A Medical Decision Support System for the Prediction of the Coronary Artery Disease Using Fuzzy Cognitive Maps

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Abstract. There is a lot discussion nowadays regarding the decision-making problem. The Making decisions and creating computational models using the tools of Fuzzy Cognitive Maps and Neural Systems is presented. The reason is that the contributing factors are several and complicated themselves. The medical problem of coronary artery disease (CAD) is considered and briefly presented. In medicine, factors such as age, symptoms, clinical tests all play their role and have their own importance when it comes to examine a patient, or to decide action. The development of a Medical Decision Support System (MDSS) using fuzzy cognitive maps (FCM) for the first time to study the coronary artery disease (CAD) is formulated. A number of physician experts were used in developing a FCM with thirty concepts. Medical data from a number of real cases were used and simulations were conducted. Interesting results were obtained and discussed. Future directions for this medical application are provided.

Keywords: Coronary artery disease · Medical decision support systems · Fuzzy cognitive maps

1 Introduction

During the last years, there has been a development of an enormous number of medical decision support systems (MDSS). The traditional medical expert systems were equipped with a rule knowledge base which was offered by experts (physicians) [1]. On the basis of rules inserted in the expert system, it is possible to classify new instances of medical observations by matching symptoms to the conditional part of a rule and then to perform forward and backward reasoning to achieve the diagnosis or construct a therapy plan.

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It is believed that the classic technique of the rule-based knowledge representation in medical DSS has one main disadvantage, which is summarized by its limitation of representing, in reality, some of the more complex associations that may be experienced in medical data. For example, in a rule-based DSS, the representation of the complex phenomenon of causality is, in fact, left to the interpretation and expertise of the doctor [2].

In this work, we illustrate the development for the first time of an MDSS prediction of a very complex medical problem that of Coronary Artery Disease (CAD) using fuzzy cognitive maps (FCM) [3]. FCM is a soft computing technique capable of dealing with situations including uncertain descriptions using a similar procedure such as human reasoning [3, 5, 18]. FCMs are originated from cognitive maps and are used to model knowledge and experience for describing particular domains using nodes-concepts (representing i.e. variables, states, inputs, and outputs) and the relationships between them in order to outline a decision-making process.

What Is Coronary Artery Disease (CAD)?

Coronary artery disease is the most common type of heart disease. It is the leading cause of death all around the world and especially in the United States in both men and women.

For the Physicians, Coronary artery disease, also known as ischemic heart disease (IHD) and by some Acute Coronary Syndrome (ACS), [1, 6, 7] is a group of diseases that include: stable angina, unstable angina, myocardial infarction, and sudden cardiac death. It is within the group of cardiovascular diseases of which it is the most common type [6–9]. This serious condition is a result of plaque buildup in your arteries. The arteries, which start out smooth and elastic, get a plaque on their inner walls, which can make them more rigid and narrowed. This restricts blood flow to your heart, which can then become starved of oxygen. The plaque could rupture, leading to a heart attack or sudden cardiac death. A common symptom is chest pain or discomfort which may travel into the shoulder, arm, back, neck, or jaw. Usually, symptoms occur with exercise or emotional stress, last less than a few minutes, and get better with rest, [12] Shortness of breath may also occur and sometimes no symptoms are present [12]. The first sign is occasionally a heart attack. Other complications include heart failure or an irregular heartbeat. CAD happens when the arteries that supply blood to heart muscle become hardened and narrowed. This is due to the buildup of cholesterol and other material, called plaque, on their inner walls. This buildup is called atherosclerosis. As it grows, less blood can flow through the arteries. As a result, the heart muscle can't get the blood or oxygen it needs. This can lead to chest pain (angina) or a heart attack. Most heart attacks happen when a blood clot suddenly cuts off the hearts' blood supply, causing permanent heart damage.

FCM was chosen because of the nature of the application problem. The medical problem is very complex and depends on many parameters. The prediction of diseases like CAD is a complex process with sufficient interacting parameters and FCMs have been proved suitable for this kind of problems. Similar MDSS have been suggested for the prediction of diseases like pulmonary infection [4].

Before we begin, an introduction to the FCM case is needed and is provided in Sect. 2. Then our medical problem, the Coronary Artery Disease (CAD) is briefly presented in Sect. 3 while Sect. 4 outlines a methodology of a Fuzzy Cognitive Map

(FCM) for Prediction of the Disease (CAD). Simulations for Eleven scenarios and discussion of results are provided in Sect. 5 and Sect. 6 gives conclusions and future research directions.

2 Basics of Fuzzy Cognitive Maps (FCM)

A Fuzzy Cognitive Map (FCM) is a soft computing technique that follows an approach similar to human reasoning and the human decision-making process. Figure 1 shows a simple FCM. An FCM looks like a cognitive map; it consists of nodes (concepts) which interact with each other showing the dynamics of the model. Concepts may represent variables, states, events, trends, inputs, and outputs. The connection edges between concepts are directed and they indicate the direction of causal relationships. A brief overview is very useful. Kosko was the first to introduce the FCMs with the use of fuzzy causal functions, the numbers of which are in [−1, 1] in concept maps [3, 5]. One of the main objectives of building a cognitive map around a problem is the prediction of the outcome, especially in medical applications. This can be done by letting all the issues regarding this problem interact with each other. These predictions can be used in a medical DSS for predicting the possibility of infection in certain diseases. Other research results can be found in [17–20] and many others are easily accessible on the open literature. A brief overview is very useful. The most important element in describing the system is the determination of which concept influences which other and with which degree. Between concepts, there are three possible types of causal relationships that express the type of influence from one concept to another:

(1) $Wij > 0$, $(Ci \uparrow \rightarrow Cj \uparrow)$ positive causality
(2) $Wij < 0$, $(Ci \uparrow \rightarrow Cj \downarrow)$ negative causality
(3) $Wij = 0$, $(Ci, Cj) \rightarrow$ no causality

Important remark: We should distinguish Probability and probability density functions versus Fuzzy Logic and Membership functions as well as Correlation versus Causality.

The full procedure of the development of a FCM follows the below steps [18]:

- **Step 1:** Experts select the number and the kind of concepts Ci that constitute the Fuzzy Cognitive Map
- **Step 2:** Each expert defines the relationship between the concepts
- **Step 3:** They define the kind and the value of the relationship between the two nodes
- **Step 4:** Experts describe the existing relationship firstly as “negative” or “positive” and secondly, as a degree of influence using a linguistic variable, such as “low”, “medium”, “high” etc.

The value of each concept is influenced by the values of the connected concepts with the corresponding causal weights and by its previous value. Mathematically the value of each concept C_i at the iteration step $k + 1$, is calculated applying the following equation:

$$C_i^{(k+1)} = f(C_i^k + \sum_{j=1, j\neq i}^{n} C_j^{(k)} w_{ji}) \quad (1)$$

Where f is the sigmoid function ($\lambda > 0$ steepness of the function):

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \quad (2)$$

In the above equations: the value of concept C (k + 1) is at step k + 1, C(k) is the value of concept C_j at step k, Wji is the weight of the interconnection from concept C_j to concept Ci at step k and f is the threshold function that squashes the result of the multiplication in the interval [0, 1]. This equation indicates that a FCM is free to interact; at every step of interaction, every concept has a new value. FCM approach is based on experts' knowledge for the construction of matrix W_{ij}. This experience is not always reliable though.

That is the reason why the weights need to be trained by a learning algorithm. Several learning principles originally developed for Artificial Neural Networks (ANN) have been applied to FCM. These approaches were based on the concept of Hebbian learning. More specifically Nonlinear Hebbian Learning (NHL) method has been used in many applications. In this learning algorithm, the nodes are triggered simultaneously and interact in the same iteration step with their values to be updated through this process of interaction. The training weight algorithm is computed as follows:

$$w_{ij}^{(k)} = g \cdot w_{ij}^{(k-1)} + h \cdot A_j^{(k-1)} \cdot \left(A_i^{(k-1)} - \mathrm{sgn}(w_{ij}) \cdot w_{ij}^{(k-1)} \cdot A_j^{(k-1)}\right) \quad (3)$$

where the coefficient h is a very small positive scalar factor called learning parameter, and the coefficient g called weight reduction parameter. Two stopping criteria terminate the procedure. The first one concerns the minimization of the sum of the squared differences between each Desired Output Concept i (DOC_i) and a target value T_i. T_i is defined as the mean value of the range of DOC_i = [Timin, Timax]. The second criterion is the minimization of the variation of two subsequent values of Desired Output Concepts. Although we do not use learning on the present paper it is very important to have this in mind when future research on this particular medical problem is to be explored.

3 The Coronary Artery Disease (CAD)

As mentioned above, the CAD includes some risk factors, the presence of which increase the danger of infection. Risk factors include high blood pressure, smoking, diabetes, lack of exercise, obesity, high blood cholesterol, poor diet, and excessive alcohol, among others [12]. Other risks include depression [13]. The underlying mechanism involves atherosclerosis of the arteries of the heart [12]. A number of tests may help with diagnoses including electrocardiogram, cardiac stress testing, coronary computed tomographic angiography, and coronary angiogram, among others [12].

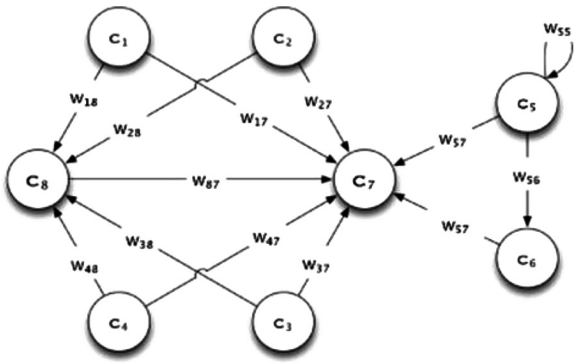

Fig. 1. A generic FCM model

Heart disease is the leading cause of death in developed nations despite known ways to prevent and treat heart problems. One common type of heart disease is called coronary artery disease (CAD). The arteries of the heart (coronary arteries) supply blood flow to the heart muscle. Plaque (buildup of fatty material) damages the coronary arteries, and blood platelets (cells in the blood that help to clot) can stick to these damaged areas, causing blockage of blood flow. This can lead to ischemia (lack of oxygen to the heart muscle cells) or myocardial infarction (heart attack). Risk factors—things that make it more likely for a person to develop coronary heart disease—have been identified through many scientific studies. The most common symptom is chest pain or discomfort, which may travel into the shoulder, arm, back, neck, or jaw. Usually, symptoms occur with exercise or emotional stress, last less than a few minutes, and get better with rest. Other complications include heart failure or an irregular heartbeat [6].

In 2013 CAD was the most common cause of death globally, resulting in 8.14 million deaths (16.8%) up from 5.74 million deaths (12%) in 1990 [7]. In 2015 CAD affected 110 million people and resulted in 8.9 million deaths [14]. It makes up 15.9% of all deaths making it the most common cause of death globally [14]. The risk of death from CAD for a given age has decreased between 1980 and 2010, especially in developed countries [15]. The number of cases of CAD for a given age has also decreased between 1990 and 2010. In the United States in 2010 about 20% of those over 65 had CAD, while it was present in 7% of those 45 to 64, and 1.3% of those 18 to 45 [16]. Rates are higher among men than women of a given age [16].

4 Methodology of a Fuzzy Cognitive Map (FCM) for Prediction of the Disease (CAD)

To begin with, we have to define all the possible input variables of the MDSS. Three physicians-experts were pooled to define the number and type of parameters-factors affecting the possibility of being affected by CAD. These parameters (concepts) are listed in Table 1 and are well documented in the bibliography and represent the main

variables that play an important role in the final diagnostic decision of CAD. For this application, concept values take either two, three, four or five possible discrete or fuzzy values, as shown in Table 1.

Table 1. Concepts of the FCM model

Variable	Possible values
A1: Typical angina	Two discrete values [0 1]
A2: Atypical angina	Three fuzzy values [low medium high]
A3: Nonanginal chest pain	Three fuzzy values [low medium high]
A4: Asymptomatic	Two discrete values [0 1]
A5: Gender – male	Two discrete values [0 1]
A6: Gender – female	Two discrete values [0 1]
A7: Age below 40	Two discrete values [0 1]
A8: Age [40 50]	Two discrete values [0 1]
A9: Age [50 60]	Two discrete values [0 1]
A10: Age above 60	Two discrete values [0 1]
A11: Smoking	Three fuzzy values [no light heavy]
A12: Arterial hypertension	Two discrete values [0 1]
A13: Dyslipidemia	Two discrete values [0 1]
A14: Obesity	Two discrete values [0 1]
A15: Family history of coronary artery disease	Two discrete values [0 1]
A16: Diabetes mellitus	Two discrete values [0 1]
A17: Renal insufficiency	Two discrete values [0 1]
A18: Baseline ECG (Electrocardiogram) normal	Two discrete values [0 1]
A19: Baseline ECG (Electrocardiogram) abnormal	Two discrete values [normal abnormal]
A20: Cardiac ultrasound normal	Two discrete values [0 1]
A21: Cardiac ultrasound abnormal	Two discrete values [0 1]
A22: Treadmill exercise test normal	Two discrete values [0 1]
A23: Treadmill exercise test abnormal	Two fuzzy values [ambiguous abnormal]
A24: Dobutamin stress cardiac ultrasound normal	Two discrete values [0 1]
A25: Dobutamin stress cardiac ultrasound abnormal	Two fuzzy values [ambiguous abnormal]
A26: Myocardial perfusion imaging normal	Two discrete values [0 1]
A27: Myocardial perfusion imaging abnormal	Four fuzzy values [ambiguous, mildly abnormal, moderately abnormal, severely abnormal]
A28: Computerized tomography coronary angiography normal	Two discrete values [0 1]
A29: Computerized tomography coronary Angiography abnormal	Three fuzzy values [mildly abnormal, moderately abnormal, severely abnormal]

These variables contain, first of all, information about the patient (i.e. Age, Gender). They also contain information regarding the heaviness of the main symptom, some Comorbidities and predisposing factors for CAD, as well as diagnostic tests that the patient has been submitted to. The main symptom of the disease is angina (chest pain), which is split into four variables (typical, atypical, nonanginal chest pain, asymptomatic). Due to the absence of any other symptoms, angina plays a more important role in the outcome. For example, all experts agree that if the patient has typical angina, then it is almost sure that the patient is affected, regardless of the other parameters.

Age and gender play also an important role, combining with the type of angina of the patient. For example, female patients have less probability of infection, due to biological reasons. In addition, men above sixty years regardless of the type of angina (except for nonasymptomatic), have a high possibility of affection [8]. Moreover, diagnose tests to female patients, especially Cardiac Ultrasound and Myocardial Perfusion Imaging are more susceptible to giving false results [9]. All these factors are been described in guidelines given by experts.

The Decision Concept (A30) represents the possibility of infection and takes four fuzzy values *(a low possibility, medium possibility, high possibility, very high possibility).*

Some fuzzy sets of the input variables as well as the fuzzy sets of the output decision concept A30 are illustrated in Table 2.

The thirty identified concepts (Table 1) keep relations with each other, in order to characterize the process of assessing infectious diseases and to provide a first front-end decision about the prediction of CAD. After the determination of fuzzy sets, each expert was asked to define the degree of influence among the concepts and describe their interrelationship using if-then rules. To illustrate how the interconnection is translated into numeric values the three experts are asked to describe the relation of the concept A2 (typical angina) with the decision concept A30 in the following example [4]:

Expert 1
"If a small change occurs in the value of concept A2 then a strong change in the value of concept A30 occurs". This means that the influence of A2 to A30 is positive high.

Expert 2
"If a small change occurs in the value of concept A2 then a medium change in the value of concept A30 occurs". This means that the influence of A2 to A30 is positive medium.

Expert 3
"If a small change occurs in the value of concept A2 then a weak change in the value of concept A30 occurs". This means that the influence of A2 to A30 is positive weak.

For the construction of the FCM, three experts are asked to define with the method described above the influence of all the inputs to the final outcome. Afterward, we need to defuzzify the linguistic variables given by experts, in order to fill the final weight of each of the inputs to the output. An algorithm for the comparison of the weights given by experts has been adopted, in order to exclude weights that deviate from the weights given by the other experts. For example if an expert defines the influence from A to B

Table 2. The experts' deffuzified values

	Physician 1	Physician 2	Physician 3	Average
A1	0.875	0.875	0.875	0.875
A2	0.625 0.875	0.375 0.625	0.625 0.875	0.667
A3	0.125 0.375	0.125 0.375	0.125 0.375	0.250
A4	−0.875	−0.625 −0.875	−0.875	−0.813
A5	0.125 0.375	0.125 0.375	0.125 0.375	0.250
A6	−0.125 −0.375	−0.125	−0.375 −0.625	−0.325
A7	−0.375 −0.625	−0.125 −0.375	−0.375 −0.625	−0.417
A8	−0.125 −0.375	−0.125	−0.125	−0.188
A9	0.125 0.375	0.125 0.375	0.125 0.375	0.250
A10	0.375 0.625	0.375 0.625	0.375 0.625	0.458
A11	0.125 0.375	0.375 0.625	0.125 0.375	0.333
A12	0.125	0.125 0.375	0.125	0.188
A13	0.125	0.125 0.375	0.125 0.375	0.225
A14	0.125	0.125 0.375	0.125 0.375	0.225
A15	0.125	0.375 0.625	0.375 0,625	0.425
A16	0.125	0.125 0.375	0.125 0.375	0.225
A17	0.125 0.375	0.375 0.625	0.375 0.625	0.417
A18	−0.375 −0.625	−0.375 −0.625	−0.375 −0.625	−0.500
A19	0.375 0.625	0.625 0.875	0.375 0.625	0.583
A20	−0.375 −0.625	−0.375 −0.625	−0.375 −0.625	−0.500
A21	0.375 0.625	0.625 0.875	0.625 0.875	0.667
A22	−0.375 −0.625	−0.375 −0.625	−0.375 −0.625	−0.500
A23	0.625 0.875	0,625 0.875	0.625 0.875	0.750
A24	−0.375 −0.625	−0.625 −0.875	−0.375 −0.625	−0.583
A25	0.375 0.625	0.375 0.625	0.375 0.625	0.500
A26	−0.375 −0.625	−0.375 −0.625	−0.625 −0.875	−0.583
A27	0.375 0.625	0.625 0.875	0.375 0.625	0.583
A28	−0.375 −0.625	−0.375 −0.625	−0.375 −0.625	−0.500
A29	0.375 0.625	0.625 0.875	0.625 0.875	0.667
A30				

as "positive strong" in opposition to the others who gave a value "negative", then this expert's opinion in not counted to the final outcome and moreover the expert is punished (by reducing his trust from 1 to 0.8 for example). Following the steps of this algorithm, a table including all the weights is created (Table 2). In the last column of the table final weight of its variable is calculated, using centroid defuzzification method. In this technique, we make use of the shape 1 to defuzzify each of the experts proposed weights into their numeric values. Afterward, the final weight is producing by calculating the average of each value.

For example, an expert describes the influence of A2 to the output as "strong". In Fig. 2 we see that the triangle of "strong" is between the values 0.5 and 1. We separate the triangle into two equal triangles and for each one we calculate the median. In this

case, the medians are 0.625 and 0.875. We work the same for each expert. To calculate the final weight of each variable we take the average of every expert's deffuzified value. In our example the final weight from A2 to the output is A + B+…/6.

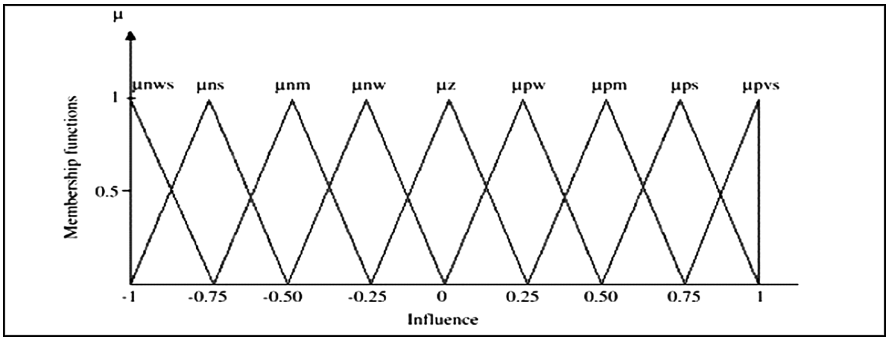

Fig. 2. Defuzzification values

This is the first step in the development of an expert system module that will help in the decision-making process, through the design of the knowledge representation and the design of reasoning with FCM to automate the decision making process. The constructed FCM model is represented in Fig. 3.

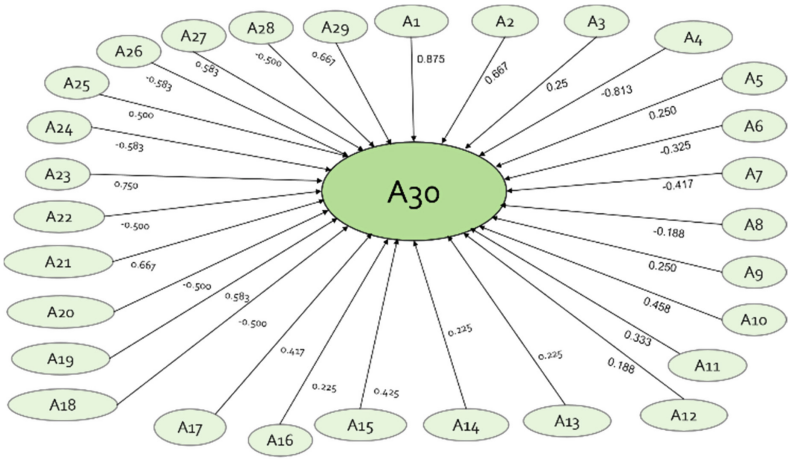

Fig. 3. The constructed FCM for the CAD

In each of the test scenarios, we have an initial vector Ai, representing the presented events at a given time of the process, and a final vector **A30_f**, representing the last state that can be arrived at. For the interpretation of the results, an average only for the

output value of the decision concept C30 is computed according to the following criteria [10]:

$$R(x) = \begin{cases} 0, x \leq 0.5 \\ \frac{x-0.5}{0.5} \times 100\%, x > 0.5 \end{cases} \quad (4)$$

In the above equation 0 represents the characteristic of the represented process by the concept is null, and 1 represents, the characteristic of the process represented by the concept is present 100%. The final value of decision concept applying this criterion is denoted by **A30_f**. This criterion can be modified according to with the expert judgment.

The algorithm used to obtain the final vector **A_f** (where the last value of the vector is the value **AD_f**) is the following:

(1) Definition of the initial vector *Ai* that corresponds to the elements identified in Table 1.
(2) Multiply the initial vector *Ai* and the matrix **E** defined by experts, as indicated in the previous Sect.
(3) The resultant vector is updating using Eqs. (1)–(2).
(4) This new vector is considered as an initial vector in the next iteration.

5 Simulations and Discussion of Results

After construction of FCM tool for the approach of assessing infectious diseases, a number of scenarios have been introduced and the decision-making capabilities of the technique will be presented by simulating these scenarios and finding the predicted outcomes according to the available data. In each of the test scenarios, we have an initial vector Ai, representing the presented events at a given time of the process, and a final vector **A_f**, representing the last state that can be arrived at.

First Scenario (Theoretical)
We consider a patient with atypical angina (C2 = 1), male (C5 = 5) at the age of 70 (C10 = 1), with dyslipidemia (C13 = 1) and obesity (C14 = 1). This patient has been proceeded to Treadmill Exercise Test the results of which can be described as ambiguous (C23 = 0.25). Thus the initial concept vector is: A (0 1 0 0 1 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0). After FCM inference, the system converges as in the following state vector named final concept vector: A_f (0 0.667 0 0 0.25 0 0 0 0 0 0.458 0 0 0.225 0.225 0 0 0 0 0 0 0 0 0.1875 0 0 0 0 0 0). The calculated value of decision concept (C30) is A30_f = 0.8985. The result after inserting that value to function (3) suggests that there is a possibility of 79.7% infection, which corresponds after the fuzzification to the linguistic value of "very strong" possibility.

Second Scenario (Theoretical)
We consider a patient with Nonanginal Chest Pain (C3 = 1), Female (C6 = 1) at the age of 65 (C10 = 1), smoker (C11 = 1). That patient were submitted to Treadmill Exercise Test, which was ambiguous (C23 = 0.5) and in Myocardial Perfusion

Imaging, the results of which was characterized as normal (C26 = 1). The initial concept vector is: A (0 0 1 0 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0). After FCM inference the final state vector A_f is created, as in the previous scenario. The calculated value of the decision concept (C30) is A30_f = 0.61. Using the function (3) the FCM suggests that there is a 23% possibility of infection, which after the fuzzification would take the linguistic value "low" possibility.

Third Scenario (A Real Scenario)
In this case, an asymptomatic (C4 = 1) patient was analyzed. The patient is male (C5 = 1) at the age of 70 (C10 = 1), smoker (C11 = 1), with Arterial Hypertension (C12 = 1) and Dyslipidemia (C13 = 1). Two tests took place, the results of which were both abnormal (C19 = 1), (C27 = 1). The initial concept vector is: A (0 0 0 1 1 0 0 0 0 1 1 1 1 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0). After FCM inference the final state vector A_f is created. The calculated value of the decision concept (C30) is A30_f = 0.8782. Using the function (3) the FCM suggests that there is a 75% possibility of infection, which after the fuzzification would take the linguistic value "high" possibility. After the Invasive Coronary Angiography, the results suggested that the patient was infected by one vessel disease. The extraordinary point of this case is that this patient was infected by the disease even though he had been asymptomatic.

Fourth Scenario (A Real Scenario)
In this scenario, the patient is a man at the age of 79. He has atypical angina, dyslipidemia, arterial hypertension and had been submitted to the test of Myocardial Perfusion Imaging, which is characterized as ambiguous. The initial concept vector is: A (0 1 0 0 1 0 0 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0.25 0 0). The calculated value of the decision concept (C30) is A30_f = 0.874. Using the function (3) the FCM suggests that there is a 74.8% possibility of infection, which after the fuzzification would take the linguistic value "high" possibility. In this case, the patient was infected by the disease.

Fifth Scenario (A Real Scenario)
In this very interesting scenario, we have a 59-year-old female patient, smoker, with dyslipidemia and arterial hypertension. The patient had been submitted to Myocardial Perfusion Imaging and Baseline ECG (Electrocardiogram). Both of the tests were characterized as severely abnormal. The initial concept vector is: A (0 0 0 1 0 1 0 0 1 0 1 1 1 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0). The calculated value of the decision concept (C30) is A30_f = 0.728. Using the function (3) the FCM suggests that there is a 46% possibility of infection, which after the fuzzification would take the linguistic value "medium" possibility. After the Invasive Coronary Angiography, the results suggested that the patient was infected by one vessel disease. The extraordinary point of this case is that this patient was infected by the disease even though he had been asymptomatic and female. The FCM corresponds satisfactorily in this exceptional scenario, considering that a 46% possibility for a female patient is a relatively high possibility.

Sixth Scenario (A Real Scenario)
Similar to the previous scenario, a female patient at the age of 45 is been examined. The patient has a family history of CAD and had been submitted to Treadmill Exercise Test, which was characterized as abnormal. Thus, the initial vector is A (0 0 0 1 0 1 0 1

0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0). The calculated value of the decision concept (C30) is A30_f = 0.2985. Using the function (3) the FCM suggests that there is a 29.85% possibility of infection, which after the fuzzification would take the linguistic value "low" possibility. In this case, the patient was not infected by the disease. Again, in this case, the FCM corresponds satisfyingly, as is predicts a relatively low possibility of risk.

Seventh Scenario (A Real Scenario)
In this case scenario a male patient at the age of 49, with Nonanginal chest pain is been examined. The patient is a smoker and the diagnose tests he underwent were the Treadmill Exercise Test and the Baseline ECG (Electrocardiogram). The first was considered as abnormal and the second as normal. Thus, the initial vector is A (0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0). The calculated value of the decision concept (C30) is A30_f = 0.71. Using the function (3) the FCM suggests that there is a 66% possibility of infection, which after the fuzzification would take the linguistic value "high" possibility. In this case, the patient was infected by the disease.

Eighth Scenario (A Real Scenario)
A 38-year-old female patient with nonanginal chest pain had been submitted to the Treadmill Exercise Test and the Baseline ECG (Electrocardiogram). As in the previous case, the first was considered as abnormal and the second as normal. Thus, the initial vector is A (0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0). The calculated value of the decision concept (C30) is A30_f = 0.58. Using the function (3) the FCM suggests that there is a 17.71% possibility of infection, which after the fuzzification would take the linguistic value "very low" possibility. In this case, the patient as it was expected was not infected by the disease.

Ninth Scenario (A Real Scenario)
A diabetic and smoker female patient at the age of 41 with arterial hypertension, obesity and dyslipidemia underwent the Treadmill Exercise Test and the Dobutamine Stress Cardiac Ultrasound test. The first test was considered normal and the second one was considered abnormal. The patient had atypical angina. Thus, the initial vector is A (0 0 1 0 0 1 0 1 0 0 1 1 1 1 0 1 0 0 0 0 0 1 0 0 0 0 0 0). The calculated value of the decision concept (C30) is A30_f = 0.84. Using the function (3) the FCM suggests that there is a 68% possibility of infection, which after the fuzzification would take the linguistic value "high" possibility. In this case, the patient as it was expected was infected by the disease.

Tenth Scenario (A Real Scenario)
A smoker male patient at the age of 67 with arterial hypertension, obesity and dyslipidemia underwent the Myocardial Perfusion Imaging Test and the Baseline ECG test. The first test was considered abnormal and the second one was considered normal. The patient had nonanginal chest pain and a family history of coronary artery disease. Thus, the initial vector is A (0 0 1 0 1 0 0 0 0 1 1 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0). The calculated value of the decision concept (C30) is A30_f = 0.90. Using the function (3) the FCM suggests that there is an 80% possibility of infection, which after the fuzzification would take the linguistic value "high" possibility. In this case, the patient as it was expected was infected by the disease.

Eleventh Scenario (A Real Scenario)
This scenario is similar to the above. Their difference is that the patient is female, at the age of 68 with the other factors to be the same. The first test was considered moderately abnormal and the second one was considered normal. The initial vector is A (0 0 1 0 0 1 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0.55 0 0). The calculated value of the decision concept (C30) is A30_f = 0.69. Using the function (3) the FCM suggests that there is a 30% possibility of infection, which after the fuzzification would take the linguistic value "low" possibility. In this case, there was no infection.

From the above two theoretical scenarios and nine real scenarios, interesting information can be obtained. First of all, it has been proven that the FCM model for the prediction of CAD, which was constructed, is applicable to real scenarios and is responding satisfactorily both into male patients and female patients, despite the fact that there is a complexity as to how each gender affects the risk of infection in real life. Moreover, it has been illustrated that the model is handling well the simultaneous presence of different risk factors and diagnostic tests, notwithstanding the different nature of these concepts. It has been an encouraging attempt to construct a computational model for the prediction of a disease and certainly the future research should deal with the ways of improving the accuracy of the model and its sufficiency in dealing with controversial scenarios.

6 Conclusions and Future Research Directions

The constructed FCM-MDSS model was tested into several real examples, the results of which can't be presented in this paper. The constructed FCM responded satisfactorily to the tests and offered an accurate prediction on the likelihood of infection. One main advantage using the fuzzy cognitive maps is the fact that they can correspond to cases with "missing data" as the scenarios above. The outcome, of course, would be more accurate assuming that all the concept values were inserted into the model. The weight value of each concept that defines the interaction between the concept and the decisive concept A30 are given by the experts. The weights between the concepts play the most decisive role in the procedure. As a matter of fact, the experts must be chosen wisely and moreover, they have to cooperate with each other.

After several simulations, we summarize some weaknesses that could be a field of future research, as to how those weaknesses could be overpassed. One main weakness is that all the factors, from the special characteristics of the patients to the test results are been described as similar type values, though they aren't. The test results, for example, have a completely different nature than the age and the gender of the patient. After the simulation, variable as the age for example and a test result might have the similar numerical influence to the output value. Another disadvantage of the model is that in this level is static. This means that the weights given by experts can't change during the process in order to achieve a more exact result. So for future research directions, this is a very challenging problem and can be investigated using learning algorithms and using the knowledge and expertise of the physician experts [11]. Another future research problem is to take into consideration another parameters and

factors of the CAD medical problem such as diet (e.g. Mediterranean), exercise, weight, drinking a lot and other possible diseases such as depression, and some others. Using also intelligent system concepts in connection with FCM modeling approach is a very challenging and promising research topic [19]. Appropriate and more friendly user software tools are needed. One thing is for sure that FCMs will be useful for these future studies.

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