while using the same data for testing.

M. Gudadhe et al., 2010 achieved an accuracy of 80.4% using SVM while they have used 13 attributes and

103 data for testing. We achieved accuracy of 88.34% and 83.49% using SVM and MLP respectively while using the same data for testing.

A. khemphilia et al., 2011 achieved accuracy 80.99% using MLP while they have used 122 data for testing and reduced feature from 13 to 8. We achieved an accuracy of 85.25% and 82.78% using SVM and MLP respectively while using the same data for testing.

M. A. M. Abusharian et al., 2014 achieved accuracy 87.04% using ANN while they have used 83 data for testing. We achieved an accuracy of 87.95% and 85.54% using SVM and MLP respectively while using the same data for testing.

S. Roostaee et al., 2016 achieved accuracy 84.44% using BCOA and SVM while they have used 5 fold cross-validation. We achieved an accuracy of 78.68% and 84.72% using SVM and MLP respectively while using 5 fold cross-validation.

S. Pouriyeh et al., 2017 achieved accuracy 84.15% using SVM and MLP while they have used 10 fold cross-validations. We achieved an accuracy of 82.15% and 84.84% using SVM and MLP respectively while using 10 fold cross-validation. Table IX shows performance comparison with previous work for two-class classification.

TABLE IX. COMPARISON RESULTS WITH PREVIOUS WORKS

Writers	Year	Approach	Testing data	Accuracy %	Accuracy Of Our work
S. Bhatia et al.	2008	GA+SVM	53	90.57%	SVM **92.45%**
					MLP 90.57%
M. Gudadhe et al.	2010	SVM	103	80.41%	SVM **88.34%**
					MLP **83.49%**
A. K. et al.	2011	MLP	122	80.99%	SVM **85.25%**
					MLP **82.78%**
M..A. M. et al.	2014	ANN	83	87.04%	SVM **87.95%**
					MLP 85.54%
S. Roostaee et al.	2016	BCOA+ SVM	5 Fold	84.44%	SVM **84.72%**
					MLP 78.68%
S. Pouriyeh	2017	SVM+ MLP	10 Fold	84.15%	SVM **84.84%**
					MLP 82.15%

VII. CONCLUSION

According to table IX, our proposed approach MLP and SVM have the best accuracy than the previous works. We have also found that for two-class classification SVM has an accuracy 92.45% which is better than MLP has an accuracy 90.57%. But for five-class MLP has an accuracy 68.86% which is better than SVM has an accuracy 59.01%. So we can conclude that for five class problem MLP is better than SVM while for two-class problem SVM is better than MLP for heart disease diagnosis. In future, we may use some others classifier in order to improve the prediction performance as well as may collect real-time data from different clinics in order to detect heart disease patients and compute the accuracy of classifiers for more dependable diagnosis of heart disease.

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