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Fuzzy Soft Expert System in Prediction of Coronary Artery Disease

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Abstract Coronary artery disease affects millions of people all over the world including a major portion in Egypt every year. Although much progress has been done in medical science, early detection of this disease is still a challenge for prevention. In this paper we, will extend the concept of fuzzy soft set theory so as to develop a knowledge-based system in medicine and devise a prediction system named fuzzy soft expert system consisting of four main components. These are a fuzzification which translates inputs into fuzzy values, fuzzification of data sets to obtain fuzzy soft sets, a new fuzzy soft set by normal parameter reduction of fuzzy soft set and an algorithm to produce the resultant output. The fuzzy soft expert system developed is then used to predict for coronary artery disease using systolic blood pressure, low-density lipoprotein cholesterol, maximum heart rate, blood sugar, old peak and age of patients. A preliminary study is conducted on nine male patients undergoing treatment in the Cardiac Unit of the Faculty of Medicine, Assiut University, Egypt. It is found that the fuzzy soft expert system developed is able is to help the expert doctor to decide whether a patient needs to be given drug therapy or intervention.

Keywords Fuzzy soft set · Fuzzy soft expert system · Low-density lipoprotein cholesterol · Maximum heart rate · Systolic blood pressure

1 Introduction

Coronary artery disease (CAD) has become one of the mostly occurring diseases in the world and has increasing trend in its incidence in future. It is the cause of 20–30 % of deaths in most industrialized countries [1]. CAD is the leading cause of death worldwide for both men and women and occurs when the arteries that supply blood to the heart muscle stiffened and become narrowed. This is due to the accumulation of fat, calcium, cholesterol and other substances found in blood which form the so-called plaque. Plaque sticks to the soles of the walls of the arteries. Over time, this plaque hardens and leads to arterial stenosis which reduces blood flow to the heart muscle. When the growing plaque ruptures, it blocks the blood flow in the arteries. This blockage prevents the blood to flow to parts of the heart muscle which will then lead to angina or a heart attack. Furthermore, cholesterol has been identified as one of the main risk factor for myocardial infarction and subsequent sudden death [2]. In order to circumvent such a life-threatening problem, one of the possible solutions is to make people aware of their respective CAD risks in advance and take preventive measures accordingly. It is

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only possible when an early detection of CAD occurs. According to medical experts, an early detection at the stage of angina may prevent the death due to CAD if proper medication is given there after. In view of this, we will develop a CAD fuzzy soft expert system based on fuzzy soft sets. This system which can mimic the reasoning of doctors shall be called as expert system. Till date many medical expert systems have been developed, such as INTERNIST [3] and CADIAG-2 [4]. However, these are multiple disease expert systems. Research on risk factor analysis [5–9] has been conducted. Studies on 18-lead electro cardiogram (ECG) analysis [9], wavelet transformed ECG analysis [10], heart valve disease analysis [11, 12] have been done extensively for detection of cardiovascular diseases. Artificial immune recognition system (AIRS) was used to detect heart diseases [13, 14], while single lead ECG classification methodology was proposed using time domain principal components [15–17] after a methodology for CAD diagnosis based on neuro-fuzzy model [18] was suggested. In another study, decision tree was used to find preliminary rules based on the extracted rules of a fuzzy model [19] developed for CAD detection. A comparative [20] study of logistic regression, classification and regression tree, neural network, radial basis function and self-organizing feature maps were parameterized in a model to predict the absence or presence of CAD. This was followed by a methodology which uses SAS base software 9.1.3 for diagnosing of the heart disease [21]. A neural networks ensemble method is incorporated into the proposed system. A fuzzy expert system (FES) includes a set of fuzzy rules and membership functions, i.e., knowledge acquisition, considered to be the most important issue in the design of fuzzy expert system. Generally, knowledge could be obtained from experts in the particular area. However, experts might find it difficult to define the complete rule set if there are too many possible rules. A fuzzy expert system [22] for heart disease diagnosis was designed based on the V. A. Medical Center, Long Beach and Cleveland Clinic Foundation database. The system has 13 input fields and one output field. Input fields are chest pain type, blood pressure, cholesterol, resting blood sugar, maximum heart rate, resting electrocardiography (ECG), exercise, old peak (ST depression induced by exercise relative to rest), thallium scan, sex and age. Computational intelligence combines fuzzy systems, neural network and evolutionary computing, where neuro-fuzzy integrated system for coronary heart disease is presented. In order to show the effectiveness of the proposed system, simulation for automated diagnosis is performed by using realistic causes of coronary heart disease. The performance of the system can be increased by tuning of membership function using optimization algorithms [23]. A hybrid particle swarm optimization-based fuzzy expert system for the diagnosis of coronary artery disease was proposed [24]. Association rule mining using a computational intelligence approach is used to identify these factors, and the UCI Cleveland data set, a biological database, is considered along with the three rule generation algorithms—Apriori, Predictive Apriori and Tertius [25]. Current research indicates the accuracy of fuzzy rule-based classification that could noninvasively predict CAD based on myocardial perfusion scan test and clinical–epidemiological variables [26]. CAD detection using a fuzzy-boosting PSO approach has also been proposed [27]. Automated diagnosis of CAD using tunable-Q wavelet transform applied on heart rate signals has been presented [28], along with CAD diagnosis using supervised fuzzy c-means with differential search algorithm based on the generalized Minkowski metrics [29].

The rest of the paper is organized as follows. Section 2 introduces the fuzzy soft sets, fuzzy expert system and database description. In Sect. 3, methodology and implementation of the proposed system are presented. Details of the experimental results are discussed in Sect. 4. Finally, conclusions are given in Sect. 5.

2 Background

2.1 Fuzzy Soft Sets

Soft set theory [30] was firstly proposed by a Russian researcher-Molodtsov, in 1999. Maji et al. [31] discussed the theoretical aspect of soft sets and introduced several operations for soft sets. They presented the concept of fuzzy soft set [32] based on a combination of the fuzzy set and soft set models. Roy and Maji [33] proposed the concept of a fuzzy soft set and provided its properties and an application in decision making under an imprecise environment. Kong et al. [34] argued that the Roy and Maji method [33] was incorrect and presented a revised algorithm. Feng et al. [35] presented an adjustable approach to fuzzy soft set-based decision making by means of level soft sets. They discussed the validity of the Roy–Maji method [33] and showed its limitations.

Fuzzy set theory was initially proposed by Zadeh [36]. It is based on the fuzzy membership function μ_A. Using the fuzzy membership function, we can determine the membership grade of an element with respect to a set. The following definition and example describes this notion.

Definition 2.1 ([36]) A fuzzy subset A of a universal set X is defined by a membership function $\mu_A : X \rightarrow [0, 1]$, where $\mu_A(x)$ is interpreted as a grade in which an element $x \in X$ has a property A, or a grade in which x is consistent to A. The closer the value of $\mu_A(x)$ is to **1**, the more x belongs to A.

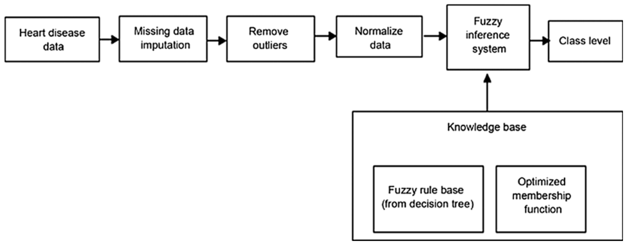

Fig. 1 Components of the proposed fuzzy expert system

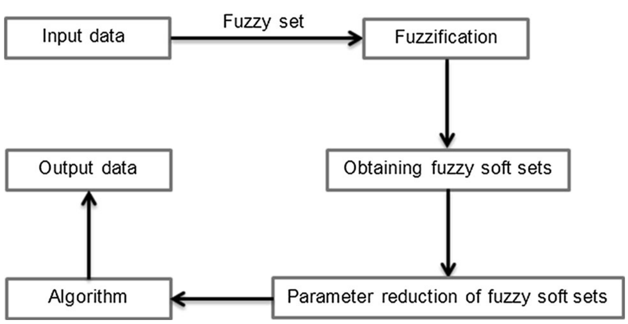

Fig. 2 Basic structure of a fuzzy soft expert system

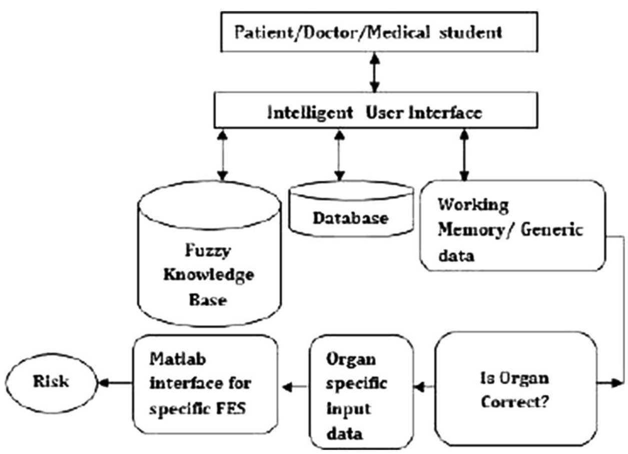

Fig. 3 Basic structure of Sikchi's fuzzy expert system

A is completely characterized by the set of pairs $A = \{(x, \mu_A(x))|x \in X \text{ and } \mu_A : X \to [0, 1]\}$.

The classical union and intersection of ordinary subsets of X can be extended by the following formula,

$$\forall x \in X, \qquad \mu_{A \cap B}(x) = \min\,[\mu_A(x), \mu_B(x)],$$
$$\forall x \in X, \qquad \mu_{A \cup B}(x) = \max\,[\mu_A(x), \mu_B(x)],$$

where $\mu_{A \cap B}$ and $\mu_{A \cup B}$ are, respectively, the membership functions of $A \cap B$ and $A \cup B$.

Example 2.2 Let $X = \{\text{red, yellow, green, brown}\}$ be a set of colors. Suppose that a fuzzy membership function sets μ_A of colors are as follows: $\mu_A(\text{red}) = 0.3, \mu_A(\text{yellow}) = 0.5, \mu_A(\text{green}) = 0.8,$ and $\mu_A(\text{brown}) = 0.9$.

Table 1 Classification of systolic blood pressure

Input field	Range	Fuzzy sets
Systolic blood pressure	< 134	L
	127–153	M
	142–172	H
	154>	VH

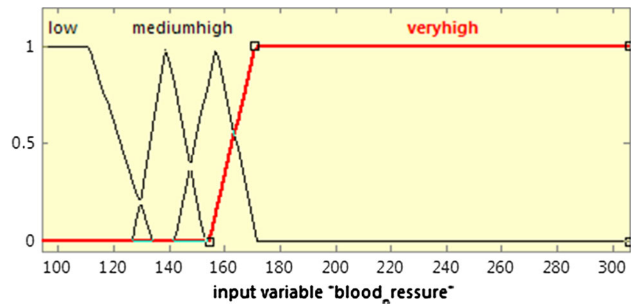

Fig. 4 Membership functions of systolic blood pressure

We can write the fuzzy sets as follows: $\mu_A = \{(\text{red}, 0.3), (\text{yellow}, 0.5), (\text{green}, 0.8), (\text{brown}, 0.9)\}$.

The theory of fuzzy sets, however, is inadequate in assigning the membership function to cater for multiple parameters. Molodtsov [30] then proposed the soft set theory below for dealing with uncertainties to avoid the problem of setting the membership functions.

Definition 2.3 ([30]) Let X refers to an initial universe and E is a set of parameters. Let $P(X)$ denote the power set of X and $A \subset E$. A pair (F, A) is called a soft set over X, where F is a mapping given by $F : A \to P(X)$.

In other words, a soft set over X is a parametrized family of subsets of the universe X. For $\varepsilon \in A, F(\varepsilon)$ may be considered as the set of ε-approximate elements of the soft set (F, A), as illustrated in the following example.

Example 2.4 Assume that a fund manager in a wealth management firm is assessing four potential investment opportunities $X = \{h_1, h_2, h_3, h_4, h_5\}$. The firm mandates that the fund manager has to evaluate the following four parameters $A = \{e_1, e_2, e_3, e_4\}$, where e_1 stands for the parameter 'risk,' e_2 stands for the parameter 'growth,' e_3 stands for the parameter 'sociopolitical issues' ande_4 stands for the parameter 'environmental impacts.' Suppose that $F(e_1) = \{h_1, h_3\}, F(e_2) = \{h_2, h_3, h_4\}, F(e_3) = \{h_1, h_4, h_5\}$, $F(e_4) = \{h_2, h_5\}$. Then, we can view the soft set (F, A) describing the 'opportunities of the potential investment' as below: $(F, A) = \{$risk potential investment $= \{h_1, h_3\}$, growth potential investment $= \{h_2, h_3, h_4\}$, sociopolitical issues potential investment $= \{h_1, h_4, h_5\}$,and environmental impacts potential investment $= \{h_2, h_5\}\}$.

Combining the concepts of fuzzy set and soft set, Maji et al. [32] proposed the following three definitions of fuzzy

Table 2 Classification of LDL cholesterol

Input field	Range	Fuzzy sets
Cholesterol	<197	L
	188–250	M
	217–307	H
	281>	VH

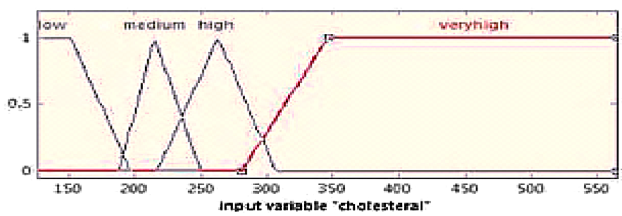

Fig. 5 Membership functions of cholesterol level

soft set, fuzzy soft subset, fuzzy soft super set and the fuzzy union of fuzzy soft sets below.

Definition 2.5 ([32]) Let $X = \{o_1, o_2, \ldots, o_k\}$ be a set of k objects, which may be characterized by a set of parameters $A_1, A_2, \ldots, A_i$. The parameter space E may be written as $E \supseteq A_1 \cup A_2 \cup \cdots \cup A_i$. Let each parameter set A_i represent the ith class of parameters and the elements of A_i represents a specific property set. Here, we assume that these property sets may be viewed as fuzzy sets.

We may now define a fuzzy soft set $(\widetilde{F}_i, A_i)$ which characterizes a set of objects having the parameter set A_i.

Let $\mathcal{F}(X)$ denotes the set of all fuzzy sets of X. Let $A_i \subset E$. A pair $(\widetilde{F}_i, A_i)$ is called a fuzzy soft set over X, where $\widetilde{F}_i$ is a mapping given by $\widetilde{F}_i : A_i \to \mathcal{F}(X)$.

Example 2.6 Consider the Example 2.4. We can characterize the fuzzy information by a membership instead of the crisp number 0 or 1. The fuzzy soft set $(\widetilde{F}, A)$ can then describe the 'opportunities of the potential investment' under the fuzzy information as indicated below.

$$\widetilde{F}(e_1) = \{h_1/0.4, h_2/0.6, h_3/0.5, h_4/0.7, h_5/0.2\},$$

$$\widetilde{F}(e_2) = \{h_1/0.3, h_2/0.5, h_3/0.9, h_4/1.0, h_5/0.4\},$$

$$\widetilde{F}(e_3) = \{h_1/0.1, h_2/0.4, h_3/0.7, h_4/0.0, h_5/0.3\},$$

$$\widetilde{F}(e_4) = \{h_1/0.0, h_2/1.0, h_3/0.8, h_4/1.0, h_5/0.5\}.$$

Definition 2.7 ([32]) For two fuzzy soft set $(\widetilde{F}, A)$ and $(\widetilde{G}, B)$ over a common universe X, (F, A) is a fuzzy-soft-subset of (G, B) if

1. $A \subset B$, and
2. $\forall \varepsilon \in A, \widetilde{F}(\varepsilon)$ is a fuzzy subset of $\widetilde{G}(\varepsilon)$.

Table 3 Classification of maximum heart rate

Input field	Range	Fuzzy sets
Maximum heart rate	<141	L
	111–194	M
	152>	H

We write $(\widetilde{F}, A) \widetilde{\subset} (\widetilde{G}, B)$.

$(\widetilde{F}, A)$ is said to be a fuzzy soft super set of $(\widetilde{G}, B)$, if $(\widetilde{G}, B)$ is a fuzzy-soft-subset of $(\widetilde{F}, A)$. We denoted it by $(\widetilde{F}, A) \widetilde{\supset} (\widetilde{G}, B)$.

Definition 2.8 ([32]) If $(\widetilde{F}, A)$ and $(\widetilde{G}, B)$ are two fuzzy soft sets, then '$(\widetilde{F}, A)$ OR $(\widetilde{G}, B)$' denoted by $(\widetilde{F}, A) \vee (\widetilde{G}, B)$ is defined by $(\widetilde{F}, A) \vee (\widetilde{G}, B) = (\widetilde{O}, A \times B)$, where $\widetilde{O}(\alpha, \beta) = \widetilde{F}(\alpha) \widetilde{\cup} \widetilde{G}(\beta), \forall (\alpha, \beta) \in A \times B$, where $\widetilde{\cup}$ is the operation 'fuzzy union' of two fuzzy sets.

Example 2.9 Let $X = \{h_1, h_2, h_3, h_4\}$ be a set of air-condition systems and $E = \{e_1$= economical, e_2= energy efficient, e_3= low maintenance, e_4= quality$\}$ be a set of parameter. Let A and B be a subset of E, where $A = \{e_1, e_3\}$ and $B = \{e_2, e_4\}$. Suppose that $(\widetilde{F}, A)$ and $(\widetilde{G}, B)$ be two fuzzy soft sets over X defined as follows:

$$\widetilde{F}(e_1) = \{h_1/0.7, h_2/0.8, h_3/0.5, h_4/0.3\},$$

$$\widetilde{F}(e_3) = \{h_1/0.4, h_2/0.2, h_3/0.1, h_4/0.5\},$$

$$\widetilde{G}(e_2) = \{h_1/0.6, h_2/0.9, h_3/1.0, h_4/0.4\},$$

$$\widetilde{G}(e_4) = \{h_1/0.0, h_2/0.7, h_3/0.8, h_4/0.1\}.$$

Then we have $(\widetilde{F}, A) \vee (\widetilde{G}, B) = (\widetilde{O}, A \times B)$, where

$$\begin{aligned} \widetilde{O}(e_1, e_2) &= \widetilde{F}(e_1) \widetilde{\cup} \widetilde{G}(e_2) \\ &= \{h_1/0.7, h_2/0.9, h_3/1.0, h_4/0.4\}, \\ \widetilde{O}(e_1, e_4) &= \widetilde{F}(e_1) \widetilde{\cup} \widetilde{G}(e_4) \\ &= \{h_1/0.7, h_2/0.8, h_3/0.8, h_4/0.3\}, \\ \widetilde{O}(e_3, e_2) &= \widetilde{F}(e_3) \widetilde{\cup} \widetilde{G}(e_1) \\ &= \{h_1/0.6, h_2/0.9, h_3/1.0, h_4/0.5\}, \\ \widetilde{O}(e_3, e_4) &= \widetilde{F}(e_3) \widetilde{\cup} \widetilde{G}(e_4) \\ &= \{h_1/0.4, h_2/0.7, h_3/0.8, h_4/0.5\}. \end{aligned}$$

Comparison table is a square table in which the number of rows and number of columns are equal, rows and columns both are labeled by the object names $o_1, o_2, o_3, \ldots, o_n$ of the universe and the entries are $c_{ij}, i, j = 1, 2, \ldots, n$, given by c_{ij} = the number of parameters for which the membership value of o_i exceeds or equal to the membership value of o_j. Clearly, $0 \le c_{ij} \le k$, and $c_{ii} = k, \forall i, j$, where k is the number of parameters present in a fuzzy soft set. Thus, c_{ij} indicates a numerical measure, which is an integer number and o_i dominates o_j in c_{ij} number of parameters out of

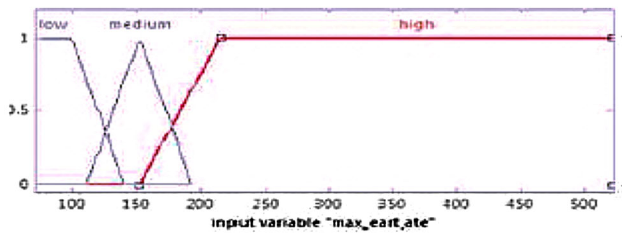

Fig. 6 Membership functions of maximum heart rate

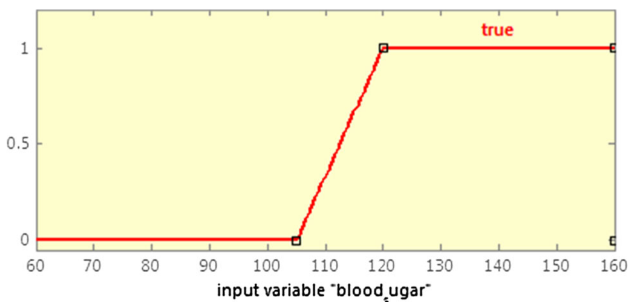

Fig. 7 Membership functions of blood sugar level

Table 4 Classification of old peak

Input field	Range	Fuzzy sets
Old peak	<2	L
	1.5–4.2	R
	2.55>	T

k parameters. The row sum of an object o_i is denoted by r_i and is calculated by using the formula,

$$r_i = \sum_{j=1}^{n} c_{ij}, \tag{1}$$

Clearly, r_i indicates the total number of parameters in which o_i dominates all the members of X.

Likewise, the column sum of an object o_j is denoted by t_j and may be computed as

$$t_j = \sum_{i=1}^{n} c_{ij}, \tag{2}$$

The integer t_j indicates the total number of parameters in which o_j is dominated by all the members of X.

The score of an object o_i is S_i may be given as

$$S_i = r_i - t_i. \tag{3}$$

The following algorithm encapsulates Roy and Maji's method.

1. **Algorithm** ([33]).

   1. Input the fuzzy soft set $(\widetilde{F}, A), (\widetilde{G}, B)$ and $(\widetilde{H}, C)$.

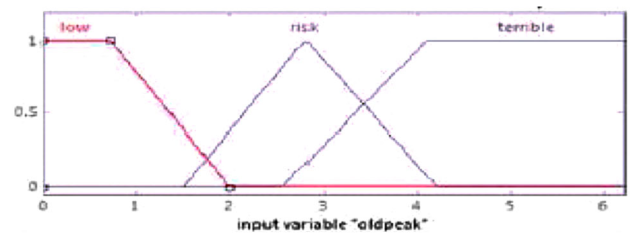

Fig. 8 Membership functions of old peak

Table 5 Classification of age

Input field	Range	Fuzzy sets
Age	<38	Y
	33–45	M
	40–58	O
	52>	VO

   2. Input the parameter set P as observed by the observer.
   3. Compute the corresponding resultant fuzzy soft set $(\widetilde{S}, P)$ from the fuzzy soft sets $(\widetilde{F}, A), (\widetilde{G}, B)$ and $(\widetilde{H}, C)$ and place it in tabular form.
   4. Construct the Comparison table of the fuzzy soft set $(\widetilde{S}, P)$ and compute r_i and t_i for $o_i, \forall i$.
   5. Compute the score of $o_i, \forall i$.
   6. The decision is S_k if $S_k = \max_i S_i$.
   7. If k has more than one value then any one of o_k may be chosen.

Kong et al. [34] argued that the Roy and Maji's method [33] was incorrect and presented a revised algorithm below which is to be used in our fuzzy expert system approach.

2. **Algorithm** ([34]). From Step 4 the algorithm is revised as below: c_{ij} and r_i should be redesigned as

$$\begin{aligned} c_{ij} &= \sum_{k=1}^{m} (f_{ik} - f_{jk}), \\ r_i &= \sum_{j=1}^{m} c_{ij}, \end{aligned} \tag{4}$$

   where f_{ik} is the membership value of object o_i for the kth parameter, m is the number of parameters. Step 5: the decision is k if $r_k = \max_i r_i$.

2.2 Fuzzy Expert System

The extracted rules from the decision tree will change to fuzzy rules. This requires having a fuzzy model. To create

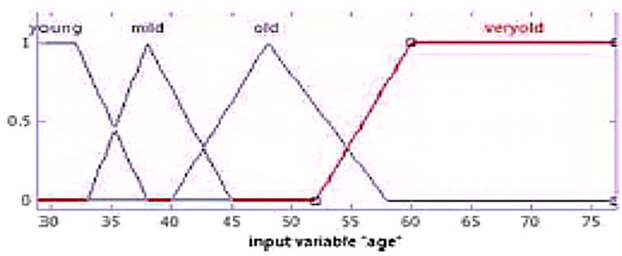

Fig. 9 Membership functions of age

Table 6 The input values of nine male patients

U	SBP	LDL-C	MHR	BS	OP	Age
u_1	137	250	143	108	2.8	55
u_2	150	255	146	111	3	63
u_3	144	264	150	117	3.1	67
u_4	160	281	200	130	2.9	45
u_5	153	286	216	125	3.4	48
u_6	139	276	194	120	2.55	50
u_7	156	290	165	123	2.7	54
u_8	164	296	218	113	3.6	66
u_9	170	300	220	133	4	70

a fuzzy model, there are three main steps to perform: the fuzzification process, fuzzy inference system and defuzzification process. The fuzzy model design process includes the following definitions:

1. Input and output variables;
2. Fuzzy membership functions for each variable; and
3. Fuzzy rules.

The input variables are designed based on features selected by a decision tree. The output variable is the class field in the data set. Fuzzy membership functions are defined based on the boundary values of each branch of the decision tree. Fuzzy rules are designed based on decision tree rules and membership functions. The proposed fuzzy expert system components are illustrated in Fig. 1. As shown in Fig. 1, after the preprocessing step, heart disease data are entered into the fuzzy inference system and are classified. This classification and inference are based on knowledge base information.

2.3 Database Description

Data for our present work is obtained from the Cardiac Unit, Department of Cardiology, Faculty of Medicine, Assiut University, Egypt. This database collected from 200 patients contains 76 attributes, but we used only 6 of them which are relevant to coronary artery disease. The attributes that we considered in this work are:

1. Blood pressure
2. Cholesterol
3. Maximum heart rate
4. Blood sugar
5. Old peak
6. Age

3 The Proposed Methodology and Implementation

The present system provides diagnostic assistance concerned with artery diseases. The system output is compared to an independent diagnosis given by physicians. The designed generic medical fuzzy soft expert system has been tested and found to be diagnosing the disease risk with accuracy. A fuzzy soft expert system is a rule-based system that uses fuzzy set and fuzzy soft set. Its basic structure includes four main components, as depicted in Fig. 2: (1) a fuzzification, which translates inputs (real-valued) into fuzzy values; (2) from fuzzification of data set to obtain fuzzy soft sets; (3) a new fuzzy soft set by normal parameter reduction of fuzzy soft sets; and (4) an algorithm to get the output data.

Our basic structure differs to that of Sikchi et al. [38]. Their basic structure using fuzzy sets is as in Fig. 3.

Table 7 The membership functions of nine male patients

U	SBP	LDL-C	MHR	BS	OP	Age
u_1	0.83 M	0.71 H	0.78 M	0.2 VH	1R	0.3 O, 0.37 VO
u_2	0.21 M, 0.53 H	0.82 H	0.85 M	0.4 VH	0.85 R, 0.31 T	1 VO
u_3	0.64 M, 0.13 H	0.97 H	0.95 M	0.8 VH	0.78 R, 0.37 T	1 VO
u_4	0.8 H, 0.35 VH	0.59 H	0.75 H	1 VH	0.92 R, 0.24 T	0.62 O
u_5	0.73 H	0.47 H, 0.07 VH	1 H	1 VH	0.57 R, 0.58 T	1 O
u_6	1 M	0.7 H	0.65 H	1 VH	0.8 R	0.8 O
u_7	0.93 H, 0.11 VH	0.38 H, 0.13 VH	0.69 M, 0.2 H	1 VH	0.92 R, 0.1 T	0.4 O, 0.25 VO
u_8	0.53 H, 0.58 VH	0.25 H, 0.22 VH	1 H	0.53 VH	0.42 R, 0.72 T	1 VO
u_9	0.13 H, 0.94 VH	0.15 H, 0.28 VH	1 H	1 VH	0.14 R, 1 T	1 VO

Table 8 Fuzzy soft set of $(\widetilde{L}, A)$

U	$(\mathrm{SBP})_{\mathrm{M}} = \alpha_1$	$(\mathrm{SBP})_{\mathrm{H}} = \alpha_2$	$(\mathrm{SBP})_{\mathrm{VH}} = \alpha_3$
u_1	0.83	0.0	0.0
u_2	0.21	0.53	0.0
u_3	0.64	0.31	0.0
u_4	0.0	0.8	0.35
u_5	0.0	0.73	0.0
u_6	1.0	0.0	0.0
u_7	0.0	0.93	0.11
u_8	0.0	0.53	0.58
u_9	0.0	0.13	0.94

Table 9 Fuzzy soft set of $(\widetilde{M}, B)$

U	$(\text{ LDL-C })_{\mathrm{H}} = \beta_1$	$(\text{ LDL-C })_{\mathrm{VH}} = \beta_2$
u_1	0.71	0.0
u_2	0.82	0.0
u_3	0.97	0.0
u_4	0.59	0.0
u_5	0.47	0.07
u_6	0.7	0.0
u_7	0.38	0.13
u_8	0.25	0.22
u_9	0.15	0.28

Figure 2 represents the basic structure of a fuzzy soft expert system. In the domain of coronary artery disease risks: blood pressure, cholesterol, maximum heart rate, blood sugar, old peak and age are the main risk factors. There are many uncertain risk factors in the coronary artery risk. Having all these six main risk factors included in the diagnostic tool offers great help for an expert to obtain certain results in uncertain terms.

Figure 3 represents the basic flow of information of Sikchi's fuzzy expert system in which the knowledge base fuzzy expert system contains both static and dynamic information. There are qualitative and quantitative variables, which are analyzed to arrive at a diagnostic conclusion. The fuzzy logic methodology involves fuzzification, inference engine and defuzzification as the significant steps. A disease is usually characterized by directly observable symptoms that prompt the patient to visit a physician. A series of clinical observations are undertaken to detect the presence of a disease. The symptoms of the disease are usually expressed by the deviation of the observations from their normal state or value. The correct classification of the symptoms leads to diagnosis of the disease that enables the doctor to plan further treatment. Thus, our proposed fuzzy soft expert system provides a simpler implementation to diagnose coronary artery disease risk, using the six main attributes.

Table 10 Fuzzy soft set of $(\widetilde{N}, C)$

U	$(\mathrm{MHR})_{\mathrm{M}} = \gamma_1$	$(\mathrm{MHR})_{\mathrm{H}} = \gamma_2$
u_1	0.78	0.0
u_2	0.85	0.0
u_3	0.95	0.0
u_4	0.75	0.75
u_5	0.0	1.0
u_6	0.0	0.65
u_7	0.69	0.2
u_8	0.0	1.0
u_9	0.0	1.0

Table 11 Fuzzy soft set of $(\widetilde{R}, D)$

U	$(\mathrm{BS})_{\mathrm{VH}} = \delta 1$
u_1	0.2
u_2	0.4
u_3	0.8
u_4	1.0
u_5	1.0
u_6	1.0
u_7	1.0
u_8	0.53
u_9	1.0

3.1 Computing Membership Functions of Data Set

The membership function editor in the fuzzy tool box is used to define the shapes of all membership functions associated with each membership variable. For each of the input variable, the membership functions are defined as following:

1. *Blood Pressure* Different values of blood pressure may easily contribute a change to the results. In this blood pressure field, we use the systolic blood pressure. This input variable is divided into four fuzzy sets. The four fuzzy sets are Low (L), Medium (M), High (H) and Very high (VH). Membership functions of 'Low' and 'Very high' sets are trapezoidal, while membership functions of 'medium' and 'high' sets are triangular. We defined the fuzzy membership expressions for blood pressure input field as in Eq. (5) and classified it in Table 1. The membership functions of blood pressure field are shown in Fig. 4.

$$\mu_{\mathrm{L}}(x)=\begin{cases}1 & ; \quad x<111 \\ (134-x)/23 & ; \quad 111\le x<134\end{cases},$$
$$\mu_{\mathrm{M}}(x)=\begin{cases}(x-127)/12 & ; \quad 127\le x<139 \\ 1 & ; \quad x=139 \\ (153-x)/14 & ; \quad 139\le x<153\end{cases},$$
$$\mu_{\mathrm{H}}(x)=\begin{cases}(x-142)/15 & ; \quad 142\le x<157 \\ 1 & ; \quad x=157 \\ (172-x)/15 & ; \quad 157\le x<172\end{cases}, \tag{5}$$
$$\mu_{\mathrm{VH}}(x)=\begin{cases}(x-154)/17 & ; \quad 154\le x\le 171 \\ 1 & ; \quad x\ge 171\end{cases}$$

Thus, for a patient having blood pressure $x = 130$, the fuzzy membership functions obtained from Table 1 and Fig. 4 would be $\mu_{\mathrm{BP}}(x)=\{(L,0.17),(M,0.25),(H,0.0),(VH,0.0)\}$.

2. *Cholesterol* Cholesterol level has salient effect on the result and can change it easily. For this input field, we use the value of low-density lipoprotein cholesterol (LDL-C). The cholesterol field is categorized into four fuzzy sets [Low (L), Medium (M), High (H) and Very high (VH)]. These fuzzy sets are shown in Table 2. Membership functions of 'Low' and 'Very high' sets are trapezoidal, whereas membership functions of 'medium' and 'high' sets are triangular. Membership functions of cholesterol field are shown in Fig. 5. Equation (6) is the membership function expressions of cholesterol.

$$\mu_{\mathrm{L}}(x)=\begin{cases}1 & ; \quad x<151 \\ (197-x)/46 & ; \quad 151\le x<197\end{cases},$$
$$\mu_{\mathrm{M}}(x)=\begin{cases}(x-188)/27 & ; \quad 188\le x<215 \\ 1 & ; \quad x=215 \\ (250-x)/35 & ; \quad 215\le x<250\end{cases},$$
$$\mu_{\mathrm{H}}(x)=\begin{cases}(x-217)/46 & ; \quad 217\le x<263 \\ 1 & ; \quad x=263 \\ (307-x)/44 & ; \quad 263\le x<307\end{cases}, \tag{6}$$
$$\mu_{\mathrm{VH}}(x)=\begin{cases}(x-281)/66 & ; \quad 281\le x<347 \\ 1 & ; \quad x\ge 347\end{cases}$$

Thus, for a patient having cholesterol level $x = 200$, the fuzzy membership functions obtained from Table 2 and Fig. 5 would be $\mu_{LDL-C}(x)=\{(L,0.0),(M,0.26),(H,0.0),(VH,0.0)\}$.

3. *Maximum Heart Rate* The value of this input field is the maximum heart rate (MHR) taken within a 24-h time frame. It is noted that an increase in age resulted in a decrease in the maximum heart rate within the 24-h time frame. In this field, we have three linguist variables (fuzzy sets) [Low (L), Medium (M) and High (H)] which are classified accordingly as in Table 3. Membership functions of 'Low' and 'High' fuzzy sets are trapezoidal, while membership function of 'Medium' fuzzy set is triangular as shown in Fig. 6. Equation (7) is the fuzzy membership function expressions.

$$\mu_{\mathrm{L}}(x)=\begin{cases}1 & ; \quad x<100 \\ (141-x)/41 & ; \quad 100\le x<141\end{cases},$$
$$\mu_{\mathrm{M}}(x)=\begin{cases}(x-111)/41 & ; \quad 111\le x<152 \\ 1 & ; \quad x=152 \\ (194-x)/42 & ; \quad 152\le x<194\end{cases}, \tag{7}$$
$$\mu_{\mathrm{H}}(x)=\begin{cases}(x-152)/64 & ; \quad 152\le x<216 \\ 1 & ; \quad x\ge 216\end{cases}$$

Thus, for a patient having maximum heart rate $x = 120$, the fuzzy membership functions obtained from Table 3 and Fig. 6 would be $\mu_{MHR}(x)=\{(L,0.51),(M,0.21),(H,0.0)\}$.

4. *Blood Sugar* (Diabetes) Blood sugar level (BS) field is one of the most important factors considered in this system. This input field has just one fuzzy set. In this system, we presumed that if the value of fasting blood sugar level is higher than 120 (mg/dL), then the patient is diabetic. Figure 7 shows the membership function of blood sugar which is trapezoidal. The fuzzy membership expression for blood sugar level field is as in Eq. (8).

$$\mu_{\mathrm{VH}}(x)=\begin{cases}(x-105)/15 & ; \quad 105\le x<120 \\ 1 & ; \quad x\ge 120\end{cases} \tag{8}$$

For example, suppose that the patient has blood sugar level $x = 115$. The fuzzy membership function obtained from Fig. 7 would be $\mu_{\mathrm{BS}}(x)=\{(VH,0.66)\}$.

5. *Old Peak* (ST depression induced by exercise relative to rest). This input field divides the old peak group into three fuzzy sets [Low (L), Risk (R) and Terrible (T)], as classified in Table 4. Membership functions of 'Low' and 'Terrible' fuzzy sets are trapezoidal, whereas membership function of 'Risk' fuzzy set is triangular as shown in Fig. 8. The fuzzy membership function expressions are as in Eq. (9).

$$\mu_{\mathrm{L}}(x)=\begin{cases}1 & ; \quad x<1 \\ (2-x)/1 & ; \quad 1\le x<2\end{cases},$$
$$\mu_{\mathrm{R}}(x)=\begin{cases}(x-1.5)/1.3 & ; \quad 1.5\le x<2.8 \\ 1 & ; \quad x=2.8 \\ (4.2-x)/1.4 & ; \quad 2.8\le x<4.2\end{cases}, \tag{9}$$
$$\mu_{\mathrm{T}}(x)=\begin{cases}(x-2.55)/1.45 & ; \quad 2.55\le x<4 \\ 1 & ; \quad x\ge 4\end{cases}$$

Table 12 Fuzzy soft set of $(\widetilde{P}, F)$

U	$(\mathrm{OP})_{\mathrm{R}} = \zeta_1$	$(\mathrm{OP})_{\mathrm{T}} = \zeta_2$
u_1	1.0	0.0
u_2	0.85	0.31
u_3	0.78	0.37
u_4	0.92	0.24
u_5	0.57	0.58
u_6	0.8	0.0
u_7	0.92	0.1
u_8	0.42	0.72
u_9	0.14	1.0

Table 13 Fuzzy soft set of $(\widetilde{T}, G)$

U	$(\mathrm{Age})_{\mathrm{O}} = \eta_1$	$(\mathrm{Age})_{\mathrm{VO}} = \eta_2$
u_1	0.3	0.37
u_2	0.0	1.0
u_3	0.0	1.0
u_4	0.62	0.0
u_5	1.0	0.0
u_6	0.8	0.0
u_7	0.4	0.25
u_8	0.0	1.0
u_9	0.0	1.0

Thus, a patient with old peak $x = 2.2$, will have fuzzy membership functions $\mu_{\mathrm{OP}}(x) = \{(L, 0.0), (R, 0.7), (T, 0.0)\}$, obtained from Table 4 and Fig. 8.

6. *Age* This input field divides the age group into four fuzzy sets [Young (Y), Mild (M), Old (O) and Very old (VO)]. These fuzzy sets are classified as in Table 5. Membership functions of 'Young' and 'Very old' are trapezoidal, while membership functions of 'Mild' and 'Old' are triangular. The membership function expressions are as in Eq. (10).

$$\begin{aligned}
\mu_{\mathrm{Y}}(x) &= \begin{cases} 1 & ; \quad x < 29 \\ (38 - x)/9 & ; \quad 29 \le x < 38 \end{cases}, \\
\mu_{\mathrm{M}}(x) &= \begin{cases} (x - 33)/5 & ; \quad 33 \le x < 38 \\ 1 & ; \quad x = 38 \\ (45 - x)/7 & ; \quad 38 \le x < 45 \end{cases}, \\
\mu_{\mathrm{O}}(x) &= \begin{cases} (x - 40)/8 & ; \quad 40 \le x < 48 \\ 1 & ; \quad x = 48 \\ (58 - x)/10 & ; \quad 48 \le x < 58 \end{cases}, \\
\mu_{\mathrm{VO}}(x) &= \begin{cases} (x - 52)/8 & ; \quad 52 \le x \le 60 \\ 1 & ; \quad x \ge 60 \end{cases}
\end{aligned} \tag{10}$$

Table 14 Resultant fuzzy soft set $(\widetilde{K}, S)$

U	e_{11}	e_{12}	e_{13}	e_{14}	e_{21}	e_{22}
u_1	0.83	0.21	0.71	0.0	0.71	0.0
u_2	0.82	0.64	0.82	0.53	0.82	0.0
u_3	0.97	0.0	0.97	0.31	0.97	0.0
u_4	0.59	0.0	0.8	0.8	0.59	0.35
u_5	0.47	1.0	0.73	0.73	0.47	0.07
u_6	1.0	0.0	0.7	0.0	0.7	0.0
u_7	0.38	0.13	0.93	0.93	0.38	0.13
u_8	0.25	0.22	0.53	0.53	0.58	0.58
u_9	0.15	0.28	0.15	0.28	0.94	0.94

Hence, from Table 5 and Fig. 9, a patient of age $x = 44$ will have fuzzy membership functions $\mu_{\mathrm{Age}}(x) = \{(Y, 0.0), (M, 0.14), (O, 0.5), (VO, 0.0)\}$.

4 Experimental Results and Discussion

The present study used only a small number of patients in the Cardiac Unit, Department of Cardiology, Faculty of Medicine, Assiut University, Egypt, and the laboratory data belong to nine male patients. The input values of these patients are shown in Table 6.

Using these input values, we then obtain the membership functions of each patient as shown in Table 7.

4.1 Obtaining Fuzzy Soft Sets

The combined result of fuzzy set and soft set theory is a fuzzy soft set. Thus, we can transform fuzzy set to fuzzy soft set.

Let $U = \{u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8, u_9\}$, be the set of nine male patients and the parameter set, $E = \{(\mathrm{SBP})_{\mathrm{L}}, (\mathrm{SBP})_{\mathrm{M}}, (\mathrm{SBP})_{\mathrm{H}}, (\mathrm{SBP})_{\mathrm{VH}}, (\text{ LDL-C })_{\mathrm{L}}, (\text{ LDL-C })_{\mathrm{M}}, (\text{ LDL-C })_{\mathrm{H}}, (\text{ LDL-C })_{\mathrm{VH}}, (\mathrm{MHR})_{\mathrm{L}}, (\mathrm{MHR})_{\mathrm{M}}, (\mathrm{MHR})_{\mathrm{H}}, (\mathrm{BS})_{\mathrm{VH}}, (\mathrm{OP})_{\mathrm{L}}, (\mathrm{OP})_{\mathrm{R}}, (\mathrm{OP})_{\mathrm{T}}, (\mathrm{Age})_{\mathrm{Y}}, (\mathrm{Age})_{\mathrm{M}}, (\mathrm{Age})_{\mathrm{O}}, (\mathrm{Age})_{\mathrm{VO}}\}$. Let *A*, *B*, *C*, *D*, *F* and *G* denote six subsets of the set of parameters *E*, where $A = \{(\mathrm{SBP})_{\mathrm{L}}, (\mathrm{SBP})_{\mathrm{M}}, (\mathrm{SBP})_{\mathrm{H}}, (\mathrm{SBP})_{\mathrm{VH}}\}$, $B = \{(\mathrm{LDL\text{-}C})_{\mathrm{L}}, (\mathrm{LDL\text{-}C})_{\mathrm{M}}, (\mathrm{LDL\text{-}C})_{\mathrm{H}}, (\text{ LDL-C })_{\mathrm{VH}}\}$, $C = \{(\mathrm{MHR})_{\mathrm{L}}, (\mathrm{MHR})_{\mathrm{M}}, (\mathrm{MHR})_{\mathrm{H}}\}$, $D = \{(\mathrm{BS})_{\mathrm{VH}}\}$, $F = \{(\mathrm{OP})_{\mathrm{L}}, (\mathrm{OP})_{\mathrm{R}}, (\mathrm{OP})_{\mathrm{T}}\}$, and $G = \{(\mathrm{Age})_{\mathrm{Y}}, (\mathrm{Age})_{\mathrm{M}}, (\mathrm{Age})_{\mathrm{O}}, (\mathrm{Age})_{\mathrm{VO}}\}$.

Assume that the fuzzy soft set $(\widetilde{L}, A)$ describes the 'SBP', the fuzzy soft set $(\widetilde{M}, B)$ describes the 'LDL-C', the fuzzy soft set $(\widetilde{N}, C)$ describes the 'MHR.' the fuzzy soft set $(\widetilde{R}, D)$ describes the 'BS,' the fuzzy soft set $(\widetilde{P}, F)$ describes the 'OP' and the fuzzy soft set $(\widetilde{T}, G)$ describes the 'Age.' From Table 3, we obtain the fuzzy soft set as follows:

Table 15 All the resultant fuzzy soft sets $(\widetilde{I}, Q)$

U	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5	ϵ_6	ϵ_7	ϵ_8	ϵ_9	ϵ_{10}	ϵ_{11}	ϵ_{12}	ϵ_{13}	ϵ_{14}	ϵ_{15}	ϵ_{16}
u_1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.83	0.78	0.78	0.78
u_2	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
u_3	0.97	0.95	0.97	0.97	0.97	0.97	0.97	0.8	0.97	0.8	0.97	0.8	0.97	0.95	0.97	0.97
u_4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_7	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_8	0.53	0.53	0.53	0.53	0.58	0.58	1.0	1.0	1.0	1.0	1.0	1.0	0.72	0.72	0.72	0.72
u_9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

$$
\begin{aligned}
(\widetilde{L}, A) &= \{(\mathrm{SBP})_{\mathrm{L}} = \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.0, u_6/.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\mathrm{SBP})_{\mathrm{M}} &= \{u_1/.83, u_2/.21, u_3/.64, u_4/.0, u_5/.0, u_6/1.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\mathrm{SBP})_{\mathrm{H}} &= \{u_1/.0, u_2/.53, u_3/.31, u_4/.8, u_5/.73, u_6/.0, u_7/.93, u_8/.53, u_9/.13\},\\
(\mathrm{SBP})_{\mathrm{VH}} &= \{u_1/.0, u_2/.0, u_3/.0, u_4/.35, u_5/.0, u_6/.0, u_7/.11, u_8/.58, u_9/.94\}\},\\
(\widetilde{M}, B) &= \{(\text{ LDL-C })_{\mathrm{L}} = \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.0, u_6/.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\text{ LDL-C })_{\mathrm{M}} &= \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.0, u_6/.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\text{ LDL-C })_{\mathrm{H}} &= \{u_1/.71, u_2/.82, u_3/.97, u_4/.59, u_5/.47, u_6/.7, u_7/.38, u_8/.25, u_9/.15\},\\
(\text{ LDL-C })_{\mathrm{VH}} &= \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.07, u_6/.0, u_7/.13, u_8/.22, u_9/.28\}\},\\
(\widetilde{N}, C) &= \{(\mathrm{MHR})_{\mathrm{L}} = \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.0, u_6/.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\mathrm{MHR})_{\mathrm{M}} &= \{u_1/.78, u_2/.85, u_3/.95, u_4/.75, u_5/.0, u_6/.0, u_7/.69, u_8/.0, u_9/.0\},\\
(\mathrm{MHR})_{\mathrm{H}} &= \{u_1/.0, u_2/.0, u_3/.0, u_4/.75, u_5/1.0, u_6/.65, u_7/.2, u_8/1.0, u_9/1.0\}\},\\
(\widetilde{R}, D) &= \{(\mathrm{BS})_{\mathrm{VH}} = \{u_1/.2, u_2/.4, u_3/.8, u_4/1.0, u_5/1.0, u_6/1.0, u_7/1.0, u_8/.53, u_9/1.0\}\},\\
(\widetilde{P}, F) &= \{(\mathrm{OP})_{\mathrm{L}} = \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.0, u_6/.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\mathrm{OP})_{\mathrm{R}} &= \{u_1/1.0, u_2/.85, u_3/.78, u_4/.92, u_5/.57, u_6/.8, u_7/.92, u_8/.42, u_9/.14\},\\
(\mathrm{OP})_{\mathrm{T}} &= \{u_1/.0, u_2/.31, u_3/.37, u_4/.24, u_5/.58, u_6/.0, u_7/.1, u_8/.72, u_9/1.0\}\}, \text{and}\\
(\widetilde{T}, G) &= \{(\mathrm{Age})_{\mathrm{Y}} = \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.0, u_6/.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\mathrm{Age})_{\mathrm{M}} &= \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.0, u_6/.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\mathrm{Age})_{\mathrm{O}} &= \{u_1/.3, u_2/.0, u_3/.0, u_4/.62, u_5/1.0, u_6/.8, u_7/.4, u_8/.0, u_9/.0\},\\
(\mathrm{Age})_{\mathrm{VO}} &= \{u_1/.37, u_2/1.0, u_3/1.0, u_4/.0, u_5/.0, u_6/.0, u_7/.25, u_8/1.0, u_9/1.0\}\}.
\end{aligned}
$$

4.2 Normal Parameter Reduction of Fuzzy Soft Sets

Parameter reduction is very important in decision making problem. By this process, the number of parameters in a problem can be efficiently minimized, thus highlighting only the key parameters. For a fuzzy soft set $(\widetilde{F}, E); E = \{e_1, e_2, \ldots, e_m\}$ if there exists a subset $A = \{e_1^{'}, e_1^{'}, \ldots, e_m^{'}\}$ of E satisfying $\sum_{e_k \in A} d_{1k} = \sum_{e_k \in A} d_{2k} = \cdots = \sum_{e_k \in A} d_{nk}$, [where $d_{ik}; i = 1, 2, \ldots, n; k = 1, 2, \ldots, p$ be the entries of the tabular representation of (F, A)], A is dispensable, otherwise A is indispensable. $B \subset E$ is a normal parameter reduction of E if B is indispensable and $\sum_{e_k \in E-B} d_{1k} = \sum_{e_k \in E-B} d_{2k} = \cdots = \sum_{e_k \in E-B} d_{nk}$, [here d_{ik} be the entries of the tabular representation of $(\widetilde{F}, E - B)$], that is to say $E - B$ is the maximal subset of E that the value of $f_{E-B}(\cdot)$. keeps constant [37]. Now, we can get a new fuzzy soft sets as follows:

$$
\begin{aligned}
(\widetilde{L}, A) &= \{(\mathrm{SBP})_{\mathrm{M}} = \{u_1/.83, u_2/.21, u_3/.64, u_4/.0, u_5/.0, u_6/1.0, u_7/.0, u_8/.0, u_9/.0\},\\
(\mathrm{SBP})_{\mathrm{H}} &= \{u_1/.0, u_2/.53, u_3/.31, u_4/.8, u_5/.73, u_6/.0, u_7/.93, u_8/.53, u_9/.13\},\\
(\mathrm{SBP})_{\mathrm{VH}} &= \{u_1/.0, u_2/.0, u_3/.0, u_4/.35, u_5/.0, u_6/.0, u_7/.11, u_8/.58, u_9/.94\}\},\\
(\widetilde{M}, B) &= \{(\text{ LDL-C })_{\mathrm{H}} = \{u_1/.71, u_2/.82, u_3/.97, u_4/.59, u_5/.47, u_6/.7, u_7/.38, u_8/.25, u_9/.15\},\\
(\text{ LDL-C })_{\mathrm{VH}} &= \{u_1/.0, u_2/.0, u_3/.0, u_4/.0, u_5/.07, u_6/.0, u_7/.13, u_8/.22, u_9/.28\}\},\\
(\widetilde{N}, C) &= \{(\mathrm{MHR})_{\mathrm{M}} = \{u_1/.78, u_2/.85, u_3/.95, u_4/.75, u_5/.0, u_6/.0, u_7/.69, u_8/.0, u_9/.0\},\\
(\mathrm{MHR})_{\mathrm{H}} &= \{u_1/.0, u_2/.0, u_3/.0, u_4/.75, u_5/1.0, u_6/.65, u_7/.2, u_8/1.0, u_9/1.0\}\},\\
(\widetilde{R}, D) &= \{(\mathrm{BS})_{\mathrm{VH}} = \{u_1/.2, u_2/.4, u_3/.8, u_4/1.0, u_5/1.0, u_6/1.0, u_7/1.0, u_8/.53, u_9/1.0\}\},\\
(\widetilde{P}, F) &= \{(\mathrm{OP})_{\mathrm{R}} = \{u_1/1.0, u_2/.85, u_3/.78, u_4/.92, u_5/.57, u_6/.8, u_7/.92, u_8/.42, u_9/.14\},\\
(\mathrm{OP})_{\mathrm{T}} &= \{u_1/.0, u_2/.31, u_3/.37, u_4/.24, u_5/.58, u_6/.0, u_7/.1, u_8/.72, u_9/1.0\}\}, \text{ and}\\
(\widetilde{T}, G) &= \{(\mathrm{Age})_{\mathrm{O}} = \{u_1/.3, u_2/.0, u_3/.0, u_4/.62, u_5/1.0, u_6/.8, u_7/.4, u_8/.0, u_9/.0\},\\
(\mathrm{Age})_{\mathrm{VO}} &= \{u_1/.37, u_2/1.0, u_3/1.0, u_4/.0, u_5/.0, u_6/.0, u_7/.25, u_8/1.0, u_9/1.0\}\}.
\end{aligned}
$$

4.3 Algorithm

We can predict which patient will suffer coronary artery disease by using the algorithm of Kong et al. [34]. The steps are as follows:

1. Input a new fuzzy soft set $(\widetilde{L}, A), (\widetilde{M}, B), (\widetilde{N}, C), (\widetilde{R}, D), (\widetilde{P}, F)$ and $(\widetilde{T}, G)$.

Table 16 All the resultant fuzzy soft sets $(\widetilde{I}, Q)$

U	ϵ_{17}	ϵ_{18}	ϵ_{19}	ϵ_{20}	ϵ_{21}	ϵ_{22}	ϵ_{23}	ϵ_{24}	ϵ_{25}	ϵ_{26}	ϵ_{27}	ϵ_{28}	ϵ_{29}	ϵ_{30}	ϵ_{31}	ϵ_{32}
u_1	0.78	0.78	0.83	0.21	0.71	0.2	0.71	0.2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_2	0.85	0.85	0.82	0.64	0.82	0.53	0.82	0.4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_3	0.97	0.97	0.97	0.8	0.97	0.8	0.97	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_7	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_8	0.72	0.72	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Table 17 All the resultant fuzzy soft sets $(\widetilde{I}, Q)$

U	ϵ_{33}	ϵ_{34}	ϵ_{35}	ϵ_{36}	ϵ_{37}	ϵ_{38}	ϵ_{39}	ϵ_{40}	ϵ_{41}	ϵ_{42}	ϵ_{43}	ϵ_{44}	ϵ_{45}	ϵ_{46}	ϵ_{47}	ϵ_{48}
u_1	1.0	1.0	1.0	1.0	0.83	0.78	0.78	0.78	0.78	0.78	0.83	0.37	0.71	0.37	0.71	0.37
u_2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_7	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
u_9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

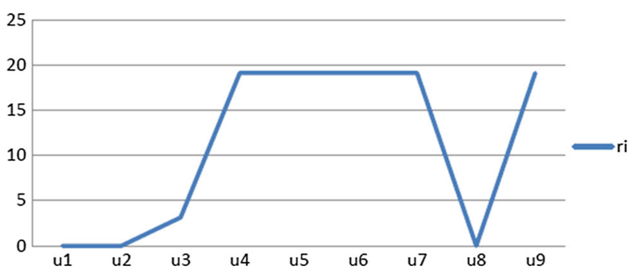

Fig. 10 The relationship between u_i and r_i

Table 18 Decision from specialist doctor

U	SBP	LDL-C	MHR	BS	OP	Age	Decision
u_1	137	250	143	108	2.8	55	Drug therapy
u_2	150	255	146	111	3	63	Drug therapy
u_3	144	264	150	117	3.1	67	Drug therapy
u_4	160	281	200	130	2.9	45	Intervention
u_5	153	286	216	125	3.4	48	Intervention
u_6	139	276	194	120	2.55	50	Intervention
u_7	156	290	165	123	2.7	54	Intervention
u_8	164	296	218	113	3.6	66	Drug therapy
u_9	170	300	220	133	4	70	Intervention

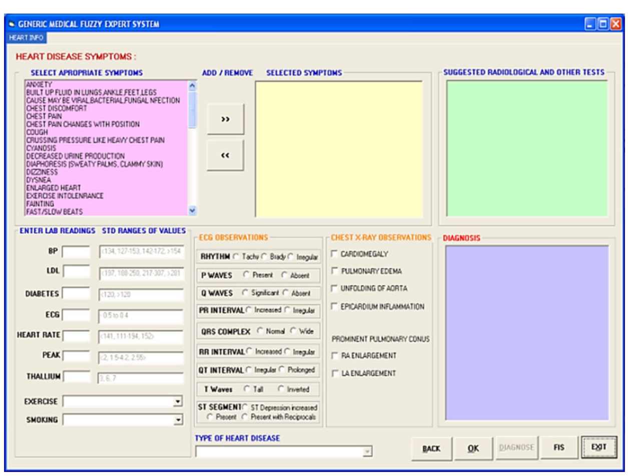

Fig. 11 Selection of clinical parameters and symptoms

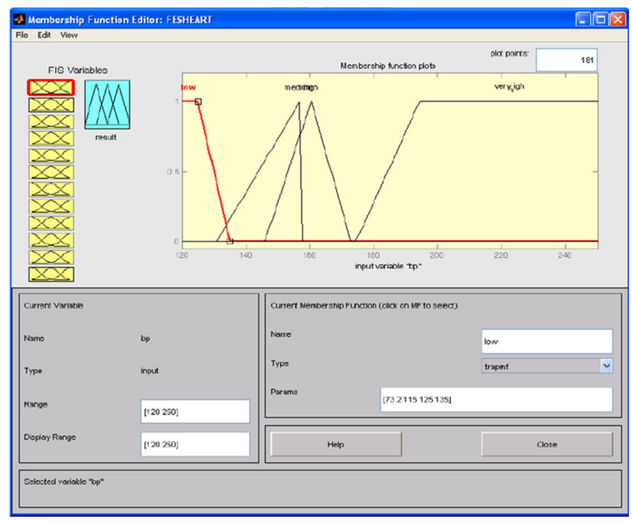

Fig. 12 Membership functions in MATLAB

Table 19 Proposed Sikchi's fuzzy expert system design

U	SBP	LDL-C	MHR	BS	OP	Age	Risk	Decision
u_1	137	250	143	108	2.8	55	3	Drug therapy
u_2	150	255	146	111	3	63	4	Intervention
u_3	144	264	150	117	3.1	67	3	Drug therapy
u_4	160	281	200	130	2.9	45	0	None
u_5	153	286	216	125	3.4	48	0	None
u_6	139	276	194	120	2.55	50	2	Drug therapy
u_7	156	290	165	123	2.7	54	2	Drug therapy
u_8	164	296	218	113	3.6	66	3	Intervention
u_9	170	300	220	133	4	70	4	Intervention

The tabular representations of the new fuzzy soft sets $(\widetilde{L}, A), (\widetilde{M}, B), (\widetilde{N}, C), (\widetilde{R}, D), (\widetilde{P}, F)$ and $(\widetilde{T}, G)$ are shown in Tables 8, 9, 10, 11, 12 and 13, respectively.

From Tables 8 and 9, if we perform '$(\widetilde{L}, A)$ OR $(\widetilde{M}, B)$' then we will have $3 \times 2 = 6$ parameters of the form e_{ij}, where $e_{ij} = \alpha_i \vee \beta_j$, for all $i = 1, 2, 3.$ and $j = 1, 2$. If we require the fuzzy soft sets for the parameters $S = \{e_{11}, e_{12}, e_{21}, e_{22}, e_{31}, e_{32}\}$, then the resultant fuzzy soft set for the fuzzy soft sets $(\widetilde{L}, A)$ and $(\widetilde{M}, B)$ will be $(\widetilde{K}, S)$. The tabular representation of the resultant fuzzy soft set is shown in Table 14.

2. Compute the corresponding fuzzy soft sets $(\widetilde{I}, Q)$ from the fuzzy soft sets $(\widetilde{L}, A)$, $(\widetilde{M}, B), (\widetilde{N}, C), (\widetilde{R}, D)$, $(\widetilde{P}, F)$ and $(\widetilde{T}, G)$ to obtain results presented in Tables 15, 15 and 17.
3. Compute c_{ij} and r_i, as described by Kong et al. [34]. From Tables 15, 16 and 17, we can obtain $r_1 = -55.71, r_2 = -30.16, r_3 = 3.15, r_4 = 19.17, r_5 = 19.17$, $r_6 = 19.17, r_7 = 19.17, r_8 = -20.43$ and $r_7 = 19.17$.
4. As can be seen, patients u_4, u_5, u_6, u_7 and u_9 have very high values of r_i. Hence, these patients are potentially suffering from coronary artery disease. The relationship between u_i and r_i where $i = 1, \ldots, 9$ is illustrated in Fig. 10.

Table 18 shows the final score for these nine male patients and the corresponding action taken by the assigned specialist doctor.

Sikchi et al. [38] designed a fuzzy expert system for diagnosis of cardiac diseases. The difference lies in the fuzzy counterpart. We use the fuzzy soft set instead of the fuzzy set. The clinical parameters and symptoms used by Sikchi et al. [38] are shown in Fig. 11 and the membership functions in MATLAB as shown in Fig. 12.

Figure 11 shows the screen for selection of more specific clinical parameters and symptoms. In the proposed Sikchi's fuzzy expert system design, the first step is determination of input and output attributes. There are 11 input variables and one output variable considered for design of the system. The inputs are accepted through a form designed in visual basic and exported to MATLAB in which fuzzy logic toolbox computes the membership function parameters that best allow the fuzzy inference system to track the given input/output data. Figure 12 shows the screen of membership functions in MATLAB. The system uses Mamdani approach for design of inference mechanism and the defuzzification process uses a centroid method to aggregate the inference of Sikchi's fuzzy expert system.

If we are to use the data from Tables 6 and 7 and apply Sikchi's et al. [38] fuzzy expert system, we will get the results as in Table 19.

Comparing Table 18 to Table 19, note the differences in the decision for patients u_2, u_4, u_5, u_6, u_7 and u_8. Patient u_2 should be given drug therapy instead of intervention since all of the patient's six attributes are higher than that of patient u_1. Patients u_4 and u_5 have significantly higher values in the five main attributes compared to that of u_1. Hence, intervention should be in order due to their younger ages. All of patient's u_6 six main attributes are less than that of u_5. Thus, it is advisable that the patient undergo intervention instead of being given drug therapy. Patient u_7 five main attributes are less than that of patient u_8. Thus, patient u_7 is advisable to be given intervention, while patient u_8 be given drug therapy.

Hence, our proposed fuzzy soft expert system is shown to provide a remarkable improvement to that of the fuzzy expert system of Sikchi et al. [38].

5 Conclusions

In this study, we developed a fuzzy soft expert system to predict those patients who may suffer coronary artery disease using systolic blood pressure (SBP), low-density lipoprotein cholesterol LDL-C, maximum heart rate (MHR), blood sugar level (BS), old peak (OP) and age of patients. It is a pioneering approach in applying fuzzy soft sets to a medical diagnosis problem in the form of predicting patients who may be suffering from coronary artery disease. Fuzzy soft sets has not been applied before in the diagnosis of ailments; hence, this pioneering application can be extended further to other databases such as cancer of the breast, lung and liver. The proposed fuzzy soft expert system approach is better than the fuzzy expert system in the sense that the former approach does not depend on configuration rules which vary according to the number of parameters leading to different results, as does the latter. Our proposed method is economical since it does not require the utilization of programming softwares such as MATLAB or Visual Basic, as required by fuzzy expert system [22, 38, 39]. Thus, the fuzzy soft expert system can be performed quickly, without risk compared to traditional diagnostic systems, is highly reliable and can be easily taught to be utilized by medical students. This proposed methodology is a suitable tool to diagnose coronary artery diseases, since it provides an interpretable model that can be easily comprehended by doctors.

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