Identifying the Predictive Capability of Machine Learning Classifiers for Designing Heart Disease Detection System

Conference Paper · December 2019

DOI: 10.1109/ICCWAMTIP47768.2019.9067519


Jalaluddin Khan
Koneru Lakshmaiah Education Foundation


Muhammad Hammad Memon
Southwest University of Science and Technology


Mordecai Raji
University of Electronic Science and Technology of China


Wasif Akbar
University of Electronic Science and Technology of China

IDENTIFYING THE PREDICTIVE CAPABILITY OF MACHINE LEARNING CLASSIFIERS FOR DESIGNING HEART DISEASE DETECTION SYSTEM

AMIN UL HAQ[1], JIANPING LI[1*], JALALUDDIN KHAN[1], MUHAMMAD HAMMAD MEMON[1], SHADMA PARVEEN[3], MORDECAI FOLARIN RAJI[1], WASIF AKBAR[1], TANVIR AHMAD[2], SANA ULLAH[4], LATIPOVA SHOISTA[1], HAPPY N. MONDAY[1]

[1]School of Computer Science and Engineering, University of Electronic Science and Technology of China Chengdu 611731-China
[2]School of Control and Computer Engineering, North China Electric Power University, Beijing, China
[3]School of Management Science and Economics University of Electronic Science and Technology of China
[4]School of Information and Software Engineering, University of Electronic Science and Technology of China
E-MAIL: khan.amin50@yahoo.com

Abstract:

The diagnosis of heart diseases through invoice based techniques as well as ordinary medical based methods are not reliable. On other hand, non-invoice based techniques are more effective for heart disease diagnosis. Therefore, we check the capability of various Machine Learning (ML) classifiers and deep learning classifier for heart disease identification in this paper. Six machine-learning classifiers and BPNN were used in order to check which one classifier is more effective for diagnosis the heart disease. The feature selection algorithm Relief was used for selection of important features and on these selected features, classifiers performances were also computed. Ensemble machine learning techniques (boosting, bagging, stacking) were used to further increase the classifiers performance. Furthermore, cross-validation techniques k-folds was also used. Additionally backward propagation neural network (BPNN) was also used for classification purpose because deep learning algorithm not need feature selection algorithms and it automatically select important features for good result. Based on model performance evaluation metrics the SVM (RBF) performed excellently on full features achieved accuracy 86%, and 88% accuracy on selected features as compared other classifiers. Through Ensemble learning techniques, SVM obtained the classification accuracy 92.30%. The BPNN achieved 93% classification accuracy. Thus the performance of deep neural networks learning algorithm is better than traditional machine learning algorithms. As per our experimental results shows that the performance of BPNN based diagnosis system is more effective for heart disease diagnosis

Keywords:

Heart Disease; Machine learning; Features selection; Accuracy; Decision support system

1. Introduction

One main cause of human death is heart disease (HD) worldwide which commonly occur when heart is not able to push enough quantity of oxidized fresh blood to remaining body [1]. I united State (US), the heart disease rate is very high [2]. Symptoms heart patients include the weakness of the body, shortness of breath and swollen feet [3]. The early methods have identified HD and its complexity as one of the big reason which effects standard of life as well as mortality in developed states in the world [4]. The diagnosing and treatment of heart disease are extremely complicated and especially in poor countries due to the unavailability medical experts and technology [5]. Therefore, accurately and efficient based diagnosing of heart disease is necessary. Moreover, enhanced techniques are required that assist heart patients in their daily life activities [6]. The traditional/invasive methods to identifying HD are conducted through investigation of patient medical records but diagnosis HD through these methods IS not effective [7]. Different research studies have been conducted for HD detection using ML algorithms some of these studies are the following. To overcome these problems, Machine learning and fuzzy logic based methods [39] have been proposed by various researchers in early studies and widely deployed for diagnosis of HD [8]. In [43] study the relationship of fish consumption and coronary HD an optimal control method. The experimental results demonstrated that the prevalence and mortality of coronary HD effectively deduced at age of 10 years. In [9] developed a diagnosis system used logistic regression classifier for HD detection and 77% accuracy obtained. B. Edmonds in [11] Cleveland dataset used the author with Global Evolutionary method and obtained good results. In [12] the authors developed a HD detection system by using m MLP and SVM classifiers. The presence and absence of heart disease respectively achieved classification an accuracy of 80.41% for two classes. Humar et al. [13] developed diagnosis system and obtained 87.4% accuracy by utilizing a Hybrid-Neural-Network, a Fuzzy-Neural-Network and ANN. In [14 authors developed HD diagnosis system using ML algorithms. Classifiers NB, ANN and DT achieved accuracy 86.12 and 88.12%, 80.4% respectively. In [15] developed a HD diagnosis system by using ANN and obtained 88.89% accuracy. Resul et al. [16] developed ANN ensemble based diagnosis system for HD and achieved good accuracy. IN [17] the author Proposed HD diagnosis system based on MLP and ANN drove back propagation learning with features selection algorithms and produce good results. The system gives excellent performance in term of accuracy. In [18] developed HD diagnosis system based on ANN and Fuzzy approach and achieved 91.10% accuracy. Amin ul haq et al. proposed a Heart disease Prediction System Using Model of Machine Learning and Sequential Backward Selection Algorithm for Features Selection and achieved high accuracy [46].

In this research study, we check the feasibility of various ML classifiers and deep neural network classifiers for designing a medical expert system. For these purposes six popular ML classifiers performance were tested on HD dataset that available online UCI repository which used by other researchers also [9], [10]. Furthermore, we also used features processing techniques for improving quality of the data for effective training and testing of classifiers. Features selection method used to select more important features for improving accuracy and reduced computation time of classifiers. Deep neural network model was used for classification also and compared it performance with traditional ML algorithms. Cross-validation (CV) technique k-folds was used for learning best practices for model evaluation and hyper parameter tuning. The model's measuring metrics including accuracy, sensitivity, specificity, MCC, and processing time were calculated for best model identification.

The paper remaining is organized as follows: The Section 2 brief information and description of the dataset and theoretical background of feature selection, ML, DNN algorithms and classifiers performance measuring techniques have been discussed. Experimental results are discussed in details in section 3. Paper conclusion is expressed in section 4.

2. Research materials and methodology

The following sections research materials and methods in details

2.1. Data set

The HD dataset collected from UCI repository and used in this study which was used by various researchers [9, 10]. The 303 instances of the subject with few missing values and 76 features include in the dataset. During the analysis, 297 instances with 13 features were obtained. Thus, 201 instances male and 96 of female. The out label has two classless for presence and absence of HD. Thus, the Dataset is 297*13 matrix.

2.2. Proposed System Methodology

This system is developed for HD identification. The proposed system methodology has these modules preprocessing of features, Relief based features selection, Machine learning classifiers, Model cross-validation methods, Model performance evaluation methods.

2.2.1. Preprocessing

Data pre-processing is one of steps in solving every machine-learning problem. The dataset used in machine learning need to be processed, cleaned/transformed so that the data representation, training and testing processes are perform effectively. Techniques such as removing missing values, standard scalar, Min Max Scalar we applied to the dataset.

2.2.2. Algorithm of Features Selection (FS)

The FS algorithms to remove irrelevant features from dataset and these selected features improve accuracy and reduced computational time.

Relief Algorithm:

It is a FS algorithm [19], all features in the dataset assigned weights and modifying accordingly by relief. The most important features to target output have weights greater value and irrelevant features have small weights. Relief uses same approach as adopted in K-NN weights of features [20].

Algorithm 1 Pseudo-code for the Relief algorithm

Require: For each training instance set S, a vector of feature values and the class value
n ← number of training instances
a ← number of features
Parameter: m ← number of random training instances out of n used to update W
Initialize al l feature weights W[A] := 0.0
For k: =1 to m do
Randomly select a 'target' instance R_k
Find a nearest hit 'H' and nearest miss' (instances)
For A: = 1 to a do
W [A]:= W [A] −diff (A, R_k, H) / m + diff(A,R_k , M)/m
End for
End for
Return the weight vector W of feature scores that compute the quality of features

2.2.3. Classification algorithms

To identify HD classification techniques are used, basic theories of these classification models are discussed as follows.

2.2.3.1. Logistic Regression (LR)

LR is most widely used algorithm for problems of classification [21-23][38]. It is used for binary problem classification to predict the value of predictive variable y when $y \in \{0, 1\}$, '0' is negative class and '1' is positive class.

To classify two classes 0 and 1 we should develop a hypothesis $h(\theta) = \theta^T x$.

The threshold output of classifier is $h\theta(x)$ at value 0.5 and If $h\theta(x)>=0.5$, it will predict y =1 and if value of $h\theta(x) < 0.5$, then predict y=0. So the prediction of LR under the condition $0<=h\theta(x)<=1$. The sigmoid function or logistic function of LR mathematically expressed as shown in equation (1).

$$h\theta(x) = \boldsymbol{g}(\theta^T x) \quad (1)$$

Where $\mathbf{g}(\mathbf{z}) = \frac{\mathbf{1}}{\mathbf{1}+x^{-z}}$, $h\theta(x) = \frac{1}{1+x^{-z}}$

Similarly, the LR cost function can be expressed in equation (2).

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} Cost(h\,\theta(\ x^{(i)}), y^{(i)}) \quad (2)$$

LR implementation can fit binary and multinomial LR with optional L2 or L1 regularization.

In optimization problem, binary class L2 LR minimize the cost function expressed in equation (3).

$$\min_{w,c} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \log\left(\exp\left(-y_i (X_i^T \mathrm{w} + \mathrm{C})\right) + 1\right) \quad (3)$$

L1 regularized LR can solve an optimization problem using this cost function written in equation (4).

$$\min_{w,c} ||\mathrm{w}||1 + C \sum_{i=1}^{n} \log\left(\exp\left(-y_i (X_i^T \mathrm{w} + c)\right) + 1\right) \quad (4)$$

2.2.3.2. Support Vector Machine

It is a well-known predictive model which has been widely used for problems of classification [24-25]. It is use for classification problems[26-28][42][45]. The hyper plane can separate the samples in classification related machine learning problem.

$\mathrm{w}^T x + b = 0$

Where w and d-dimensional coefficient vector, and b, is offset value, x is data set values. The SVM get results of w and b. The solution of w can write as $w = \sum_{i=1}^{n} \alpha_i y_i x_i$

Where n is the number of Support vectors, y i are target labels to x. The value of w and b are calculated, the linear discriminant function can be written in equation (5).

$$g(x) = \mathrm{sgn}\left(\sum_{i=1}^{n} \alpha_i y_i\, x_i^T x + b\right) \quad (5)$$

The non-linear scenario, for kernel trick and decision function written in equation (6)

$$\mathrm{g(x)} = \mathrm{sgn}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + \mathrm{b}\right) \quad (6)$$

2.2.3.3. K-Nearest-Neighbor

K-NN is ML algorithm [30]. K-NN algorithm predicts the class label of a new input; K-NN utilizes the similarity of new input to its input's samples in the training set. If the new input is same the samples in the training set. The K-NN show high performance or the K-NN classification performance is not good.

2.2.3.4. Naive Bayes

NB is ML algorithm and specifically good for text classification problem [31].

2.2.3.5. Artificial-Neural-Network

ANN supervised machine learning classifier. The artificial neural network is a model that combines different neurons passing messages. The ANN has three parts such as inputs, outputs, and transfer functions. Different combinations of neurons form different structures like MLP [32][40].

2.2.3.6. Decision Tree (DT)

It is ML algorithm and use for problems of classification [33].

2.2.3.7. Ensemble learning techniques

It is the combinations of the output of various models. Bagging, Boosting and stacking are thee models [34]. Bagging is the integration of predictions is the same as voting. The Boosting is similar to bagging, however, the efficiency of previous models effect on the new models. Stacking is the combining of models of various types.

2.2.3.8. Back propagation Neural network (BPNN) for heart disease classification

The BPNN is a multi-layer feed forward neural network also known as error back-propagation algorithm. The accumulated error at output layer is back propagated into network for weights setting [45]. There is no backward pass of computation only for in training operation is used. All the functioning operations proceed in the forward direction during simulation.

The BPNN algorithm pseudo code is given below.

Step1. Initialization of network: weights are randomly selected

Step2. Choose the training pair

Step 3.Forward computation has the following steps:

a. Input to network

b. compute the output for every neuron from input layer, through hidden(s) ,to output layer

c. Adjusted the weights

Step 4 Backward computation

a. The output error to compute error signals for pre output layer

b. Error signals are used to compute weights adjustments

c. Deploy weights adjustment

Step 5. Iterate forward and backward calculations for others training pairs

Step6. Periodically compute the performance of the network repeat forward and backward computations for the network coverages on the target output.

2.2.4. Validation methods of classifier

To check the performance of the system K-folds cross-validation method. In this method data set is split into K components. The k-1 groups use for training and reaming for testing in each step.

2.2.5. Model Measuring Metrics

The classifiers performance can be checked by performance evaluation metrics.

Table 1 Confusion matrix [35-37][43][47]

	Predicted HD patient (1)	Predicted healthy person (0)
Actual HD patient (1)	TP	FN
Actual healthy person (0)	FP	TN

The following performances evaluation metrics are used to evaluate the models performance which are expressed in equations (7), (8), (9), (10), and (11) respectively.

$$\text{Accuracy} = Ac = \frac{TN+TP}{TP+TN+FP+FN}*100\ \% \quad (7)$$

$$\text{Classification error} = \frac{FP+FN}{TP+Tn+FP+FN}*100\ \% \quad (8)$$

$$\text{Sensitivity}=Sn = \frac{TP}{Tp+FN}*100\% \quad (9)$$

$$\text{Specificity} = Sp = \frac{TN}{TN+FP}*100\% \quad (10)$$

$$MCC = \frac{TP*Tn-Fp*FN}{\sqrt{(TP+FP)(Tp+FN)(TN+FP)(TN+FN)}}*100\% \quad (11)$$

ROC-AUC:

The ROC is graphical tool for model performance analysis which compares the "TPR" and "FPR" in the classification results ML classifiers. AUC characterizes the ROC of the model. AUC high value show good performance of model.

3. Experiments and Results Discussion

In this part of the paper, we evaluate different algorithms performance includes LR, K-NN, ANN, SVM, NB, DT and BPNN. Relief algorithm used for importance features selection. The performances of models were checked on full and selected features set. To improve the performance of classifiers ensemble machine-learning techniques (bagging, boosting, and stacking) has also applied to K-folds, validation methods and the performance measuring used for classifiers performance evaluation. All computations were conducted in python on an IR- C™ i5 -2400CPU @3.1 GHz PC.

3.1. Results Relief Algorithm

The important features were ranked by relief and features score weights are arranged in descending order. According to Relief FS Thallium scan is an important feature for diagnosing heart disease and FBS feature is low score feature that means it has low impact on heart disease. The six important features are tabulated in in table 2

Table 2 Selected features set

Order	Feature	Feature Name	Feature Code	Scores
1	13	Thallium scan	THA	0.247
2	9	Exercise–InducedAgina	EIA	0.227
3	3	Type of chest pain	CPT	0.217
4	11	Slope of the peak exercise ST Segment	PES	0.131
5	12	Number of major vessels (0–3) colored by fluoroscopy	VCA	0.128
6	8	Maximum heart rate	MHR	0.123

3.2. Classifiers performance evaluation with missing values of attributes of the dataset

In this part of the paper want to check the performance of ML classifier on Cleveland heart disease dataset that have missing values. The missing values Cleveland dataset has 303 instances and 13 real values features and one is target column. The data set is 303X13 matric. The experimental results of classifiers with missing values reported in table 3.

Table 3 Classifiers evaluation of performance with missing values dataset

Classifier	Metrics		
	Spe (%)	Sen (%)	Acc (%)
LR (C=10)	75	93	85
K-NN, K=1	36	65	52
K-NN, K=3	57	69	64
K-NN ,K=9	60	74	68
ANN (13,16, 2)	72	74	78
SVM	86	75	86
NB	85	76	85
DT	72	79	76

The table 3 show that instances some attributes missing values effect the classifiers prediction capability. Hence missing features attribute instances are deleted from the dataset. Performances metrics are demonstrated graphically for better understanding in fig.1.

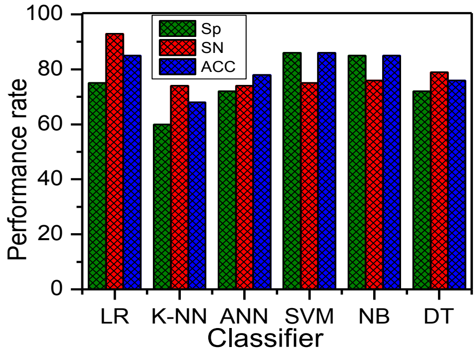

Fig.1 Classifiers performances with missing attributes

3.3. Classifiers performance on Full and on selected features

In this section, we used various numbers of important features models performance evaluation. We performed experiments with 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,12 features set and full features set. However, with 6 features set results were good. Hence we only report the classifiers evaluation full and on six features sets with 10 fold cross validation in table 4.

The logistic regression accuracy increased 1% from 85% to 86%, on reduced features as compared to full features. A-NN increased from 74% to 77%. SVM (RBF) performance on reduces features was excellent and improved accuracy from 86 % to 88%. The remaining classifiers have a small change in their performance on a reduced set of features as compared to full. In fig.2 show performance comparison of different classifiers on full features set and selected features by relief. The execution time (s) on full and selected features of classifiers also shown in fig.3.

3.4. Results of different classifiers for ensemble learning techniques

Three ensemble learning methods used to improve the classification accuracy.

Bagging:

The experimental results with bagging [41] technique improve the performance of models. The fig.4 shows that bagging improved the accuracy of some of the classifiers. For DT improved accuracy from 77.55% to 78.54%. NB improved classification accuracy 85 % to 86%. SVM (RBF) did not improve but reduced accuracy from 88% to 87%.

Boosting:

In boosting weak models, running it multiple times on

Table 4 Results of classifiers performance evaluation on full and on selected features sets with 10 folds CV

classifier	Feature	Performance Evaluation Metrics				
		Acc (%)	Sp (%)	Sen (%)	MCC (%)	P-Time(s)
LR(C=10)	6	86	86	88	88	2.313
	13	85	85	87	84	2.344
K-NN at K=5	6	72	71	90	89	25.390
	13	71	81	87	84	27.304
A-NN 3 layer, 16 hidden units	6	77	78	100	50	10.231
	13	74	73	78	73	21.011
SVM(RBF)	6	88	84	94	86	13.167
	13	86	81	89	90	14.111
SVM(linear)	6	79	77	94	77	15.710
	13	78	80	79	79	15.919
NB	6	85	87	78	80	15.100
	13	84	87	80	81	15.110
DT	6	75	66	85	75	18.061
	13	75	70	80	77	18.123

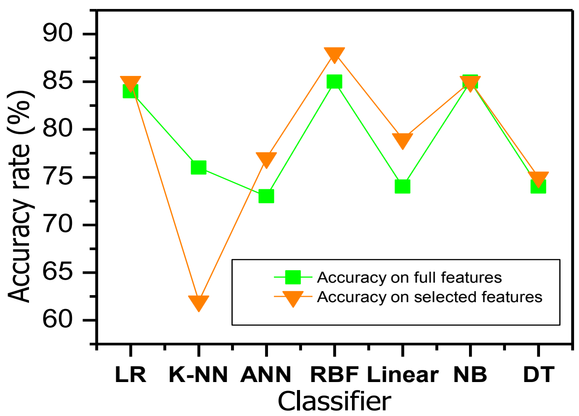

Fig.2 Accuracy on full and on selected features with 10 folds validation

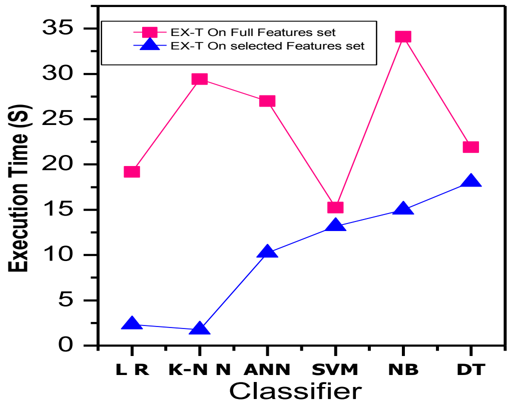

Fig.3 Execution time of classifiers on full and selected features.

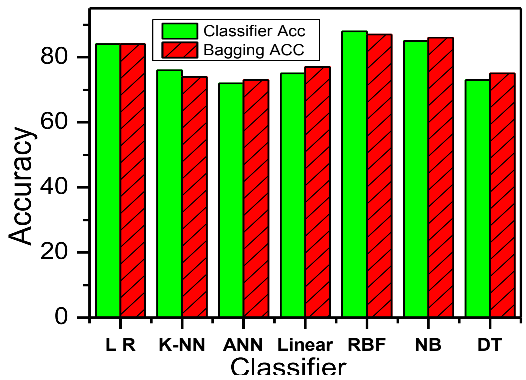

Fig.4 Different classifiers accuracy with bagging techniques

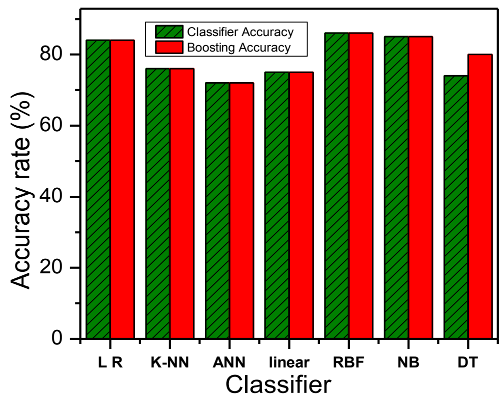

Fig.5 Different classifiers accuracy with boosting techniques

the training data and then allowing the learned model to vote. We applied to boost on DT, NB, K-NN, ANN, RBF, and SVM, and it worked well on the weakest models. As fig.5 shows, it increased the accuracy of DT from 75% to 80%. The others remained approximately the same.

Stacking:

The different predictive models have been combined used stacking method in order to improve the accuracy of classifiers. In the table 5 shows, a combination of SVM, Logistic regression, and ANN has been achieved the best accuracy, 92%.

Table 5 The performance of classifiers with a stacking technique

Stacking	Accuracy
K-NN, NB, Logistic regression, SVM(RBF)	79%
K-NN, NB, SVM(RBF) ANN	87%
NB, ANN, Logistic regression SVM(RBF)	89%
ANN, Logistic regression, SVM(RBF)	92%

In table 5 the SVM with ensemble method accuracy is 92%. Therefore, from all above experiments shows that the performance of SVM predictive model is excellent as compared others predictive models. Therefore, we proposed Relief–SVM with method for HD diagnosis.

Table 6 Accuracy of our proposed method to other previously methods

S.No	Authors	Method	Acc (%)
1	Robert Detrano	Logistic regression (LG)	77.85
2	Newton heung	Naïve Bayes (NB)	81.48
3	Sahan et al	Attribute weighted artificial immune system (AWAIS)	82.59
4	Ozsen & unes	Modified artificial immune system (MAIS)	87.43
5	Das et al	Neural networks ensemble (NNE)	89.01
6	Oluwarotimi Williams Samuel et al	ANN and Fuzzy-AHP (ANN-F-AHP)	91.10
7	The proposed study	Relief-SVM with ensemble (R-SVM-E)	92.30

The accuracy of our proposed method is 92.30% which is pretty good as compared to previous methods as shown in table 6. Moreover, The Relief–SVM with ensemble method for heart disease diagnosis is more effective in term of accuracy and computational time.

3.5. Heart Disease Detection using Backward propagation Neural Network(BPNN)

BPNN is supervised learning algorithm and use for classification problem. The training parameters are updated of BPNN in order to generate good classification results. Therefore different of hidden layers, hidden neurons, learning rate and epochs are applied for producing excellent result in our experiments. In table 7 the BPNN architectures of different networks are given such as BPNN1, BPNN2, and BPNN3.

Table 7 Training parameters for BPNs

Networks	BPNN1	BPNN2	BPNN3
Training instances	240	240	240
Validating instances	27	27	27
Learning rate	0.0110	0.0001	0.0101
Activation function	relu	relu	relu
Epochs	200	600	400
Training time(s)	120	150	125
Accuracy	90	93	91

According to table 7 the performance of BPNN2 is good and achieves 93% classification accuracy. Thus deep neural network performance is good as compared to transitional machine learning classifiers. The traditional classification algorithm achieved 92.30% accuracy on selected features. However, deep backward neural network no need feature selection for classification. Deep neural network automatically selects import features for improving the result of classification. These are great advantages of deep neural network.

4. Conclusion

In this research study, we have been performed experiments to identify the performance of various algorithms. FS algorithm Relief used for important features selection because features selection increased classifier performance in terms of accuracy and reduce processing time of classifier. The ensemble learning techniques such as bagging, boosting and stacking used to further improve the classification accuracy of classifiers. BPNN algorithm was also used for classification and compared it performance with machine learning algorithms. The experimental results demonstrated that SMV performed excellent with respect to others classifiers performance in term of classification accuracy and achieved classification accuracy of 86% on full features.

The relief features selection selected important features and on selected features SVM obtained classification 88% which is pretty good as compared others classifiers. Moreover, the Ensemble learning techniques have a great effect on SVM classification accuracy and it improved the classification accuracy of 92.30%. The Deep neural network performance is better than traditional classification method because DNN no need feature selection algorithm and it automatically selected appropriate feature for good result. In our experiments the BPNN achieved 93% accuracy. Finally based on all experimental analysis and results that deep neural network algorithm (BPNN) is more effective for detection of heart disease.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (Grant No. 61370073), the National High Technology Research and Development Program of China (Grant No. 2007AA01Z423), the project of Science and Technology Department of Sichuan Province

References

[1] A. L. Bui, et al., "Epidemiology and risk profile of heart failure " Nature Reviews Cardiology, vol. 8, pp. 30-41, 9, November 2011.

[2] P. A. Heidenreich, et al., "Forecasting the Future of Cardiovascular Disease in the United States:A Policy Statement From the American Heart Association," Journals - American Heart Association, pp. 933-944, 1, March 2011.

[3] M. Durairaj and N. Ramasamy, "A Comparison of the Perceptive Approaches for Preprocessing the Data Set for Predicting Fertility Success Rate," International Journal of Control theory and Applications, vol. 9, pp. 256-260, 2016.

[4] L. A. Allen, et al., "Decision Making in Advanced Heart Failure:A Scientific Statement From the American Heart Association," American Heart Association, vol. 125, pp. 1928-1952, 2012.

[5] S. Ghwanmeh, et al., "Innovative artificial neural networks-based decision support system for heart diseases diagnosis," Journal of Intelligent Learning Systems and Applications, vol. 5, pp. 176-183, 29, August 2013.

[6] Q. K. Al-Shayea, "Artificial neural networks in medical diagnosis," International Journal of Computer Science Issues, vol. 8, pp. 150-154, March 2011.

[7] K. Vanisree and J. Singaraju, "Decision support system for congenital heart disease diagnosis based on signs and symptoms using neural networks," International Journal of Computer Applications pp. 0975–8887, 2011.

[8] P. K. Anooj, "Clinical decision support system: Risk level prediction of heart disease using weighted fuzzy rules," Journal of King Saud University – Computer and Information Sciences, vol. 24, pp. 27-40, 22 November 2012.

[9] R. Detrano, "International Application of a New Probability Algorithm for the Diagnosis of Coronary Artery Disease," American Journal of Cardiology, vol. 64, pp. 304-310, 1989.

[10] J. H. Gennari, et al., "Models of Incremental Concept Formation," Artif. Intell, vol. 40, p. 11, March 1989.

[11] B. Edmonds, "Using Localised 'Gossip'to Structure Distributed Learning," 2005, pp. 1-12.

[12] M. Gudadhe, et al., "Decision Support System for Heart Disease based on Support Vector Machine and artificial Neural Network," in Computer and Communication Technology (ICCCT), International Conference 2010, pp. 741-745.

[13] H. Kahramanli and N. Allahverdi, "Design of a hybrid system for the diabetes and heart diseases," Expert systems with applications, vol. 35, pp. 82-89, 2008.

[14] S. Palaniappan and R. Awang, "Intelligent heart disease prediction system using data mining techniques," in Computer Systems and Applications, 2008. AICCSA 2008. IEEE/ACS International Conference on, 2008, pp. 108-115.

[15] E. O. Olaniyi and O. K. Oyedotun, "Heart diseases diagnosis using neural networks arbitration," International Journal of Intelligent Systems and Applications, vol. 12, pp. 75-82, 2, jun 2015.

[16] R. Das, et al., "Effective diagnosis of heart disease through neural networks ensembles," Expert systems with applications, vol. 36, pp. 7675-7680, 2, september 2009.

[17] M. A. Jabbar, et al., "Classification of Heart Disease using Artificial Neural Network and Feature Subset Selection " Global Journal of Computer Science and Technology Neural & Artificial Intelligence, vol. 13, p. 11, 4, may 2013.

[18] O. W. Samuel, et al., "An integrated decision support system based on ANN and Fuzzy_AHP for heart failure risk prediction," Expert systems with applications ElSEIER, vol. 68, pp. 163-172, 13, october 2017.

[19] K. Kira and L. A. Rendell, "A practical approach to feature selection," in Machine Learning Proceedings ed: Elsevier, 1992, pp. 249-256.

[20] R. Gilad-Bachrac, et al., "Margin based feature selection-theory and algorithms," in Proceedings of the twenty-first international conference on Machine learning, 2004, p. 43.

[21] F. E. Harrell and J. (auth.), "Ordinal logistic regression," in Regression modeling strategies, ed: Springer, 2015, pp. 311-325.

[22] K. Lawen, et al., "Interpreting parameters in the logistic regression model with random effects," Biometrics, vol. 56, pp. 909-914, September 2000.

[23] V. Vapnik, The nature of statistical learning theory: Springer science & business media, 2013.
[24] Cristianini, et al., An introduction to support vector machines and other kernel-based learning methods: Cambridge university press, 2000.
[25] C.-C. CHANG and C.-J. LIN, "LIBSVM: a library for support vector machines," ACM transactions on intelligent systems and technology (TIST), vol. 2, p. 27, April 2011.
[26] H.-L. Chen, et al., "A new hybrid method based on local fisher discriminant analysis and support vector machines for hepatitis disease diagnosis," Expert Systems with Applications, vol. 38, pp. 11796-11803, 2011.
[27] H.-L. Chen, et al., "A support vector machine classifier with rough set-based feature selection for breast cancer diagnosis," Expert systems with applications, vol. 38, pp. 9014-9022, 2011.
[28] J. Moura˜o-Miranda, et al., "Classifying brain states and determining the discriminating activation patterns: Support Vector Machine on functional MRI data," NeuroImage Elsevier, vol. 28, pp. 980-995, 4, November 2005.
[29] V. D. S. a. A, "Advanced support vector machines and kernel methods," Neurocomputing, vol. 55, pp. 5-20, 13, March 2003.
[30] X. Wu, et al., "Top 10 algorithms in data mining," Springer, pp. 1-37, 4, December 2007.
[31] N. FRIEDMAN, "Bayesian network classifiers," springer, vol. 29, pp. 131-163, 1997.
[32] A. K. Jain and R. P. W. Duin, "Statistical Pattern Recognition," IEEE Transactions on pattern analysis and machine intelligence, vol. 22, pp. 1-37, 1, January 1999.
[33] [P. W. Wagacha, "Induction of Decision Trees," Foundations of Learning and Adaptive Systems, vol. 12, pp. 1-14, 9, May 2003.
[34] I. H. Witten, et al., Data Mining: Practical machine learning tools and techniques: Morgan Kaufmann, 2016.
[35] Amin Ul Haq et.al "A Hybrid Intelligent System Framework for the Prediction of Heart Disease Using Machine Learning Algorithms", Mobile Information Systems, vol:2018, pages 21, 2, December 2018.
[36] Amin Ul Haq et.al, "Feature Selection Based on L1-Norm Support Vector Machine and Effective Recognition System for Parkinson's Disease Using Voice Recordings" IEEE Access, issue date December 2019, volume: 7, Issue: 1, on page(s)37718-37734, Print ISSN:2169-3536.
[37] Amin Ul Haq et.al ,Comparative Analysis of the Classification Performance of Machine Learning Classifiers and Deep Neural Network Classifier for Prediction of Parkinson Disease, 2018 15th International Computer Conference on Wavelet Active Media Technology and Information Processing(ICCWAMTIP),IEEE,14-16Dec.2018.
[38] Ouyang, Xinyu, et al. "An Efficient Twin Projection Support Vector Machine for Regression." Engineering Letters 27.1 (2019): 103-107.
[39] Rukchart Prasertpong, Manoj Siripitukdet, "Rough Set Models induced by Serial Fuzzy Relations Approach in Semigroups." Engineering Letters 27.1 (2019).
[40] Rivero, Jesus E., et al. "Thermal neutron classification in the hohlraum using artificial neural networks." Engineering Letters23.2 (2015): 87-91.
[41] Shigei, Noritaka, et al. "Land-Use Classification Using Convolutional Neural Network with Bagging and Reduced Categories." Proceedings of the International MultiConference of Engineers and Computer Scientists 2019 IMECS 2019, March 13-15, 2019, Hong Kong.
[42] Mehta, S. S., & Lingayat, N. S. (2007, May). Support Vector Machine for Cardiac Beat Detection in Single Lead Electrocardiogram. In IMECS (pp. 1630-1635).
[43] Al-Jallad NT, Ning X, Khairalla MA. An Interpretable Predictive Framework for Students' Withdrawal Problem Using Multiple Classifiers. Engineering Letters. 2019 Mar 1;27(1).
[44] Lamlili, E. N., Boutayeb, A., Derouich, M., Boutayeb, W., & Moussi, A. Fish Consumption Impact on Coronary Heart Disease Mortality in Morocco: A Mathematical Model with Optimal Control. Engineering Letters, 24(3), 2016.
[45] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, "Chest X-ray 8: hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," in Proceedings of IEEE CVPR 2017, Honolulu, HI, USA, 2017.
[46] Amin Ul Haq et al, "Heart Disease Prediction System Using Model of Machine Learning and Sequential Backward Selection Algorithm for Features Selection", IEEE 5th I2CT 2019 Pun international conference, India, 2019.
[47] Muhammad Hammad Memon et al., "Breast Cancer Detection in the IOT Health Environment Using Modified Recursive Feature Selection" Wireless Communications and Mobile Computing
Volume 2019, Article ID 5176705, 19 pages
https://doi.org/10.1155/2019/5176705