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A Fuzzy Expert System for Prognosis of the Risk of Development of Heart Disease

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Abstract

Fuzzy logic has a high potential for managing the uncertainty sources associated with the medical expert systems. Application of fuzzy inference model has been widely concentrated for managing uncertainties in computer based practices of medicine. This paper has proposed two fuzzy expert systems for prognosis of the heart disease based on: 1) Mamdani inference model, and 2) Sugeno inference model. These methods initially received clinical parameters as input sand define their corresponding fuzzy sets. The performance of the FESs (Fuzzy Expert System) based on the Mamdani and Sugeno model, have been evaluated using real patients dataset through conducting two different studies. The dataset includes 380 real cases collected from the Parsian Hospital in Karaj. The accuracy of the proposed Mamdani FES is equal to79.47% and its accuracy using Sugeno model is equal to 88.43%. This FES is promising for prognosis of the heart disease and consequently early diagnosis of the disease and improving survival rates.

Keywords: *Fuzzy Inference Model, Fuzzy Expert Systems, Prognosis of the Heart Disease.*

1. Introduction

The heart is the most important member of the human body. Its task is giving blood to all the members. Disruption in the work of the member makes up compromised the human health. Many factors affect the proper functioning of this organ. In this article we're going to design a system that will help to doctors in diagnosing heart disease. The rules of this system is extracted by consultation with a physician cardiologist. Mathematical models can solve problems that their inputs are number, their logic is binary and their sets are crisp. To solve problems that their input is linguistic terms and there is uncertainty in the problems and in fact processing this kind of problems is concerned with words, in this case simple mathematical models and binary logic are not capable to solve it so fuzzy logic is used for processing with words. Fuzzy logic is capable to manage uncertainty in the issues and real-world problems. Among models that have been raised in the fuzzy logic, Mamdani model, Sugeno model are two commonly applied methods. In this study a fuzzy expert system is capable to detect heart disease in the people by using clinical knowledge that are usually expressed in the form of linguistic terms. The input and output of this system are fuzzy sets and the inference model is Mamdani because it is the only model that is capable to analyze the systems that their inputs and outputs are fuzzy sets and can easily interact with the human.

2. Literature Review

A Fuzzy-logic based diagnostic algorithm was proposed for implantable cardioverter defibrillators in [1]. The study describes and validates such an algorithm and estimates its clinical value. The algorithm was based on the heart rate variability (HRV) analysis. The input data for our algorithm were: RR-interval (I), as extracted from raw intra cardiac electrogram (EGM), and in addition two other features of HRV called here onset (ONS) and instability (INST). 6 diagnostic categories were considered: ventricular fibrillation (VF), ventricular tachycardia (VT), sinus tachycardia (ST), detection artifacts and irregularities (including extra systoles) (DAI), atrial tachy arrhythmias (ATF) and no tachy-cardia (i.e. normal sinus rhythm) (NT). The initial set of fuzzy rules based on the distributions of I, ONS and INST in the 6 categories was optimized by means of a software tool for automatic rule assessment using simulated annealing. A training data set with 74 EGM recordings was used during optimization, and the algorithm was validated with a validation data set with 58 EGM recordings. Real life recordings stored in defibrillator memories were used. The total number of events in training and validation sets was 132. The fuzzy rule based diagnostic algorithm correctly recognized all episodes of VF and VT except for one case where VT was recognized as VF. The sensitivity and specificity calculated from the results were 100% and 98% respectively.

Medical diagnosis of cardiovascular diseases was proposed using an interval-valued fuzzy rule-based classification system in [2]. Linguistic fuzzy rule-based classification systems are used, since they provide a good classification rate and a highly interpretable model. More specifically, a new methodology to combine fuzzy rule-based classification systems with interval-valued fuzzy sets is proposed, which is composed of three steps: (1) the modelling of the linguistic labels of the classifier using interval-valued fuzzy sets; (2) the use of the K¸ operator in the inference process and (3) the application of a genetic tuning to find the best ignorance degree that each interval-valued fuzzy set represents as well as the best value for the parameter ¸ of the K operator in each rule. The performance of the new method is statistically better than the ones obtained with the methods considered in the comparison. The new proposal enhances both the total number of correctly diagnosed patients, around 3% with respect the classical fuzzy classifiers and around 1% vs. the previous interval-valued fuzzy classifier, and the classifier ability to correctly differentiate patients of the different risk categories.

Heart diseases prediction based on ECG signals' classification using a genetic-fuzzy system and dynamical model of ECG signals was proposed in [3]. By analyzing the ECG signals' patterns one can predict arrhythmias. Since the conventional methods of arrhythmia detection rely on observing morphological features of the ECG signals which are tedious and very time consuming, the automatic detection of arrhythmia is more preferable. In order to automate detection of heart diseases an adequate algorithm is required which could classify the ECG signals with unknown features according to the similarities between them and the ECG signals with known features. If this classifier can find the similarities precisely, the probability of arrhythmia detection is increased and this algorithm can become a useful means in laboratories. In this article a new classification method is presented to classify ECG signals more precisely based on dynamical model of the ECG signal. In this proposed method a fuzzy classifier is constructed and its simulation results indicate that this classifier can segregate the ECGs with an accuracy of 93.34%. To further improve the performance of this classifier, genetic algorithm is applied where the accuracy in prediction is increased up to 98.67%. This proposed method increases the accuracy of the ECG classification regarding more precise arrhythmia detection.

A coronary heart disease optimization system was proposed on adaptive network based fuzzy inference system and linear discriminant analysis (ANFIS-LDA) in [4]. In the present study, we have developed a prediction model capable of the risk assessment of coronary heart disease by optimizing an adaptive network-based fuzzy inference system (ANFIS) and linear discriminant analysis (LDA) on the basis of the dataset of Korean National Health and Nutrition Examinations Survey V. The ANFIS–LDA method, which is optimized using a hybrid method, exhibits a high prediction rate of 80.2 %and is more efficient and effective than the existing methods. The total number of layers is five with four inputs and one output, which is divided into 5steps, thereby creating 625 rules. A triangular function is used as a form of a membership function, and hybrid learning is used as the learning algorithm. Inputs: Age- Total cholesterol-HDL cholesterol- Systolic blood pressure. Output ANFIS is constant.

Rough-Fuzzy classifier: to Predict the Heart Disease was proposed by Blending Two Different Set Theories in [5]. The overall process of the rough-fuzzy classifier is divided into two major steps, such as (1) rule generation using rough set theory, and (2) prediction using fuzzy classifier. At first, reduct and core analysis is used to identify the relevant attributes and the fuzzy rules are generated from the rough set theory after forming the indiscernibility matrix. Then, the fuzzy system is designed with the help of fuzzy rules and membership functions so that the prediction can be carried out within the fuzzy system designed. Finally, the experimentation is carried out using the Cleveland, Hungarian and Switzerland datasets. From the results, we ensure that the proposed rough-fuzzy classifier outperformed the previous approach by achieving the accuracy of 80% in Switzerland and 42% in Hungarian datasets.

A adaptive neuro fuzzy selection of heart rate variability parameters affected was proposed by autonomic nervous system in [6].In this study an architecture for modeling complex systems in function approximation and regression was used, based on using adaptive neuro-fuzzy inference system (ANFIS).Variable searching using the ANFIS network was performed to determine how the ANS (autonomic nervous system) branches affect the most relevant HRV parameters. The method utilized may work as a basis for examination of ANS influence on HRV (heart rate variability) activity. HRV activity prediction is a very nonlinear regression problem, In which two ANS parameters could be used to predict behavior of the HRV activity. These two ANS parameters should indicate two branches of the ANS activity, sympathetic and parasympathetic. The ANS indices have different influence on each of the HRV parameters. In this study, 14 parameters of HRV signal were extracted for the analysis. Two parameters characterize the ANS functions. Those are cardiac vagal index (CVI), and cardiac sympathetic index (CSI). The main goal of this study was to determine which of the HRV parameter is more affected by the two ANS functions. To solve this problem we used an ANFIS network. The network outputs were CVI and CSI indices. For MIT Arrhythmia Database, ANFIS CSI regression error was 1.040 and the linear regression error was 6.953 and for CVI it was 0.522 and 6.953,respectively. explaining the model is difficult, irrelevant variables act as noise, deteriorating the generalization capability of the model and data collecting can be much more costly.

A fuzzy expert system approach was proposed for coronary artery disease screening using clinical parameters in [7].The objective of this paper is to describe developing of a screening expert system that will help to detect CAD at an early stage. Rules were formulated from the doctors and fuzzy expert system approach was taken to cope with uncertainty present in medical domain. This work describes the risk factors responsible for CAD, knowledge acquisition and knowledge representation techniques, method of rule organization , fuzzification of clinical parameters and defuzzification of fuzzy output to crisp value. The system implementation is done using object oriented analysis and design. The proposed methodology is developed to assist the medical practitioners in predicting the patient's risk status of CAD from rules provided by medical experts. The present paper focuses on rule organization using the concept of modules, meta-rule base, rule address storage in tree representation and rule consistency checking for efficient search of large number of rules in rule base. The developed system leads to 95.85% sensitivity and 83.33% specificity in CAD risk computation.

Diagnosis of Heart Disease Patients was proposed Using Fuzzy Classification Technique in [8].Inputs: Age- Gender (male or female)- CP (chest pain variety)- Thest bps (sleeping blood force)- Chloe (serum cholesterol)- Rest Ecg (resting electrographic marks)- Fbs (Fasting blood sugar)- Thalach (Greatest heart speed reached)- Ex ang (Exercise induced angina)- Old peak (ST despair induced byapply virtual to relax)- Solpe (Slope of the height effect ST section)- Ca (Numeral of key vessels painted by fluoroscopy)- Thal (Desert category). The work is concerned in removing the uncertainty and assigning membership values to the measured data to build a Fuzzy K-NN classifier analogous to Classical K-NN classifier. A fuzzy K-NN classifier was designed by assigning membership values to the measured data and the advantages and disadvantages of both K-NN and Fuzzy K-NN classifier was discussed. A comparison of both the classifiers was tabulated and it is observed that fuzzy K-NN rule was compared with both training and testing data sets of crisp data by computing lower error rates and the new membership values which serve as a confidence to measure the accuracy of classification. The data set consisting of 1200 records and it has been divided into 25 classes where each class consists of 48records. To predict the correctness of the system, the dataset has been divided into equal amount of training and testing sets. Accuracy obtained for dataset with K-NN method= 42%. Accuracy obtained for dataset with Fuzzy K-NN method= 80%.

Table1. Literature Review

Name	Method	Results	Advantages	Inputs	Outputs
Fuzzy-logic based diagnostic algorithm for implantable cardioverter defibrillators [1]	based on the heart rate variability (HRV) analysis	The sensitivity and specificity calculated from the results were 100% and 98% respectively.	simplicity and ability to decrease the rate of occurrence of inappropriate therapies. The algorithm can work in real time (i.e. update the diagnosis after every RR-interval) with very limited computational resources	RR-interval-	Classification the diseases in the 6 classes
Medical diagnosis of cardiovascular diseases using an interval-valued fuzzy rule-based classification system [2]	a new methodology to combine fuzzy rule-based classification systems with interval-valued fuzzy sets	The performance of the new method enhances around 3%.	provide a good classification rate and a highly interpretable model.	clinical parameters	Heart disease risk in the form of linguistic terms
Heart diseases prediction based on ECG signals' classification using a genetic-fuzzy system and dynamical model of ECG signals [3]	Analyzing the ECG signals' patterns one can predict arrhythmias.	accuracy = 93.34%	To further improve the performance of this classifier, genetic algorithm is applied where the accuracy in prediction is increased up to 98.67%.	The parameters of the 4 diseases By analyzing the ECG signals' patterns one can predict arrhythmias.	ECG in the form of number
Coronary heart disease optimization system on adaptive network based fuzzy inference system and linear discriminant analysis (ANFIS-LDA) [4]	Adaptive network-based fuzzy inference system (ANFIS) and linear discriminant analysis (LDA)	The ANFIS–LDA method, which is optimized using a hybrid method, exhibits a high prediction rate of 80.2 %.	increasing the specificity, sensitivity, and accuracy of the model .In order to increase the prediction accuracy	clinical parameters	One crisp number that shows the value of the heart disease risk.
Rough-Fuzzy Classifier: A System to Predict the Heart Disease by Blending Two Different Set Theories [5]	Rule generation using rough set theory, and prediction using fuzzy classifier	the proposed rough-fuzzy classifier outperformed the previous approach by achieving the accuracy of 80% in Switzerland and 42% in Hungarian datasets.	The proposed work can be extended by including the associative analysis to find the relevant attribute and also, the rule strength computation can be also extended with including statistical measure. achieving the accuracy of 80 %.	clinical parameters	Heart disease risk in the form of linguistic terms
Adaptive neuro fuzzy selection of heart rate variability parameters affected by autonomic nervous system [6]	adaptive neuro-fuzzy inference system (ANFIS).	For MIT Arrhythmia Database, ANFIS CSI regression error was 1.040 and the linear regression error was 6.953 and for CVI it was 0.522 and 6.953, respectively.	The performance enhance 18% .	HRV parameters	CVI CSI
Fuzzy expert system approach for coronary artery disease screening using clinical parameters [7]	This work describes the risk factors responsible for CAD, knowledge acquisition and knowledge representation techniques, using fuzzy logic	Sensitivity= 95.85% Specificity= 83.33%	it can be used as a supportive tool for the doctors as their domain knowledge is encoded into the system in computer perceptible form. Moreover it uses only easily available clinical parameters and data obtained from very low cost laboratory tests.	clinical parameters	One crisp number that shows the value of the heart disease risk.
Diagnosis of Heart Disease Patients Using Fuzzy Classification Technique [8]	To remove the uncertainty of the unstructured data and using Fuzzy KNN classifier embedded with Symbolic approach.	accuracy = 80%	This work can be enhanced by increasing the number of attributes for the existing system. And provide better accuracy in predicting and diagnosing the patients of heart disease.	clinical parameters	Heart disease risk in the form of linguistic terms

3. The Components of the Fuzzy Expert System

A fuzzy expert system consists of three main sections: [10],[11].
Inference Engine: Is associated with rule base and according to the rule base making fuzzy decision about input data.

- Data Base: This section contains all the details that is needed for the design of a fuzzy system.
- Knowledge Base (Rule Base): This part of the expert system are the same fuzzy if-then rules that are extracted via consultation with the experts.

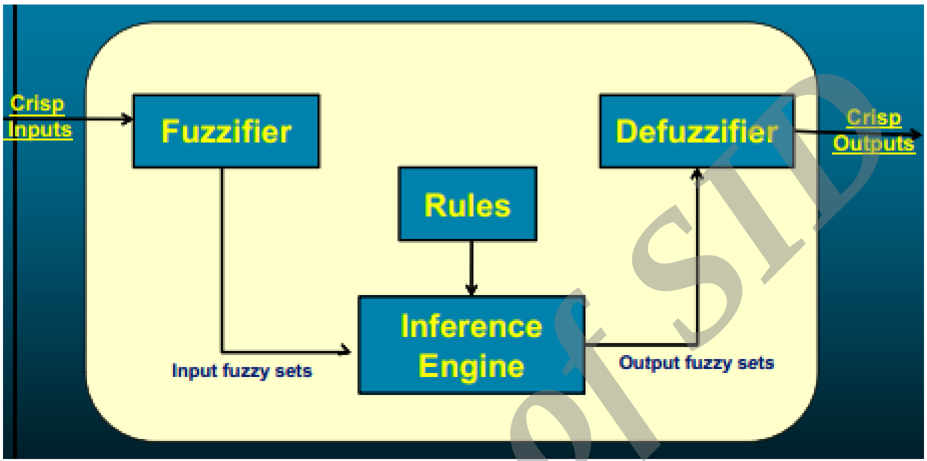

Figure 1. Fuzzy Logic Architecture

A fuzzy expert system initially receiving the inputs in the form of the crisp numbers or linguistic terms and then according to the fuzzy sets, making fuzzy them and then inference engine doing fuzzy decision for the inputs according to the rules and producing the output in the form of fuzzy and sending to the defuzzification section and in the defuzzification section according to the defuzzification method that have designed for this system, transforming fuzzy output to the crisp number and finally producing real output. [10]

4. Experimental Result

According to the design fuzzy system theory all of the parameters and details that there are for design fuzzy expert system for diagnosis of heart disease, discuss them perfectly:

- Inference Engine: Is associated with rule base and according to the rule base making fuzzy decision about input data.
- Data Base: This section contains all the details that is needed for the design of a fuzzy system.
  a. For the design of the system are used Mamdani model.
  b. For this system is considered six linguistic variable with consult a physician cardiologist that are five variables for inputs and one variable for output and then for each of the variables are described in Table 2. [9],[14]

Table 2. Inputs of the fuzzy system [12]

Linguistic variables	Linguistic terms
Blood pressure	High [13-22] Normal [10-14] Low [6-11]
Cholesterol	very high >238 high [199-239] normal ≤ 200
Sugar	high ≥120 normal ≤120
Heart rate	fast >95 normal [60-100] slow <65
Smoking	true= constant (1) false= constant (0)

Table 3. Output of this system [12]

Linguistic variables	Linguistic terms
Heart disease	high risk ≥ 0.5 low risk ≤ 0.5

c. Membership functions of linguistic terms and its values are as follows: For the design of the membership functions are used Gaussian membership function because the data distributed as normal. Gaussian function is shown below: [10]

$$f(x;\sigma,c)=e^{\frac{-(x-c)^2}{2\sigma^2}} \qquad (1)$$

d. For the design of the membership functions of linguistic term (Heart disease) are used trapezoidal membership function. Trapezoidal function is shown below: [10]

$$f(x;a,b,c,d)=\begin{cases}0, x\le a\\ \dfrac{x-a}{b-a}, a\le x\le b\\ 1, b\le x\le c\\ \dfrac{d-x}{d-c}, c\le x\le d\\ 0, d\le x\end{cases} \quad (2)$$

The parameters of the membership functions of linguistic terms depends on a range of linguistic terms and determined according to the values obtained experimentally. The values of the parameters specified in their charts of the membership functions.

e. The work of the defuzzification done with the Smallest of Maximum method in this system.
f. In this system T-norm function is min operator and S-norm function is Max operator. AND operator are used between all the rules.

- Rule Base [13]: Extracted rules for design this system have prepared by consult a physician cardiologist during several meetings when works in the Parsian hospital. This part of the expert system are the same fuzzy if-then rules that are extracted via consultation with the experts. Expert' comments on this system are as follows: The heart of the most important members of the human body which its task is giving blood to all the members. Disruption in the work of the member makes up compromised the human health. The factors that affect on the proper functioning of this member include: Normal blood pressure- Normal blood sugar- Cholesterol in desirable- Non-smoking- Regular heart rate- Increase the level of each of these factors than normal may cause disruption in the proper functioning of the heart. If all these factors are in normal range, regardless of age a person's heart disease risk is almost zero but if any of these factors, or all of them have put at a higher level than normal person in any gender and age the possible existence of heart disease in his is high.

Table4. Fuzzy Rules[10]

Rule #	**Diagnostic fuzzy rules**
R1	If blood pressure is normal and cholesterol is normal and blood sugar is normal and heart rate is normal and smoking is non-smoker then heart disease is low risk.
R2	If blood pressure is high then heart disease is high risk.
R3	If cholesterol is high then heart disease is high risk.
R4	If smoking is smoker then heart disease is high risk.

Table5. The parameters of the fuzzy system using Mamdani Inference model

type	Mamdani
And method	min
Or method	max
Defuzzification method	som
Implication method	min
Aggregation method	max
input	5
output	1
rule	4

5. Figures

In this section is shown all figures of membership functions of the linguistic terms of the system.

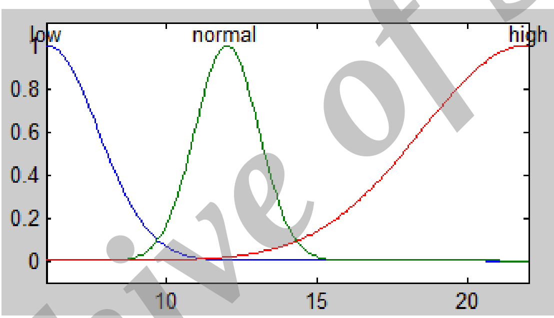

Figure 2. The membership functions of the linguistic terms of the BLOOD PRESSURE

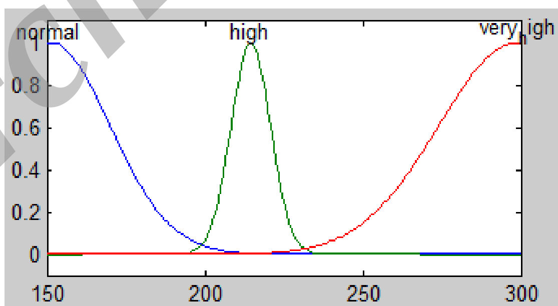

Figure 3. The membership functions of the linguistic terms of the CHOLESTEROL

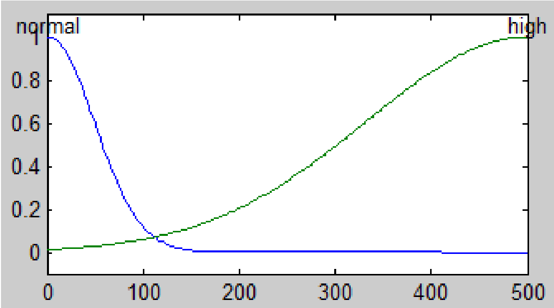

Figure 4. The membership functions of the linguistic terms of the BLOOD SUGAR

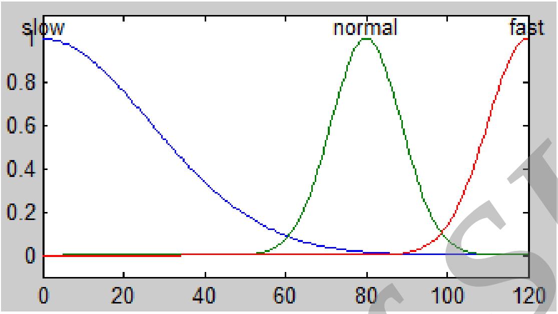

Figure 5. The membership functions of the linguistic terms of the HEART RATE

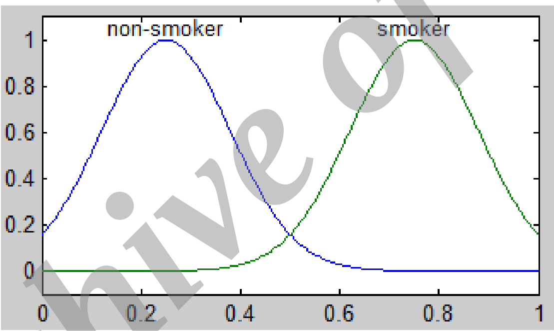

Figure 6. The membership functions of the linguistic terms of the SMOKING

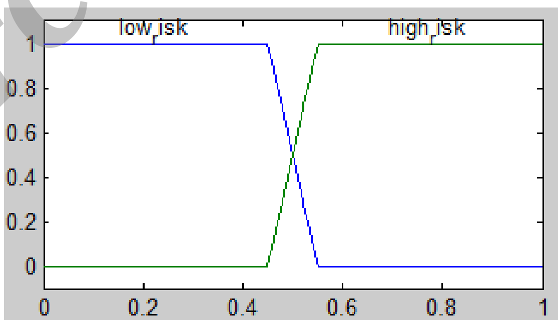

Figure 7. The membership functions of the linguistic terms of the HEART DISEASE

The system that have proposed in this study, In this study two models (Mamdani and Sugeno) were designed. The study1 and study2, there is the obtained results from these models on 380 patient's data that have provided from Parsian hospital. For this two studies have been conducted:

Study 1) Heart disease prognosis using Mamdani FIS:[10]
Heart disease prognosissystem has been designed using the Mamdani fuzzy inference model. In this model, inputs and outputs are in the form of fuzzy. The accuracy of the system with Mamdani model is 79.47%.
Study 2) Heart disease prognosis using Sugeno FIS:[10]
In this model the output of the system is in form a crisp number. The membership functions of the linguistic terms and their parameters are the same as Mamdani model and the only difference is in the output of the system that its membership functions is constant. The membership function of the linguistic term (low risk) mapped with the crisp number 0.25 and the membership function of the linguistic term (high risk) mapped with the crisp number0.75.

Table 6. The fuzzy rules of the system by using Sugeno model[10]

Rule no.	Diagnostic fuzzy rules
R1	If blood pressure is normal and cholesterol is normal and blood sugar is normal and heart rate is normal and smoking is non-smoker then heart disease is low risk.(0.25)
R2	If blood pressure is high or cholesterol is high or smoking is smoker then heart disease is high risk.(0.75)

Table 7. The parameters of the fuzzy system using Sugeno model

type	Sugeno
And method	Product
Or method	Probor
Defuzzification method	Wtsum
Implication method	Product
Aggregation method	Sum
Number of input	5
Number of output	1
Rules	2

6. Comparison of the Proposed Mamdani and Sugeno Inference Model for Heart Disease Diagnosis

The fuzzy system proposed in this project was designed using two methods; i.e., Mamdani and Sugeno. Each inference model has its own advantages. The Mamdani inference model is very understandable method and adapted to the real world and can easily interact with medical expert because the inputs and outputs of this system can be linguistic terms but its inference model is complex. The Sugeno method has simple implementation but its interpretability is less than Mamdani model because its inputs is linguistic terms but its output is a function or constant number and is more precise compared to the Mamdani method. The Sugeno method is used in such a system where accuracy is important but Mamdani method is used in systems that require to communicate with the user and users understand it.

In this section we want compare the results of the two methods in the proposed system. First fuzzy system by using Mamdani method that was designed in the previous stages of the project evaluate with the real data. The error of the system is 0.2053 and its accuracy is 79.47% then fuzzy system by using Sugeno method evaluate with the same data. The error of this system is 0.1157 and its accuracy is 88.43%. It is quite clear that the accuracy of the Sugeno method is more than the accuracy of the Mamdani method.

Table 8. Comparison of two proposed methods of Mamdani and Sugeno

Model	Accuracy measure	Accuracy amount
Mamdani	MSE	0.2053
Sugeno	MSE	0.1157

7. Experimental Results and Performance Evaluation

For performance evaluation of the FES, real data of patients was used. A dataset including 380 real patients was used. This dataset was gathered from Parsian Hospital by physician cardiologist. Of these people, are 122 males and 258 females. In fact 32.1% of the information related to the men and 67.9% of the information related to the women. These data includes 55.26% of high risk patients (210) and 44.74% of healthy (170). The dataset also has actual diagnosis that has been compared with the output of the fuzzy system. The MSE measure was considered as the performance measure.

After evaluating system with the same previous data, the accuracy of the system has been equal to 88.43% that its value is more than the accuracy of the Mamdani model.

8. Comparison With Related Works

This section presents a comparison between this study and other related studies that have addressed the issue of heart disease. For design this system have used two models (Mamdani and Sugeno) that each of them have its advantages. Designed system with Mamdani model is closer to the real world and has a greater understanding by user. Designed system with Sugeno model has less error but is its understanding less by user.

The system designed in this study, it was tried to use less and more efficient inputs to increase system performance. Number of rules in this system has been kept the minimum possible to decrease system complexity and increase its accuracy. The rules have been selected from rule set that have more compatibility with dataset and also have high activation power to fire the data. This was performed for the purpose of simplicity and the adequacy of the number of inputs and rules. The future work is to discovery new and effective parameters to improve the performance of this medical expert system.

Table 9. comparison with extant works

Name	Method	Inference model	Number of inputs	Accuracy (Measure)
Medical diagnosis of cardiovascular diseases [2]	a new methodology to combine fuzzy rule-based classification systems with interval-valued fuzzy sets	Sugeno	5	The performance of the new method enhances around 3% (ROC).
Heart diseases prediction based on ECG signals' classification [3]	Using a genetic-fuzzy system and dynamical model of ECG signals . By analyzing the ECG signals' patterns one can predict arrhythmias.	Sugeno	3	93.34% (ROC)
Coronary heart disease optimization system [4]	adaptive network-based fuzzy inference system (ANFIS) and linear discriminant analysis (LDA).	Sugeno	7	80.20% (ROC)
Rough-Fuzzy Classifier: A System to Predict the Heart Disease [5]	By blending two different set Theories (1) rule generation using rough set theory, and (2) prediction using fuzzy classifier.	Sugeno	4	80% (ROC)
Adaptive Neuro-Fuzzy selection of heart rate variability parameters [6]	adaptive neuro-fuzzy inference system (ANFIS) affected by autonomic nervous system	Sugeno	14	The performance enhance 18% (ROC)
Fuzzy expert system approach for coronary artery disease screening using clinical parameters [7]	The risk factors responsible for CAD, knowledge acquisition and knowledge representation techniques, method of rule organization, fuzzification of clinical parameters and defuzzification of fuzzy output to crisp value.	Mamdani	7	95.85% (ROC)
Diagnosis of Heart Disease Patients Using Fuzzy Classification Technique [8]	to build a Fuzzy K-NN classifier analogous to Classical K-NN classifier.	Mamdani	7	80% (ROC)
Fuzzy expert system for diagnosis of heart disease [study1]	Fuzzy technique by using Mamdani model	Mamdani	5	80% (MSE)
Fuzzy expert system for diagnosis of heart disease [study2]	Fuzzy technique by using Sugeno model	Sugeno	5	89% (MSE)

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