Heart Disease Risk Detection with Competitive Learning and Adaptive Fuzzy Inference System, A Novel Approach

Hossein Shirazi[1], **S. M. R. Farshchi**[2]
[1]Department of Computer & Information Technology, MUT University, Tehran, Iran, Shirazi@MUT.ac.ir
[2]Social Network Laboratory, C4I Department, Tehran, Iran, Farshchi@ict.gov.ir

Abstract - *In this paper, we propose an adaptive method using a neural network to solve the heart disease risk detection. For the goal of heart disease risk detection, the statistical analysis is used to reduce the dimension of feature space and normalize each input feature; the novel fuzzy neural network with competitive learning are applied to realize the nonlinear mapping relationship between hemodynamic parameters and conclusions, which does not require predefining rules and subjective defuzzification. The preliminary testing results prove that the proposed method has a great accuracy for heart disease risk detection and it's promising for e-home healthcare usage. Experimental results on the RAZAVIs hospital databases have shown that the recognition rate achieved by the novel method (87.8%) outperforms the conventional approaches (82.9%and 82.3%).*

Keywords: competitive learning, fuzzy neural network, heart disease detection.

1 Introduction

The heart diseases (HDs) are the number one cause of death globally, more people die annually due to HDs than any other diseases [1]. Therefore, the demand of HDs risk detection is increasing in recent years. Among all kinds of HDs, coronary heart disease, hypertension and hyperlipaemia are three typical and frequently encountered HDs [2]. They result from the disorder of heart, vessel and blood separately, thus, selected as representative HDs for risk detection [3].

A wide variety of measurement has been used for CVD prediction, such as electrocardiography (ECG), magnetic resonance angiography etc. However, their application in home healthcare is limited due to inconvenient operation, invasive measurement and expensive cost [4]. Hence, the sphygmogram (SPG) is promising for home healthcare usage. After long-term exploration, the hemodynamic parameters (HDPs) derived from sphygmogram analysis are proved to reflect the cardiovascular status.

Various methodologies have been proposed to implement medical decision-making. Among them fuzzy neural networks (FNNs), which merge fuzzy logic (FL) and neural networks (NNs), draw great attention recently [5]. The NNs are in consideration due to its self-adaptation, robustness and performs the nonlinear mapping between the input features and the desired outputs. However, physicians do not favor it because it lacks a structural knowledge base for review and reference. In addition to NNs, FL is another popular solution for the task since it represents imprecise concepts through linguistic variables, such as "very", "middle", etc. There are various schemes to integrate FL and NNs for classification or diagnosis. A neuro-fuzzy model [6] is a fuzzy neural network model, that competing matching degrees of premise combinations as inference model provide the retrospection of the diagnosis evidence with comparable accuracy than conventional FNNs [7].

A conventional form of fuzzy systems for HD detection has low capabilities for learning and adaptation. Fuzzy mathematics provides an inference mechanism for approximate reasoning under cognitive uncertainty, while neural networks offer exciting advantages such as learning and adaptation, generalization, approximation. These networks are also capable of dealing with computational complexity, nonlinearity, and uncertainty [8]. A possible solution to overcome the above limitations of common HDs detection algorithms is the application of artificial intelligence approaches such as neural network and Fuzzy logic.

However, to the best of the authors' knowledge, the concept of FL has not been used for BP estimation [12]. In this paper, a novel expert system based on competitive learning and adaptive fuzzy inference system (CLAF) was adapted for data preprocessing, which categorizes input HDPs extracted from SPG into three groups named as sensitive, supporting and inertia group respectively, eliminates the random error effect and greatly reduces the dimension of input variable space. Then the features of sensitive group are used for HDs risk detection and then the fuzzy membership are constructed, which realize the nonlinear mapping relationship and map such reduced input symptoms to certain HDs efficiently. Moreover, the novel method is able to provide explanation in details about the deduced conclusion and its inference. The approach is tested and validated by the historical medical diagnosis records obtained from hospital.

The rest of this paper is organized as follows. The independent data analysis is given in Sections II. The structure of CLAF is given in Sections III. Section IV describes the experiment which is using the novel model and discusses the results. Conclusions are presented in Section V.

2 Preprocessing Of CVD's Data

The medical data consist of different sample's medical records, including each patient's original SPG data and physiological information. Denote the medical record space as $HDP \in R^N$ where N indicates the dimension of input variable space. In this research, there are 45 concerned practical input variables, including 6 physiological information and 32 extracted HDPs. Obviously, it is unwise and time-consuming to carry out the HDs risk detection via all these parameters, hence, the distribution verification and dimension reduction are required.

2.1 Classification of Hemodynamic Parameters

In order to minimize the dimension of feature space, it is necessary to conclude that which parameters are comparatively more significant. By means of variance analysis, the HDPs are divided into three groups, i.e. sensitive group, supporting group, and inertia group. Symbol F denotes the ratio of variance between different groups (HDG) and variance within same group (HSG).

$$F = \frac{HDG}{HSG} = \frac{Var\left(\frac{1}{n}\sum_{i=1}^{n} x_i\right)}{\frac{1}{m}\sum_{j=1}^{m} Var(x_j)} \quad (1)$$

Where m, n are the numbers of groups and records separately; the operator "Var" means the variance calculation [12]. Here, the F value is proportional to interrelationship between the parameter and HD. As a result, 38 HDPs are categorized according to different confidence coefficient [13]. Among them, 20 HDPs are classified as inertia parameters; 15 HDPs are classified as supporting parameters; and the remaining 10 HDPs are the sensitive parameters.

2.2 Fuzzy Variables for HDs Detection

To avoid sticking at meaningless accurate absolute values of HDPs, the FL is introduced. During fuzzification step, 4 prototypical functions are adopted for HD risk detection. The linguistic variables of fuzzification are defined as: "very low" (VL), "medium low" (ML), "normal" (N), "medium high" (MH), and "very high" (VH). Here, the Gaussian function is applied to represent the distribution of ML, N, MH and CHD.

Fig. 1 shows the membership functions of pulse rate (PR) according to this fuzzification.

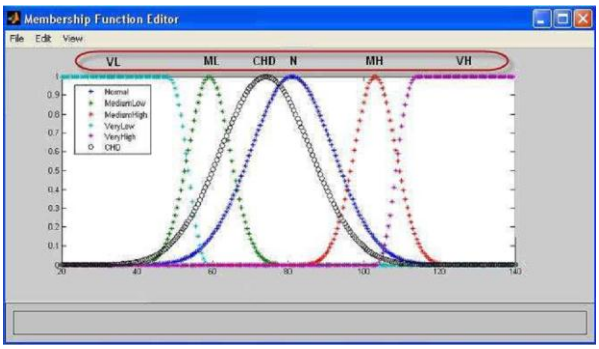

Figure 1. Membership function for fuzzification

The parameters of membership function are defined via great amount statistical analysis. For example, characteristics of Gaussian function depend on two key parameters, i.e. expected value (ξ) and standard deviation (τ). As shown in Table I, these two parameters are assigned through ξ=0 and τ =0, where are the mean and standard derivation of normal group respectively. The remaining definitions are listed in Table I.

TABLE I. PARAMETERS DEFINITIONS

Fuzzy Variable	Define Value	Parameter
Very Low	$\xi_0 - 3\tau_0$	Lower Value
	$\xi_0 - 2\tau_0$	Higher Value
Medium Low	$\xi_0 - 2\tau_0$	Lower Value
	$0.5\xi_0$	Higher Value
Normal	ξ_0	Lower Value
	τ_0	Higher Value
Medium High	$\xi_0 + 2\tau_0$	Lower Value
	$0.5\xi_0$	Higher Value
Coronary Heart Disease	ξ_C	Lower Value
	τ_C	Higher Value
Very High	$\xi_0 + 2\tau_0$	Lower Value
	$\xi_0 + 3\tau_0$	Higher Value

3 Structure of CLAF

Since the input and output data for fuzzy modeling are all crisp, the fuzzy system, which consists of fuzzy rule representation and fuzzy inference, can be simplified as follows:

Fuzzy rules:

$$if\ x\ is\ v_i, \Delta_i,\ \ then\ \ y = y_i \qquad i = 1,2,...,\xi$$

Fuzzy inference:

$$y = \frac{\sum_i s_i y_i}{\sum_i s_i} \tag{2}$$

$$s_i = \begin{cases} 1 - \dfrac{\| x - v_i \|}{\Delta_i} & if \| x - v_i \| \le \Delta_i \\ 0 & if \| x - v_i \| > \Delta_i \end{cases} \tag{3}$$

Where x is the crisp input vector, v and Δ are the center and the radius of each local input region, respectively, is the output center of each rule, is the number of fuzzy rules, and is the fuzzy membership function is used to measure the approximation degree of input in a fuzzy set. In general, only the approximation degree between input and the rule's premise is considered for fuzzy inference. It means that the strength with which a fuzzy rule is fired is assumed to be equal to the approximation degree of input in the rule's premise.

In contrast with that of traditional FNNs, the results of proposed methodology can be interpreted via the products of corresponding matching degrees, instead of a Boolean number (0 or 1) in output terminals merely. Providing an explanation in detail about the inference procedure that traditional FNNs do not provide is a novel feature of CLAF, since all knowledge is stored in the weights within the networks.

The architecture of the novel CLAF is provided in Fig. 2. The number of CLAF input in first layer is equal to the dimension of feature HDPs. In its second layer, all features are fuzzified as fuzzy variables which are well defined in Table I and explained in section II. The third layer is used for evaluating matching degrees of all possible premises.

The first step of CLAF is the initialization of weights which is the process of filling the weight tables (PC1-PCn) which are empty initially. Each table corresponds to a predefined feature of HDPs, and it consists of entries. Each entry consists of a fuzzy variable and its weight. In this step, each weight is filled with the frequency of the corresponding membership in the category corresponding to the table. Therefore, all tables owned by the learning nodes are constructed in this step.

In order to obtain the optimum weight tables T, the competitive learning method is applied for training and adjusting the link weights. The error evaluation function E is defined as:

$$E = \frac{1}{2}\sum_{k=1}^{p}(y_O - y_N)^2 \tag{4}$$

Where O and N express the real output and current output respectively.

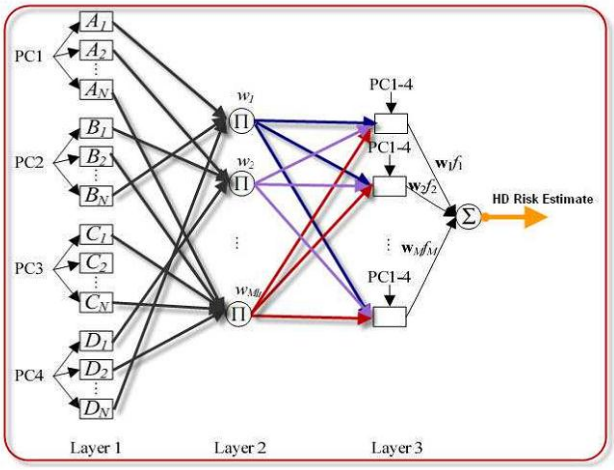

Figure 2. Architecture of the novel CLAF

4 Experimental Result

This section concerns experimental results of evaluating traditional and proposed approaches to HD risk detection on three test beds. In the experiments, two approaches, SVM, NB are evaluated as the approaches to HD risk detection. The parameters of the three approaches involved in this experiment are set by tuning them with a validation set, which is constructed by selecting 200 records randomly from training records, spanning the two test beds. Table 1 show the definition of the parameters which is obtained through this tuning.

Using novel CLAF method to detect certain HDs, the training and testing data are separately organized from site measured data of RAZAVI Hospital. There are totally 450 CHD, 150 hypertension (HT), 94 hyperlipaemia (HL) and 206 normal records. From them, 120 records with any kind of HD or combinational HDs, and 330 normal records are selected as the training set. The remaining records are used to verify the performance of trained CLAF. The testing results are shown in table 3 and recall rate of this test are depicted in Fig 3.

Fig. 3 shows that when the noise level (F1 measure) reaches 15%, the success rate of perfect recall using CLAF is 91.3%, even though those of the other methods are less than 70%. When the noise level reaches 20%, the perfect recall rate of CLAF is 85.8%, although those of other methods are less than 49%.

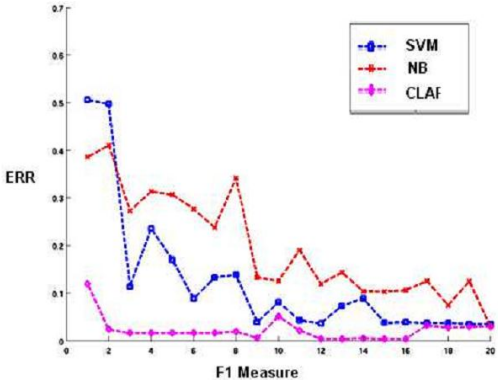

Figure 3. Error rate in HD risk detection

TABLE II. ACCURACY RATE RESULT

Algorithm	Training Record (330)			Testing Record (850)		
	HT	*HL*	*CHD*	*HT*	*HL*	*CHD*
NB	67.13	52.3	89.6	63.7	45.3	80.0
SVM	66.03	84.00	84.01	45.6	62.0	80.01
CLAF	68.13	84.01	92.03	68.1	68.3	81.2

The conventional NNs, SCM and CLAF are compared in detecting certain HDs. Table II shows that when using training data set the CLAF accuracy rate are higher than SVM, but approximately equal; while use testing data set the all methods are reduced and conventional method are still the worst.

Generally, the accuracy of detecting CHD and HT is higher than that of HL. From the testing results it can be concluded that in most situations CLAF are better than NNs with higher sensitivity in discriminating HDs.

5 Conclusion

In this research, we propose a new adaptive competitive neural network (CLAF) for heart disease risk detection. The CLAF, which provide explanation of inference procedure are applied to discriminating certain HDs. All membership functions are adjusted according to the statistical analysis. Features are also reduced so that an optimized feature set is provided for CLAF inference. This approach is tested by using site-measured data sets. Simulation result show that it promising to be applied in HDs risk detection in e-home healthcare usage. Also experiment results prove that the CLAF method has a great accuracy for heart disease risk detection. We plan to estimate the CLAF to detect another medicine risk.

6 References

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