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Neuro-Fuzzy Ensemble Model-Based Rough Set Classifier Selection for Automatic Detection of Heart Disease

A. H. El-Baz[1,2,*]

[1] Department of Mathematics, Faculty of Science, Damietta University, New Damietta, Egypt.
[2] Institute of Mathematics, Informatics and Mechanics, Warsaw University, Banacha 2, 02-097 Warsaw, Poland.

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Abstract: This paper presents a novel hybrid intelligent system based on ensemble of neuro-fuzzy classifiers (NFCs) and rough set theory for automatic detection of heart disease. A pool of NFCs which is trained using scale conjugate gradient is generated. Rough sets are used to identify the most significant classifiers which contributed in the committee. Consequently, the classifiers space of the ensemble is reduced which in turn reduce the complexity of the problem. The results of the reduced NFCs are combined by majority voting rule to obtain the final diagnosis decision. The proposed system is applied on the dataset taken from the well- known Cleveland heart disease database. Performance measures such as accuracy, specificity, sensitivity, F-score which are commonly used in medical diagnosis were evaluated to convey the qualities of the proposed method. The results obtained showing the efficiency of the proposed hybrid combined system.

Keywords: Hybrid intelligence system; Neuro-fuzzy; Rough sets; Ensemble classifier; Heart disease

1 Introduction

Heart disease is disorder of the cardiovascular system (i.e., the heart and blood vessels) that affects the heart's ability to function normally. Heart disease is also called cardiovascular disease [1].

Cardiovascular disease is a major cause of death throughout the world. Approximately 29 percent of all deaths worldwide are related to the heart disease [1]. So, early reveal and therapy of the disease are imperious. Over the past years researchers have used different machine learning techniques to upgrade heart disease diagnostics.

On the other hand, Zadeh in 1965s suggested fuzzy logic and fuzzy set [2] which have been used successfully in many disciplines as the solution of uncertain and complex problems. But, when the fuzzy system is created, determinacy of rules, type of membership function, the number of rules and choose of parameters are determined with area of expertise. The most conspicuous difficulty in the design of a fuzzy system is that membership functions are not generally optimal in terms of reproducing of desired outputs [3]. The fuzzy system can be designed by using artificial neural networks (ANNs). For this reason, many machine learning researchers have used neuro-fuzzy systems which are the combination of fuzzy logic and artificial neural networks in the solution of complex problems [3].

In many applications, it is common to train different classifiers and then to select the superior one in performance and to keep only this classifier and discard the rest. The disadvantages of this approach are the wasted time used in training the discarded classifiers, and the classifier which had best performance on the validation set might not be the one with the best performance on test data due to the noise on the data. By combining the classifiers together to form a combined classifier, these drawbacks can be overcome. The combined classifier can lead to significant improvements in performance on unseen data. It is well known that the performance of a combined classifier can be better than the performance of the best individual classifier [4].

The main contribution of the paper is to build a new hybrid intelligent system for the diagnosis of the heart

* Corresponding author e-mail: ali_elbaz@yahoo.com, elbaz@du.edu.eg

disease. This system combine two methodologies: rough set theory for selecting the most significant neuro-fuzzy classifiers which contribute in the committee and a combined classifier which uses the reduced significant subset of classifiers as members so as to automatically produce a diagnostic system. We find that the proposed hybrid system produces a system exhibiting two prime characteristics: first, it gives high classification performance; second, the resulting systems involve a few set of significant classifiers which reduce the classifiers space and this in turn reduce the complexity of the problem. The rest of the paper is organized as follows. Section 2 gives the background information including classification problem of heart disease, previous research in corresponding area and brief concepts on rough set theory. The proposed hybrid intelligent system is explained in Section 3. In section 4, different performance measurements are mentioned which are commonly used for testing the effectiveness of automatic proposed diagnosis system. The results obtained are given in Section 5. This section also includes the discussion of these results. Consequently in Section 6, the conclusion is given with summarization of the obtained results by asserting the importance of this study.

2 Background

2.1 Heart disease dataset

The popular and publicly available UCI benchmark Cleveland heart disease dataset is used in this research [5]. It contains 303 samples of which 297 are complete samples and six are samples with missing attributes, which are removed in this study. The UCI heart disease dataset consists of a total 76 attributes. However, majority of the existing studies have used only a maximum of 14 attributes [5]. Table 1 gives the attributes of the Cleveland heart disease dataset, their description and datatype [5].

The dataset has five classes indicating either healthy or one of four sick types. The ”goal” field refers to the presence of heart disease in the patient. The class attribute (target) is integer valued from 0 (healthy) to 4. Experiments with the above mentioned heart diseases dataset have concentrated on distinguish sick (values 1,2,3,4) from healthy (value 0).

2.2 Previous research in diagnosis of heart disease

Numerous machine learning methods were used for heart disease diagnosis which reached high classification accuracies using the heart disease dataset mentioned above. Table 2 summarizes the methods used in the literature and their classification accuracies.

Table 1: The attributes of Cleveland heart disease dataset, their description and datatype

Attributes	Description	Type
Age	age in years	numeric
Sex	male, female	nominal
Chest pain type (CP)	(a) typical angina (angina), (b) atypical angina (abnang), (c) non-anginal pain (notang), (d) asymptomatic (asympt)	nominal
Trestbps	patient’s resting blood pressure in mm Hg at the time of admission to the hospital	numeric
Chol	Serum cholesterol in mg/dl	numeric
Fbs	Boolean measure for fasting blood sugar	nominal
Restecg	electrocardiographic results during rest. It has three types of values normal, abnormal: having ST-T wave abnormality, ventricular hypertrophy	nominal
Thalach	maximum heart rate attained	numeric
Exang	Boolean measure indicating whether exercise induced angina has occurred: 1 = yes, 0 = no	nominal
Oldpeak	ST depression brought about by exercise relative to rest	numeric
Slope	the slope of the ST segment for peak exercise. It has three types of values upsloping, flat, downsloping	nominal
Ca	number of major vessels (0–3) colored by fluoroscopy	numeric
Thal	the heart status (normal, fixed defect, reversible defect)	nominal
The class attributes	value is either healthy or heart disease (sick type: 1, 2, 3, and 4)	numeric

2.3 Rough set

Rough Set (RS) theory proposed by Pawlak in 1982 is considered a new intelligent mathematical tool to deal with uncertainty and incompleteness [6]. Over the past few years, RST has become a topic of great interest to researchers in different disciplines and has been applied to many fields. It is based mainly on the concept of both an upper and a lower approximation of a set. One of the main advantage of RST is that it does not need any additional information about data: like membership grade in fuzzy set theory. Among the major applications of RS theory is the feature reduction to reduce the complexity of the feature space of the problem at hand. The feature reduction is accomplished by using equivalence relations generated by sets of features. By using the concept of

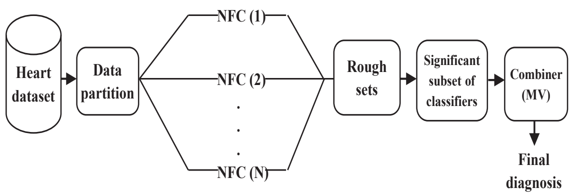

Fig. 1: Proposed ensemble system for automatic heart disease diagnosis.

dependency degree, redundancy features are removed and reduced set becomes has the same dependency degree as the original set of features. For more details see [7,8].

3 The proposed hybrid system

A neuro-fuzzy classifier (NFC) is a fuzzy system trained with some learning techniques inspired by the neural networks. The hybridization of neural networks and fuzzy systems has the advantage of the generation of a more robust, efficient and easily interpretable system.

In neuro-fuzzy system learning algorithms are used to determine parameters of fuzzy systems. This means that the main idea of a neuro-fuzzy approach is to originate or develop a fuzzy system in an automatic way by using artificial neural networks.

A neural network and a fuzzy system are combined into one integrative architecture to form hybrid neuro-fuzzy model. The resulting system is considered either as a neural network with fuzzy parameters which need to be determined by the learning algorithm, or as a fuzzy system implemented in a parallel distributed form.

In this study, the NFC used is based on Jang's neuro-fuzzy classifier [9]. There are some modifications in Jang's model, proposed by [10] and adopted here, to make the classification task faster and more suitable for large scale problems. First, the rule weights are adapted by the number of rule samples. Then the scaled conjugate gradient (SCG) is used to obtain the values of nonlinear parameters in an optimum way. As mentioned in [10], the SCG is faster than both some second order derivative based methods and steepest descent method.

In the proposed hybrid system, a pool of NFCs, which is trained by SCG, is generated. To reduce the complexity of the classifiers space, the classification results of these classifiers are fed into rough set as conditional attributes and the targets are used as decision attributes. A reduct was obtained which contained the most significant classifiers from the generated pool of classifiers. To get the final diagnosis decision, a majority voting is used as a combiner to combine the results of this subset of classifiers as shown in Figure 1.

4 System performance measurements

In automatic medical diagnosis systems, there are different metrics to measure the performance of the classification methods which are commonly and widely used. These metrics are True Positive (TP),True Negative (TN), False Positive (FP), and False Negative (FN). For more details about these metrics see [11].

5 Results and discussion

To assess the effectiveness of the proposed hybrid model for diagnosis of heart disease, experiments are conducted on benchmark Cleveland heart disease dataset mentioned above. The whole dataset is divided into two disjoint subsets, namely 70% for training and 30% for testing for all the conducted experiments.

A pool of twenty NFCs which is trained by scale conjugate gradient is generated. The classification results obtained are used as conditional attributes for rough set and the targets are employed as decision attributes. A reduct is obtained with reduced number of classifiers. According to the results obtained by reduct, only eight significant classifiers out of twenty are taken into account for building the ensemble using majority voting technique.

To illustrate the proposed system performance, the number of epochs versus root mean square errors is depicted in Figure 2. Figure 3 gives the accuracies of the pool of NFCs versus the number of epochs. It is observed that, in the case of using individual classifiers, there is an oscillation in the obtained results and the accuracy of the best individual classifier is 82.42%. Besides, the accuracy of the ensemble is 89.01% which is superior over all the individual classifiers.

Also, comparison of our results with the previous results reported in Table 2 indicates that the proposed hybrid system obtains the highest classification test accuracy.

Moreover, different performance measures are used to test the effectiveness of the proposed system. Figures 4 and 5 give the ROC curve for the best individual NFC and the proposed hybrid model. The area under the ROC curve is obtained which gives the accuracy of the classifier.

Classification results of the proposed hybrid model are displayed by using a confusion matrix, see Table 3. In a confusion matrix, each cell contains the raw number of exemplars classified for the corresponding combination of desired and actual outputs.

Also, the obtained classification accuracy and the values of different performance measures such as precision, sensitivity, F-measure and specificity are given in Table 4 and figure 6 for both the best individual NFC and the proposed hybrid model.

Table 2: Comparison between the classification accuracies obtained by the proposed model and other methods reported in the literature

Author (Reference No.)	Method	Accuracy (%)
Detrano et al. [12]	Logistic regression	77.00
Cheung [13]	C4.5	81.11
Cheung [13]	Naive Bayes	81.48
Cheung [13]	BNND	81.11
Cheung [13]	BNNF	80.96
Polat et al. [14]	AIRS	84.50
Polat et al. [15]	Fuzzy–AIRS–Knn based system	87.00
Ozsen and Gunes [16]	AWAIS	87.00
Tu et al. [17]	J4.8 Decision Tree	78.9
Tu et al. [17]	Bagging Algorithm	81.41
Shouman et al. [18]	Nine Voting Equal Frequency Discretization Gain Ratio Decision Tree	84.1
The proposed method	Hybrid system based on ensemble of neuro-fuzzy model and rough set	89.01

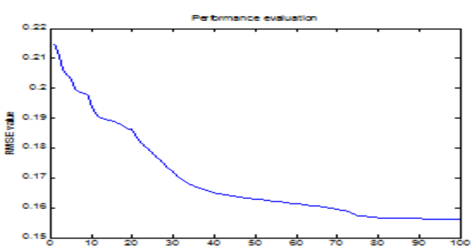

Fig. 2: The numbers of epochs versus root mean square errors.

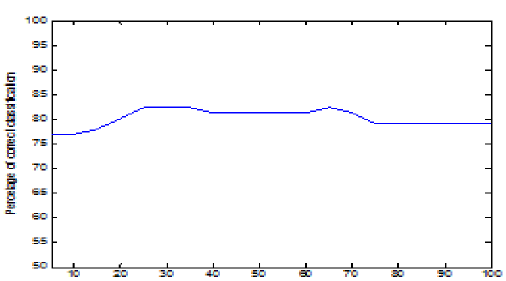

Fig. 3: Accuracies of the base neuro-fuzzy classifiers versus the number of epochs.

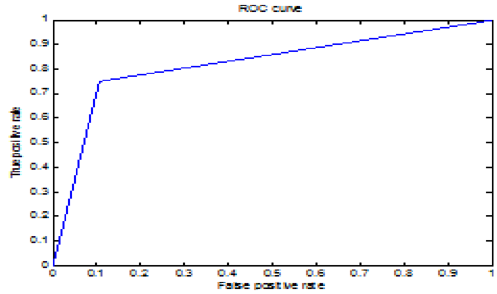

Fig. 4: The ROC curve for the best individual neuro-fuzzy classifier

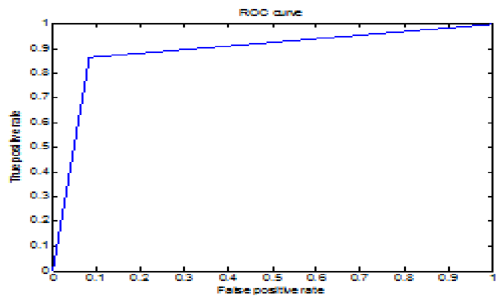

Fig. 5: The ROC curve for the proposed hybrid model

Table 3: Confusion matrix for the best individual neuro-fuzzy classifier and the proposed hybrid model

Classifier	Desired result	Output result	
		healthy	sick
Best classifier	healthy	42	5
	sick	11	33
Proposed hybrid model	healthy	43	4
	sick	6	38

Table 4: System performance measurements of the best individual neuro-fuzzy classifier and the proposed hybrid model on the test data

Proposed Method	Accuracy	Precision	Recall or Sensitivity	Specificity	F-measure
Best classifier	82.42%	86.84%	75.00%	89.36%	80.49%
Proposed hybrid model	89.01%	90.48%	86.36%	91.49%	88.37%

6 Conclusion

In this study, automatic biomedical-based system has been developed for the classification of heart disease using a hybrid system based on ensemble of neuro-fuzzy classifiers (NFCs) and rough set theory. A pool of NFCs,

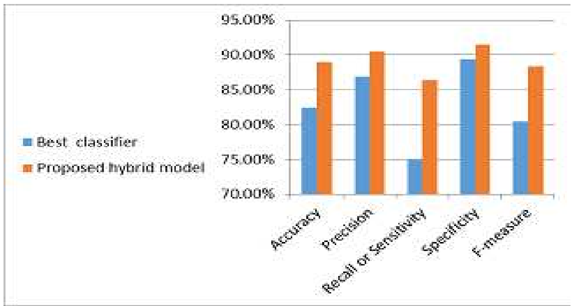

Fig. 6: System performance measurements of the best neuro-fuzzy classifier and the proposed hybrid model on the test data.

which was trained using scale conjugate gradient, was generated. Rough set theory was used to reduce the complexity of the classifiers space by selecting the most significant subset of classifiers from this pool which in turn contribute in the committee. The final diagnosis decision is obtained by using majority voting. To test the efficiency of the proposed hybrid system, different performance metrics which commonly used in medical diagnosis systems are used. Moreover, the prediction performance of the purposed technique was compared with the prediction results of previous studies in literature. According to the comparison results, the classification result of the proposed method was the best among all the classifiers presented in table 2. The obtained classification results showed that purposed method is effective for the detection of heart disease. Besides, development of this kind of automatic decision support systems will provide assistance to physicians with lacking skill and experience in diagnosing the heart disease, by simplifying this diagnosis process.

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A. H. El-Baz received his B.Sc. with honors and M.Sc. from Mathematical Department, Damietta Faculty of Science, New Damietta, Egypt in 1997 and 2002, respectively. He received his Ph.D. from Mansoura University in 2006. His research interest is in the areas of pattern recognition, signal/image processing, computer vision, machine learning and statistics. He has done research in computer vision, biometric identification, automated medical diagnosis, neural networks, combined classifiers and stochastic processes. He has published over 25 papers in these areas. He is a reviewer of many international journals.