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Prediction of Severity of Diabetes Mellitus using Fuzzy Cognitive Maps

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Abstract
The objective to develop this research paper is concerned with a system which helps diagnose the severity of diabetes. The disease named diabetes mellitus makes the body unable to handle sugar so it causes thirst, frequency of urination, tiredness and many other symptoms. The diabetes mellitus describes a metabolic disorder characterized by chronic hyperglycemia with disturbances of carbohydrate, fat and protein metabolism resulting from defects in insulin secretion, insulin action, or both. It can be caused by number of factors like pancreatic dysfunction, obesity, hereditary, stress, drugs, alcohol etc. It includes long term damage, dysfunction and failure of various organs. The effects of diabetes mellitus include long term damage and failure of various organs. Diabetes mellitus may present with characteristic symptoms such as thirst, polyuria, blurring of vision, and weight loss. This Paper is implemented on soft computing technique, namely Fuzzy Cognitive Maps (FCM) to find out the presence or absence of diabetes mellitus based on the input of sign/symptoms recorded at three fuzzy levels developed by the domain experts. The large amount of data and information that needs to be handled and integrated requires specific methodologies and tools. The FCM based decision support system was developed with a view to help medical and nursing personnel to assess patient status assist in making a diagnosis. The software tool was tested on 50 cases, showing results with an accuracy of 96%. The analysis of experimental results of different applicants checks the correctness and consistency of decision Support system for correct decision making.
Keywords: Fuzzy Logic, FCM, Diabetes Mellitus, Prediction, Symptoms.

1 Introduction

FCM have been employed to model knowledge-based systems, the most common type of artificial intelligence in medicine systems in routine clinical use for diagnosing thyroid diagnosis. They contain medical knowledge, usually about a very specifically defined task, and are able to reason with data from individual patients to come up with reasoned conclusions (Papageorgiou et al. 2008b). The computer-based model is used for differential diagnosis of specific language impairment (SLI), a language disorder that, in many cases, cannot be easily diagnosed. This difficulty necessitates the development of a methodology to assist the speech therapist in the diagnostic process. The methodology tool is based on fuzzy cognitive maps and constitutes a qualitative and quantitative computer model comprised of the experience and knowledge of specialists. The development of the model was based on knowledge from the literature and then it was successfully tested on four clinical cases (Georgopoulos et al. 2003). In the medical application area, FCMs have been used to model and analyze temporal medical data. In this proposed framework ,the division and merging of concepts depending on the time scale used for learning and learning the FCM with the use of a virtual time scale with logical time slots of variable real-time length ,the two new propositions to the adaptive algorithm used for learning FCMs are introduced. The experimental results presented by Froelich & Wakulicz-Deja (2009) show the impact of the introduced enhancements on the process of learning of FCM .A new framework for the construction of augmented Fuzzy Cognitive Maps based on Fuzzy Rule-Extraction methods for decisions in medical informatics is investigated. Fuzzy cognitive maps are knowledge-based techniques which combine elements of fuzzy logic and neural networks and work as artificial cognitive networks. The knowledge extraction methods used in this study extract the available knowledge from data in the form of fuzzy rules and insert them into the FCM, contributing to the development of a dynamic decision support system (Papageorgiou 2011). The idea of combining decision tress with FCMs was explored in order to maintain the potential advantages of both techniques. The new integrated system has been introduced for medical decision making process. This work proposes a new framework of Fuzzy Cognitive Map utilizing Decision Trees that updates the traditional Fuzzy Cognitive Map and has better characteristics. The inclusion of decision tree generators in the structure of the FCM, and the new DTFCM system gives better results. The performance of the new methodology can deal with different kind of input data eliminating numerical errors (Papageorgiou et al. 2006). The fuzzy cognitive map (FCM) is an efficient technique for characterization of Brain tumor. Brain tumors are considered as one of the most lethal and difficult to identify and be treated forms of cancer (DeAngelis 2001). Pathologists evaluate the aggressiveness of brain tumors by visually examining tissue section (biopsies) based on guidelines determined by the World Health Organization (WHO) (Kleihues 1993). A new method for characterizing brain tumors is presented (Papageorgiou et al. 2008a), which models the human thinking approach and the classification results are compared with other computational intelligent techniques proving the efficiency of the FCM methodology. Urinary Tract Infection (UTI) is a bacterial infection that affects any part of the urinary tract. It can be classified as uncomplicated (patients with urinary tracts that are normal from both structural and functional perspective) and complicated The treatment of uncomplicated urinary tract infections is a complex medical task where a number of parameters, tests, symptoms and laboratory results are present. The knowledge of physicians according to the symptoms and clinical measurements are the main point to succeed a diagnosis, suggest a therapeutic treatment and monitoring patient status.FCM based tool plays an important role for modeling and predicting the infectious diseases such as urinary tract infection. The proposed FCM can be used to make the medical knowledge widely available through computer consultation systems. The system presented is a new decision making tool to be evaluated for UTI assessment and be showed that it can produce correct decisions in cases where the doctors' suggestions may be wrong for the first therapy (Papageorgiou et al. 2009a). The process on modeling medical knowledge and making decisions in medical domain is very complex. The research goal to be achieved is to solve the problem of modeling medical knowledge and predict severity of infectious pneumonia by handling uncertainty and insufficient information for system concepts. The main idea was to provide an additional tool in the decision process analyzing the parameters (symptoms/observables) and the effects using a simplified model of the infectious diseases decision making using FCM (Papageorgiou et al. 2009b).

2. Methodology

2.1 Fuzzy Cognitive Maps

Fuzzy Cognitive Map (FCM) methodology is a symbolic representation for the description and modelling of complex system. FCM describe different aspects in the behaviour of a complex system in terms of concepts; each concept represents a state or a characteristic of the system and these concepts interact with each other showing the dynamics of the system. FCMs have been introduced by Kosko (1986) assigned directed graphs for representing causal reasoning and computational inference processing, exploiting a symbolic representation for the description and modelling of a system. Concepts are utilized to represent different aspects of the system, as well as, their behaviour. The dynamics of the system are implied by the interaction of concepts. FCM structures are used to represent both qualitative and quantitative data. The construction of an FCM requires the input of human experience and knowledge on the system under consideration. Thus, FCMs integrate the accumulated experience and knowledge concerning the underlying causal relationships amongst factors, characteristics, and components that constitute the system.

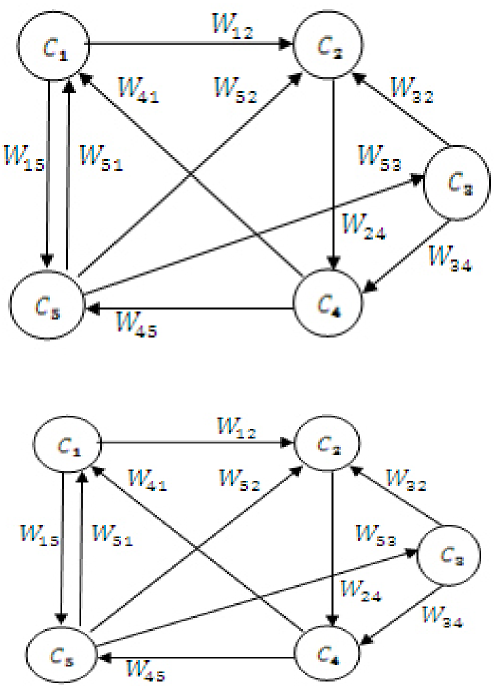


Figure 1. Basic structure of FCM

An FCM consists of nodes–concepts, C_i i = 1,…….,N, where N is the total number of concepts. Each node–concept, represents one of the key–factors of the system, and it is characterized by a value A_i Є [0, 1], i =

1,……,N. The concepts are interconnected through weighted arcs, which imply the relations among them. A simple FCM with five nodes and ten weighted arcs is illustrated in Figure. Each interconnection between two concepts C_i and C_j have weight W_{ij}, which is proportional to the strength of the causal link between C_i and C_j. The sign of W_{ij} indicates whether the relation between the two concepts is direct or inverse. The direction of causality indicates whether the concept C_i causes the concept C_j or vice versa. Thus, there are three types of weights:

$$\begin{cases} W_{ij} > 0; \text{ expresses positive causality,} \\ W_{ij} < 0; \text{ expresses negative causality,} \\ W_{ij} = 0; \text{ expresses no relation,} \end{cases}$$

Human knowledge and experience on the system determines the type and the number of nodes, as well as the initial weights of the FCM. The value A_i , of a concept C_i, expresses the quantity of its corresponding physical value and is derived by the transformation of the fuzzy values assigned by the experts, to numerical values. Having assigned values to the concepts and the weights, the FCM converges to a steady state.

At each step, the value A_i of a concept is influenced by the values of concepts–nodes connected to it, and is updated according to the scheme (Kosko 1997)

$$A_i(k+1) = f\left(A_i(k) + \sum_{\substack{j=1 \\ j \neq i}} W_{ji} A_j(k)\right) \tag{1}$$

Where k stands for the iteration counter; and W_{ji} is the weight of the arc connecting concept C_j to concept C_i . The function f is the sigmoid function:

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

where $\lambda > 0$ is a parameter that determines its steepness in the area around zero. In our approach, the value $\lambda = 1$ has been used. This function is selected since the values A_i of the concepts, by definition, must lie within [0, 1]. The interaction of the FCM results after a few iterations in a steady state, i.e. the values of the concepts are not modified further. Desired values of the output concepts of the FCM guarantee the proper operation of the simulated system. The design of an FCM is a process that heavily relies on the input from experts (Stylios & Groumpos 2000). At the beginning, experts are pooled to determine the relevant factors that will be represented in the map as concepts. Then, each expert describes the causal relationships among the concepts using a linguistic notion. First, experts determine the influence of a concept on another, as "negative", "positive" or "no influence". Then the linguistic weights, such as "strong", "weak", etc, are assigned to each arc. The linguistic variables that describe each arc, for each expert, are defined by Lin & Lee (1996). The linguistic variables are combined, and the aggregated linguistic variable is transformed to a single linguistic weight, through the SUM technique. Finally, the Center of Area (CoA) defuzzification method (Kosko 1992) (Aguilar 2002) is used for the transformation of the linguistic weight to a numerical value within the range [-1, 1]. This methodology has the advantage that experts are not required to assign directly numerical values to causality relationships, but rather to describe qualitatively the degree of causality among the concepts. Thus, an initial matrix $W^{initial} = [W_{ij}]$, i, j = 1,…,N, with W_{ii}= 0, i = 1,…,N, is obtained. Using the initial concept values, A_i, which are also provided by the experts, the matrix $W^{initial}$ is used for the determination of the steady state of the FCM, through the application of the rule of Eq. (1).

The critical dependence on the opinions of the experts and the potential convergence to undesired steady states are the two most significant weaknesses of FCMs. Learning procedures constitute means to increase the efficiency and robustness of FCMs, by updating the weight matrix so as to avoid convergence to undesired steady states. Up–to– date, there are just a few FCM learning algorithms and they are mostly based on ideas coming from the field of artificial neural networks training (Dickerson & Kosko 1994) (Papageorgiou et al. 2002). Such algorithms start from an initial state and an initial weight matrix, $W^{initial}$, of the FCM, and adapt the weights, in order to compute a weight matrix that leads the FCM to a desired steady state. The desired steady state is characterized by values of the FCM's output concept accepted by the experts.

3. Design Methodology

The process of diagnosing a Diabetes Mellitus is a complex process with enough parameters, factors, different socio economic status and life-style related conditions. The origin of this work is based on the uncertainty in deciding the severity and the cause of the disease. This is particularly important because the treatment varies depending upon the severity of the disease. The effects of diabetes mellitus include long term damage, dysfunction and failure of various organs. Diabetes mellitus may present with characteristic symptoms such as thirst, polyuria, blurring of vision, and weight loss. After discussion with Doctors-experts, we have decided 18 parameters (concepts) involved in the development of diabetes. These parameters, their impacts, and impacts levels are given in Table 1.

Table 1: Input parameters for applicant

Parameters	Impact	Impact Levels
Pancreatic Dysfunction	Positive	Low, Medium, High
Complete Insulin Deficiency or its insufficient production.	Positive	Low, Medium, High
Insulin Resistance	Positive	Low, Medium, High
Obesity	Positive	Low, Medium, High
Physical Inactivity	Positive	Low, Medium, High
Hereditary	Positive	Low, Medium, High
Extreme Birth Weight	Positive	Low, Medium, High
Drugs	Positive	Low, Medium, High
Alcohol	Positive	Low, Medium, high
Smoking	Positive	Low, Medium, High
Pregnancy	Positive	Low, Medium, High
Stress	Positive	Low, Medium, High
Pollution	Positive	Low, Medium, High
Poverty	Positive	Low, Medium, High
Age	Positive	Low, Medium, High
High Blood Pressure	Positive	Low, Medium, High
Race at Risk	Positive	Low, Medium, High
Metabolic Syndrome	Positive	Low, Medium, High

Consider the Factor: Impact of Stress on Diabetes

In the survey conducted, 3 Experts opinion suggested medium impact of stress on diabetes; while other 2 Expert's said the impact is low. In order to frame rules for fuzzy sets: Diabetes and Stress, first Membership functions are designed. A membership function maps objects in a domain of concern to their membership value in the set. For input variable, 2 triangular membership functions with parameters (0,0,0) and (1,1,1) respectively are designed. For Output variables either 3 valued MF's or 5 valued MF's are drafted. For 3 valued:- Trapezoidal membership function is used for Low and high linguistic variables with parameters(0,0,0.25,0.5) and (0.5,0.75,1,1) respectively and Triangular membership function is used for Medium with parameters(0.25,0.5,0.75).

For 5 valued:- Triangular MF is used for Very low(0,0,0.225), Low(0,0.225,0.45), Medium(0.225,0.45,0.675),High(0.45,0.675,0.9) and Trapezoidal MF is used for High(0.5,0.75,1,1). For stress on diabetes 3 valued membership functions are used.

The following 2 rules are designed based on Expert s view:

If Stress is "yes" then Diabetes is "medium" with 0.6(3/5).

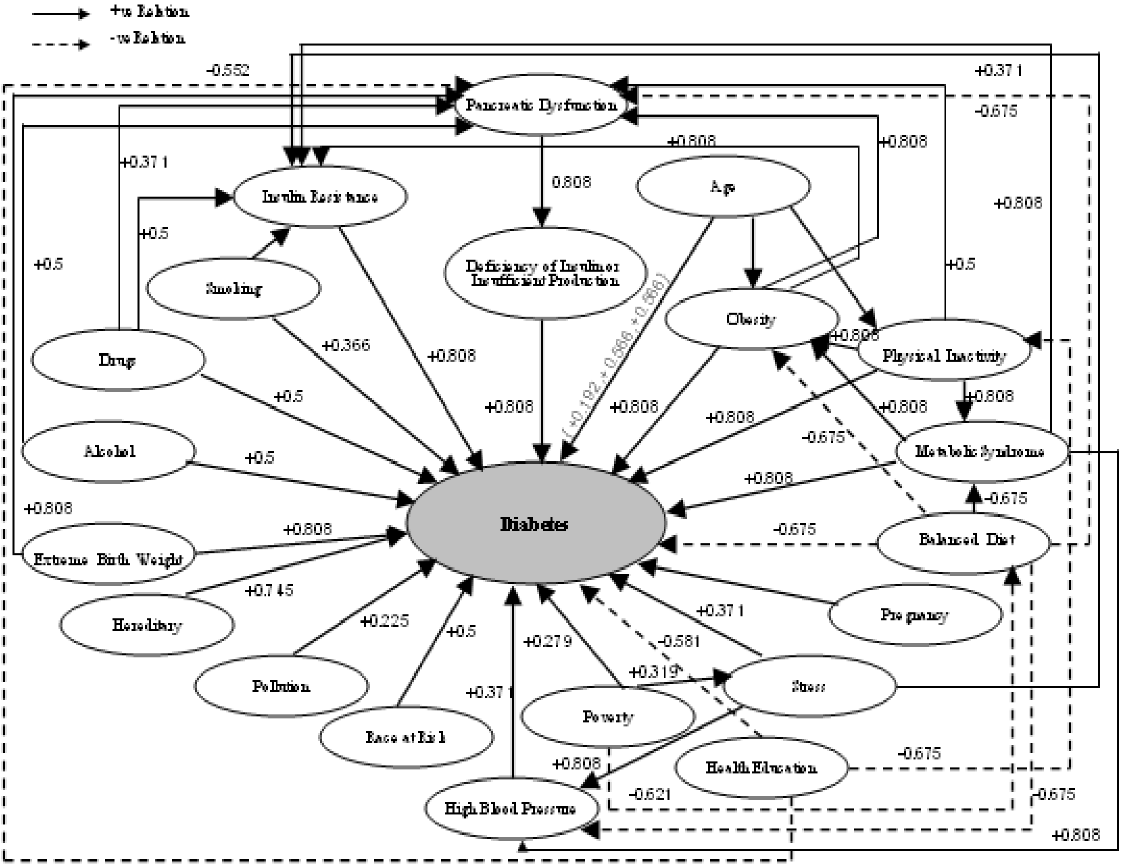
If Stress is "yes" then Diabetes is"low" with 0.4(2/5).

Then using the sum technique the linguistic weights are aggregated. After then "the centroid" deffuzification method is implemented to calculate the numerical values of the weight. The crisp weight of 0.371 has been produced and assigned to this interconnection.

The same approach was used to determine all weights of the FCM.

Fuzzy Cognitive Map with weights computation



4. *Implementation*

Fuzzy interference system as given in Figure 1 shows the mapping of inputs and outputs. The names of the processing methods and inputs can be changed.

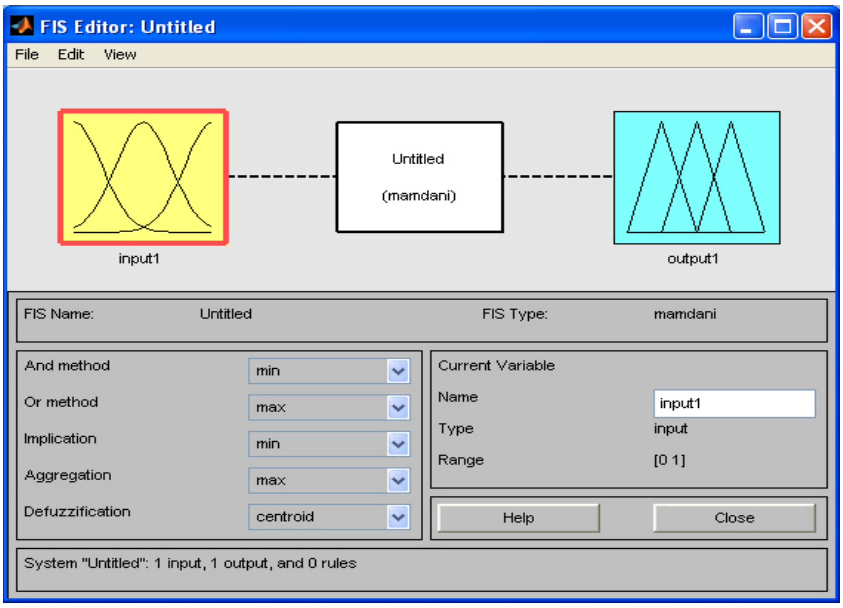


Figure 2. Input and output Parameters

Rule editor given in Figure2 helps to add, change and delete rules.

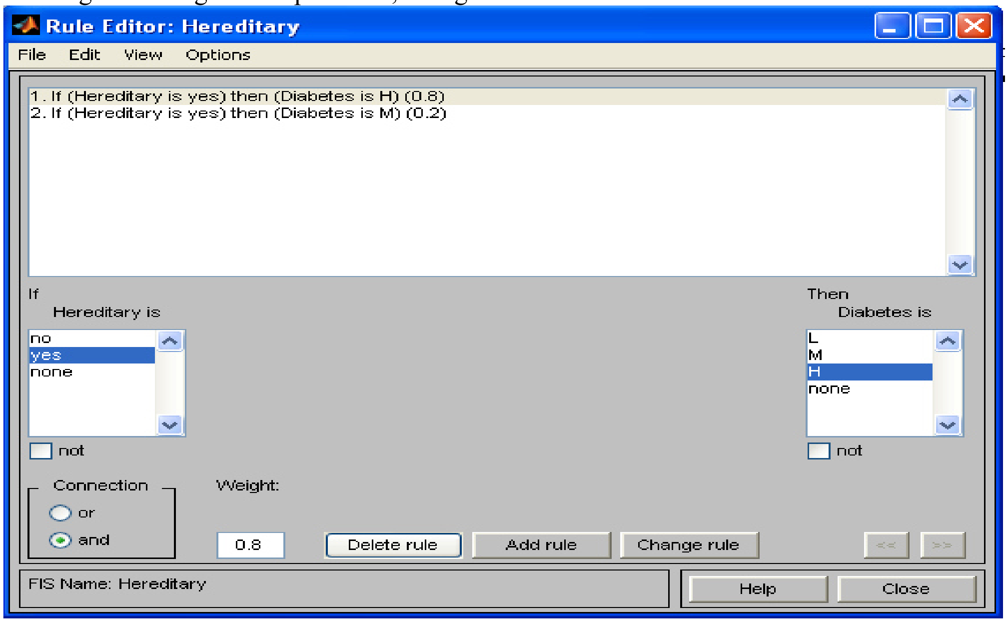


Figure 3. Rule editor for different Rules

4. Experiments and Results

After construction of FCM tool for the approach of assessing diabetes, a number of scenarios have been introduced and the decision making capabilities of the technique are presented by simulating these scenarios and finding the predicted outcomes according to the available data.

<u>First Scenario:</u> In the first scenario a patient with insulin deficiency, High blood pressure, addiction to both alcohol and smoking is considered. His age is between 41-61.

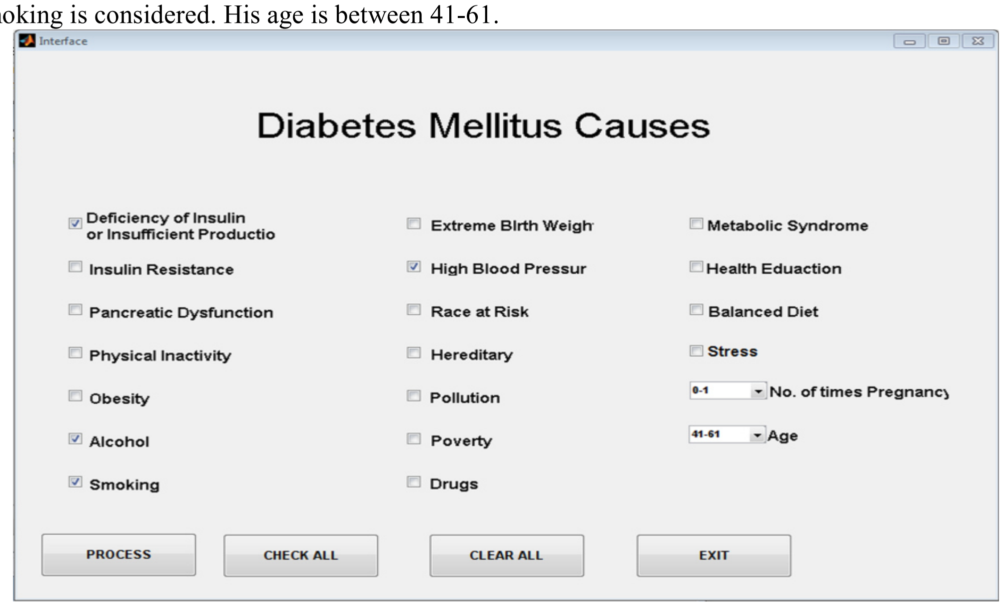


Figure 4. Inputs

Our result shows that chances of having diabetes to the patient are 70.7538%

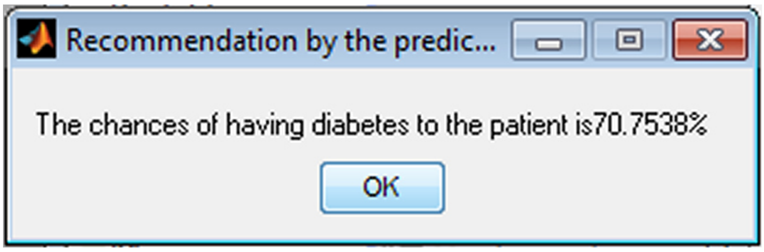


Figure 5. Recommended Results for patient.

Second Scenario: In the second scenario a patient with insulin resistance, physical inactivity, stress and pregnancy between 2-5 is considered. She age is between 41-61.

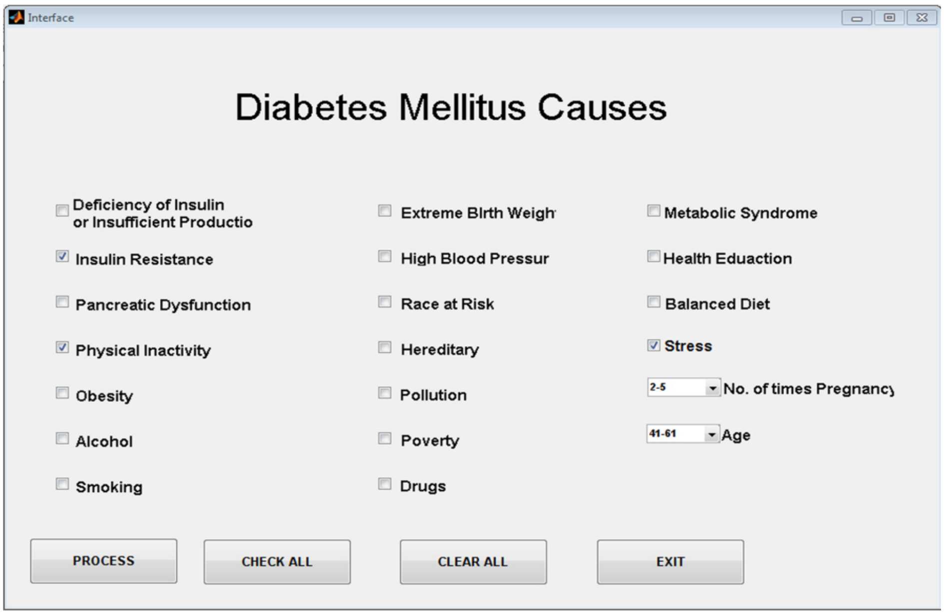


Figure 6. Inputs

In this case the predictor recommends that chances of having diabetes to the patient are 69.8488%. The patient is recommended to go for appropriate medication.

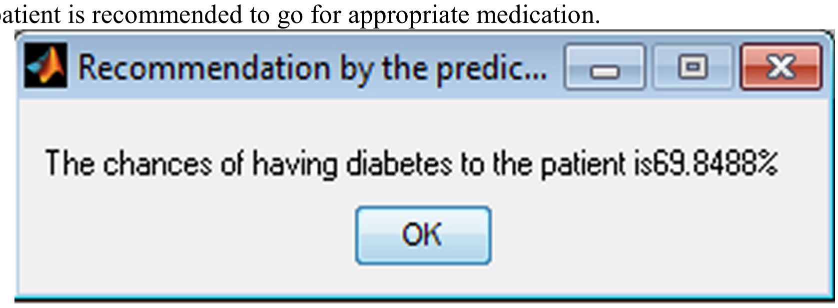


Figure 7. Recommended Results for patient.

5. Conclusion

The objective of this work was to model and efficiently predict the severity of diabetes mellitus, considering fuzzy relations between signs/symptoms/risk factors and severity of this disease based on the expert's medical knowledge. This goal was achieved by the implementation of FCMs. The proposed approach for making predictions in diabetes mellitus was established as an alternative knowledge-based system inheriting the advantages of fuzzy relations with the simplicity, flexibility, transparency and easiness of use. The resulting fuzzy relational model was used to analyze, simulate, test the influence of parameters (symptoms/risk factors) and the effects, and predict the possibility of the disease. Finally, a front-end decision support tool about was created and validated.

With the proposed methodology, it becomes feasible for the users to support their decision process. The experiments have shown that the proposed system predicts the severity of the disease with 96% accuracy.

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