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Risk Level Classification of Coronary Artery Heart Disease in Diabetic Patients using Neuro Fuzzy Classifier

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Abstract

This paper presents a recurrent fuzzy neural network for risk level classification of coronary artery heart disease (CAHD) in diabetic patients. The recurrent structure has been formed as an external loops and internal feedback by feeding the rule firing strength of each rule to others rules and itself. The consequent part of fuzzy logic system is composed of a Takagi–Sugeno–Kang (TSK) type. The proposed classifier has a functional link neural network (FLNN) to the consequent part of fuzzy rules for promoting the mapping ability. The proposed classifier learning starts with an empty rule base and all of the rules are generated through a simultaneous structure and parameter learning. The performance metrics true positive, true negative, false positive, false negative, sensitivity, specificity, classification accuracy are taken and the proposed method obtains enhanced performance results.

Keywords: CAHD, risk level classification, neuro fuzzy classifiers, recurrent neural network.

1. INTRODUCTION

Diagnosis and management of diseases are certainly a difficult task that cannot be acquired from textbooks or classroom knowledge alone. Most clinical scenarios have a vagueness varying in degree associated with them. During assessment the patients often describe their symptoms using superlatives such as “never, rarely, sometimes, often, most of the times, and always” and each specific symptom may also appear graded as “mild, moderate, or severe.” Medical problems cannot be generalized or analyzed using binary logic, that is, with a “yes” or a “no,” and an analytical program is required. Fuzzy logic, which has the capability of merging human heuristics into computer-assisted decision making, is the best solution to the problem. Diabetes is a disease of occurrence in pancreas that is situated behind the stomach. When food is taken, it is broken down into glucose which is the simple sugar that is the main source of energy for the human body's cells. Insulin assists glucose to enter the cells where it is converted to energy form. In diabetes, the pancreas either cannot produce enough insulin or cannot use insulin correctly or both. When insulin does not function right, glucose cannot enter the cells. As a result, glucose levels in the blood increase and the cells lack the energy they need to function. Cardiovascular diseases are among the most common reasons of death all over the world. One major type of these diseases is CAHD. Twenty five percent of people, who have CAHD, die suddenly without any previous symptoms [14]. CAD is one of the important types of diseases affecting the heart, and can cause severe heart attacks in patients [15]. Moreover, CAD tends to affect the younger population and thus could negatively affect the productivity and workforce [13]. The World Health Organization (WHO) estimates 11.1 million deaths from CAD in 2020.According to WHO (World Health Organization) report; CAHD has become a modern outbreak. CAHD is the result of accumulation of plaques within the coronary arteries. These arteries supply the myocardium (the muscle of heart) with oxygen-rich blood.

The plaque is made up of fat, cholesterol, calcium and other substances. When the plaque is growing it narrows the lumen of the coronary arteries. Consequently the blood flow to the heart muscle decreases. This causes a discomfort or a pain. The pain may be felt in chest, neck, jaws, abdomen, arms and shoulder also called Angina. During Angina the amount of the oxygenated blood flow decreases. But as the disease progresses the lumen of coronary arteries goes on narrowing due to the increased size of plaque. Hence the amount of blood supplied to this tissue becomes inadequate to supply the needs of the tissue. This condition is called myocardial ischemia and the tissues do not work at its fullest capacity. When the lumen of coronary artery has near-complete blockage, severely restricting the flow of oxygenated blood, the tissue in the areas f myocardium dies leading to myocardial infarction (particularly known as heart attack) which also accounts for sudden death. Though CAHD has now become much familiar disease, but death rate is high due to the lack of awareness among the common people.

2. RELATED WORKS

The motivation of this research begins here. It is presumed that women diabetic patients are at a much lower risk of coronary artery heart disease mortality than men. Also, it is thought that diabetes wipes away this female advantage which results in growing the risk of coronary artery heart disease more in women than in men. But amidst of these perceptions as a fact, the extent of this increased risk is controversial, with studies showing conflicting results and wide confidence intervals. The objective of the paper is to classify the risk of coronary artery heart disease in female diabetic patients using fuzzy logic. Several computer aided diagnosis methodologies have been proposed in the literature for the diagnosis of CAD. More specifically, the use of approaches like artificial neural networks [1], [2] and [3]), Naïve Bayes [4], support vector machines [5], decision trees [6] have been previously reported. Even though these approaches produce good classification accuracy, the interpretation of results is hard. They are popularly known as ‘‘Black Box’’ method since they focus only on the classification accuracy. Although rule based classifier systems, reported in Tsipouras et al. [7] and Adeli and Neshat [8] produces interpretable rules, they lack the robustness in the missing data. Different approaches have been discussed in Grzymala-Busse and Hu [9] and Su et al. [10]. A decision tree is a classifier that can be expressed as a recursive partition of the instance space [11], [12].

Researchers usually use two types of fuzzy if-then rules and fuzzy reasoning employed, i.e., Mamdani-type and Takagi–Sugeno–Kang (TSK)-type. For Mamdani-type fuzzy neural networks [13], [14], [15]–[19], the minimum fuzzy implication is adopted in fuzzy reasoning. For TSK-type fuzzy neural networks [18], [19], [20], [21], [22], the consequent part of each rule is a linear function of input variables. Several studies [20], [21], [22] indicate that the performance of a feed-forward TSK-type fuzzy network in network size and learning accuracy is superior to those of Mamdani-type fuzzy networks. A feed-forward TSK-type fuzzy network appears to have more free parameters to adjust input space mapping. However, each consequent part of each fuzzy rule in a standard TSK-type fuzzy neural network does not take full advantage of the mapping capabilities of local approximation by rule hyper-planes. Therefore, several studies [23]–[29] consider trigonometric functions to replace the traditional TSK-type fuzzy reasoning and also obtain the better performance.

3. PROPOSED WORK

The neuro fuzzy classifier proposed in this research work follows multiple-input-single-output fashion. The recurrent structure employed in thus neuro fuzzy classifier uses interaction feedback that has the ability to capture critical information from other rules. The consequent part of each recurrent fuzzy rule is functional link. The functional link artificial neural network is a single layer structure that is used for enhancing the input pattern. The Fig.1 shows the structure of the neuro fuzzy classifier. The mathematical function of each node, the function relationship between each layer is given below. The net input of the i-th node in layer l is represented as $u_i^{(l)}$ and the output value is represented as $O_i^{(l)}$.

Layer 1 (Input Layer): The inputs are crisp values and $\vec{x}=(x_1,\ldots,x_n)$ are fed as input to this layer. This is in contrast to feed-forward neural networks where both current and past states are fed as inputs to input layer. Weight requiring adjustment is not present in this layer.

Layer 2 (Fuzzification Layer): Each node in this layer defines a gaussian membership function and performs a fuzzification operation. For the i-th set A_j^i on the input variable
x_j, j = 1, …. , n, a Gaussian membership function is computed by

$$\mu_j^i(x_j) = O_i^{(2)} = \left\{ -\frac{1}{2}\left(\frac{u_n^{(2)} - m_j^i}{\sigma_j^i}\right) \right\} \text{ and } O_j^i$$

Layer 3 (Firing Layer -1): Each node in this layer represents one fuzzy rule that computes the firing strength. This layer does not depend on temporal input. For the obtained spatial firing strength each node performs a fuzzy operation on inputs when it receives from layer 2. The firing strength can be computed using the below formula

$$\varphi^i = O_i^{(3)} = \prod_{j=1}^{n} u_j^{(3),} and\, u_j^{(3)} = O_j^{(2)}$$

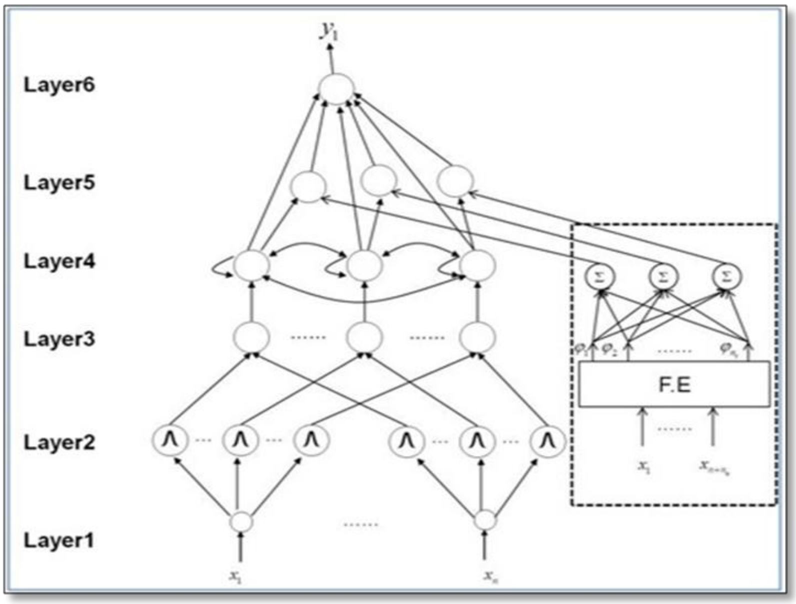

Fig. 1. Structure of the Neuro Fuzzy Classifier

Layer 4 (Firing Layer -2): Each node in this layer is a recurrent rule node that formulates self-loop and external interaction feedback loop. The output of a recurrent rule node is a temporal firing strength. It depends on both spatial and temporal firing strength. The temporal firing strength is given as

$$O_i^{(4)} = \sum_{k=1} \left(\lambda_{ik}^q . O_k^{(4)}(t-1)\right) + \left(1 - \gamma_i^q\right) u_i^{(4)}, and\, u_i^{(4)} = O_i^{(3)}$$

where γ_i^q is the rule interaction weight between itself and other rules. For the updated recurrent weights, the proposed mechanism uses gradient descent algorithm to derive the optimal values. The λ_{ik}^q shows the recurrent weights that determines the compromised ratio between the current and previous inputs to the network outputs.

Layer 5 (Consequent Layer): Each node in this layer is an optional node, called as a consequent layer of TSK – type fuzzy rules.

Layer 6 (Output Layer): Each node in this layer corresponds to one output variable. During the defuzzification process, the output layer node computes the neural network's output variable. For the TSK type neuro fuzzy classifier, the output can be expressed as

$$y_q = O^{(6)} = \frac{\sum_{i=1}^{M} O_i^{(4)} \overline{O}_i^{5}}{\sum_{i=1}^{M} O_i^{(4)}}$$

Two-phase learning is used for constructing the neuro fuzzy classifier. The recurrent fuzzy rules evolve from the simultaneous structure and parameter learning after receiving each piece of training data. The first incoming data point is used to generate the first fuzzy rule. Then subsequent new incoming data forms new fuzzy rule. When the present data do not match well according to the existing rules, a new rule is evolved. All free parameters in the neuro fuzzy classifier are also learned which includes the newly generated rules that includes for both antecedents and consequents.

4. RESULTS

4.1 Dataset

The UCI (University of California, Irvine) – ML (Machine Learning) - PIMA dataset [30] contains 768 data samples and 8 numerical features per sample. All patients are females at least 21 years old of Pima Indian heritage. The variables are allocated into two classes. The first class is labelled as "negative to diabetes" that involves 500 samples and the remaining 268 samples is labelled as "positive to diabetes".

4.2 Performance Metrics

- Sensitivity relates to the test's ability to identify a condition correctly i.e. probability of a positive test, given that the patient is having coronary artery heart disease.
- Specificity relates to the test's ability to exclude a condition correctly. i.e. probability of a negative test, given that the patient is not having coronary artery heart disease.
- Accuracy is the performance metric that projects the classification correctness of the classifier.

4.3 Results

This section discusses on the results. The proposed work - neuro fuzzy classifier is compared with artificial neural networks [1], [2] and naïve bayes [4] classifiers. From the results it can be clearly understood that the proposed work performs better in terms of sensitivity, specificity and accuracy.

Table 1. Results

Method	**Sensitivity**	**Specificity**	**Accuracy**
Neural Networks [1],[2]	91.20 %	80.46 %	88.11 %
Naïve Bayes [4]	67.59 %	95.40 %	75.51 %
Proposed Neuro Fuzzy Classifier	99.61 %	71.42 %	98.88 %

5 CONCLUSION

This paper presented a recurrent fuzzy neural network for risk level classification of coronary artery heart disease (CAHD) in diabetic patients. The recurrent structure has been formed as an external loops and internal feedback by feeding the rule firing strength of each rule to others rules and itself. The consequent part of fuzzy logic system is composed of a Takagi–Sugeno–Kang (TSK) type. The proposed classifier has a functional link neural network (FLNN) to the consequent part of fuzzy rules for promoting the mapping ability. sensitivity, specificity, classification accuracy are taken and the proposed method obtains better results.

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