Frontiers in Computer Science and Artificial Intelligence
ISSN: 2978-8048
DOI: 10.32996/fcsai
Journal Homepage: www.al-kindipublisher.com/index.php/fcsai

FCSAI
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Computational Health Informatics for Diabetes Risk Prediction: An Optimized Fuzzy Logic Framework

Mohanad F. Jwaid
Department of Business Administration, Alhadara University college, Salahaldeen, Iraq

Corresponding Author: Mohanad F. Jwaid, **E-mail**: Mohanad02jwaid@gmail.com

| ABSTRACT
In order to provide a non-categorical substitute for conventional screening methods, this study sought to create an optimum fuzzy logic system to evaluate type 2 diabetes risk for the Iraqi population. The Simulated Annealing heuristic was used to enhance the membership functions of a Mamdani-type fuzzy inference system. The system's performance was assessed using diagnostic metrics in comparison to the existing FINDRISC questionnaire after it was trained and tested on clinical data from 295 patients in Baghdad. Results showed that the optimised fuzzy system matched the gold standard's sensitivity (87.5%) but achieved superior specificity (69.41% vs. 52.55%) and improved positive predictive value (0.3097 vs. 0.2244). The conclusion affirms that the simulated annealing-optimised fuzzy system is a viable and more descriptive tool for personalised diabetes risk prediction, effectively distinguishing between healthy and at-risk individuals based on clinical profiles.

| KEYWORDS

Diabetes Risk Prediction, Fuzzy Logic, Simulated Annealing, FINDRISC, Diagnostic Accuracy, Optimization.

| ARTICLE INFORMATION

ACCEPTED: 01 March 2026 **PUBLISHED:** 25 April 2026 **DOI:** 10.32996/jcsts.2026.5.5.9

1. Introduction

The World Health Organization (WHO), in its global report on diabetes mentions that approximately 70% of adults in Iraq suffer from overweight or obesity, important factors in the development of diabetes mellitus type 2. Furthermore, the National Institute of Public Health (INSP), in the National Health and Nutrition Survey, reports that in Iraq 8.6 million people over 20 years old have been diagnosed with diabetes, corresponding to 10.3% of this sector of the population [1].

In the medical field, with the purpose of facilitating decision or classification tasks when treating a patient, and to prevent diabetes problems, various systems based on fuzzy logic have been developed. However, when developing any system of this type, it is of vital importance to have an adequate selection of the membership functions and their associated parameters, as well as the rules that govern the system, otherwise, the software will yield results that do not describe reality [2]. These systems, although initially designed by an expert in the field, the human configuration may not be the most appropriate, so it is not uncommon to use algorithms based on experience with the aim of finding viable configurations that help the system solve the problem. These algorithms, also called metaheuristic methods, have been used to optimize systems in multiple areas, thus achieving to accurately describe reality. The above justifies relying on computational systems that allow knowing the risk of suffering from the aforementioned disease to carry out prevention tasks [3].

This research shows the results of developing a fuzzy logic system to determine the percentage risk of suffering from diabetes mellitus type 2, of a patient based on simple clinical data to obtain [4-6]. The internal functions of the system were optimized with the Simulated Annealing heuristic technique [7], the system is tested with data from 295 real patients from the city of Baghdad in Iraq, the effectiveness in terms of positive predictive value, negative predictive value, sensitivity and specificity is compared with that obtained by the FINDRISC test as the gold standard, which is used as a screening test to predict the risk of suffering from type 2 diabetes within the next 10 years of the individual's life.

2. Review of literature

This section describes some works involved in the detection and classification of patients with diabetes through systems based on fuzzy logic and optimized by heuristic methods, as well as their obtained efficiency.

Reddy and Khare (2017) [8], publish a study that establishes a prediction for heart problems and risk of suffering from diabetes. Using rough set theory and binarization of data from the UCI database, from a total of 13 risk factors such as age, sex, BMI, among others, 6 were selected to then normalize and optimize them using the Cuckoo Search heuristic, subsequently an expert designs triangular membership functions that are not optimized. To evaluate the performance, both the accuracy with respect to the corpus, as well as sensitivity and specificity are reviewed, the score was 91%, 94% and 90% respectively. When establishing a comparison against a system based on firefly and bat search, it is noted that the 3 criteria are better, exceeding the 68%, 79% and 84% of that study, and the 72.6%, 100% and 0% of an existing system in the industry, although with other datasets a performance lower than expected can be perceived, the study concludes by emphasizing the reduction of data by more than 50%.

Sahu, Verma and Reddy (2017) [9], obtained a series of unspecified data from a local pathological laboratory, these data were reduced using Locality Preserving Projections and the system rules were calculated using Ant Colony Search, these rules were optimized using the Cuckoo Search technique, the membership functions were designed in a triangular shape by an expert and were not optimized. The accuracy of the results with respect to the consulted corpus, as well as sensitivity and specificity are used to measure the effectiveness of the system in 10 runs, then it is compared against another implementation of the same system optimized using a hybrid of Firefly and Bat Search. It is concluded that the use of Cuckoo Search shows better performance than the Firefly-Bat variant, however, the results in each run are variable in the system's accuracy percentage ranging between 64% and 74%.

Bressan and Molina (2020) [10], developed a fuzzy classifier to catalogue a group of people as patients who require basic care or who require specialized care. Starting from clinical data of age, triglycerides, time of disease evolution, BMI, per capita income, abdominal circumference and schooling time provided by the Unified Health System of Brazil, an expert discarded non-essential attributes and, using a decision tree with the C4.5 algorithm all the rules required by the system were generated. An implementation was made for each group, the membership functions were chosen in a triangular shape and adjusted using an Adaptive Neuro-Fuzzy Inference System, thus evading subsequent optimization. Finally, 10000 patients were simulated to be classified by the system, the results were compared against an expert system. The resulting classification was consistent with that of the expert system, so this implementation saves time and money for the health system by providing specialty treatment only in necessary cases.

Pradini, et al (2020) [11], implemented a system based on the Tsukamoto inference method to calculate the risk of suffering from diabetes with very little patient information, the corpus used consists of only 2 volunteer patients, the data provided are age, BMI and blood pressure. An expert designs triangular membership functions that are subsequently optimized by the Particle Swarm algorithm, in addition, he provided 6 rules for system control. Efficiency is obtained by calculating the mean square error with respect to the risk percentage predicted by a specialized study, an error of 0.012% is obtained after optimization and is compared with the 25.9% error obtained by the system without optimization. The authors do not rule out the possibility of using other corpora available online to continue with the development and refinement of the system.

3. Materials and methods

Next, the theoretical framework associated with this research is briefly reviewed, as well as the description of the implemented fuzzy system.

3.1. Fuzzy Logic

Traditional logic guides us to the use of two values when defining the membership of objects to a group, however, this approach does not necessarily describe the reality presented. To reduce failures derived from the classical approximation, the concept of fuzzy set proposed by Zadeh in 1965 is introduced. A fuzzy set is understood as a set of ordered pairs, each tuple is formed by an element and its membership value in the set. The membership value of an element x in set A is given by $f_A(x)$ called membership function, the degree of membership can only be in the interval [0,1]. The most used functions are triangular, but gamma type, linear, sigmoidal, etc. can also be found [12].

As an example, consider the mapping of the membership functions for temperature in degrees Celsius, where the linguistic variables or categories to use are cold, cool, warm and hot, and the universe of discourse is defined between 0° and 80°, Figure

1, shows the result of defining these linguistic variables, consider that the selection of the shapes of the membership functions, as well as their positioning in the universe of discourse may vary depending on the purpose.

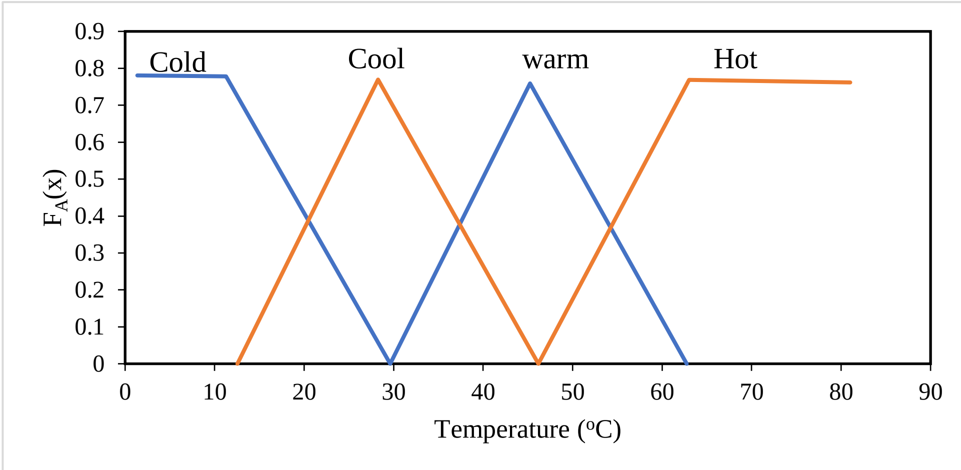

Figure 1. Membership functions for temperature**.**

Humans communicate in our own natural language with simple terms that may imply ambiguity, for example, terms like very slow, young, or very ugly. From this way of speaking, linguistic models are generated using fuzzy systems, a system of this type for any purpose includes a Fuzzy Inference System (FIS) module. Systematically, a FIS is a way of mapping the input space to the output space through decision making based on rules. In the field of artificial intelligence, there are various ways to represent knowledge, however, the most common is to encapsulate it in expressions of the type IF premise (antecedent), THEN conclusion (consequent), this model is called IF-THEN rule [13], and is associated with deductive thinking starting from a fact or premise to infer a second fact, also called conclusion.

Rule-based systems are especially useful when modeling complex systems attached to the human way of thinking, because they make use of linguistic variables, antecedents, consequents and logical connectives to establish the system rules. The logical connectives "and" and "or", have the purpose of establishing restrictions, in addition, these rules, as well as the associated membership functions, are stored in the knowledge base, which is machine readable, which is capable of obtaining automatic deductive reasoning from it, the stored knowledge must be logical and consistent with reality and can be expanded. A FIS is fundamentally composed of three stages, the first is fuzzification, the process in which a certain quantity is converted to a fuzzy quantity, this is achieved by obtaining the membership value of the input data x in each of the linguistic variables, that is, the conversion of a precise quantity to a fuzzy quantity, subsequently the inference engine is used, which applies the IF-THEN implication rules to transform the fuzzified input variables into a fuzzy output variable using the knowledge base, finally the defuzzification process is carried out, because in most cases, the fuzzy output of a system must be quantified as a single scalar or a value of the universe of discourse, the most common procedure is to calculate the weighted average because it is one of the computationally most efficient methods, although it is only applicable for output membership functions that are symmetric, the expression for the weighted average is:

$$z^* = \frac{\sum \mu_C(\bar{z}) \cdot z}{\sum \mu_C(\bar{z})} \qquad (1)$$

The basic structure of a Fuzzy Inference System is shown in Figure 2.

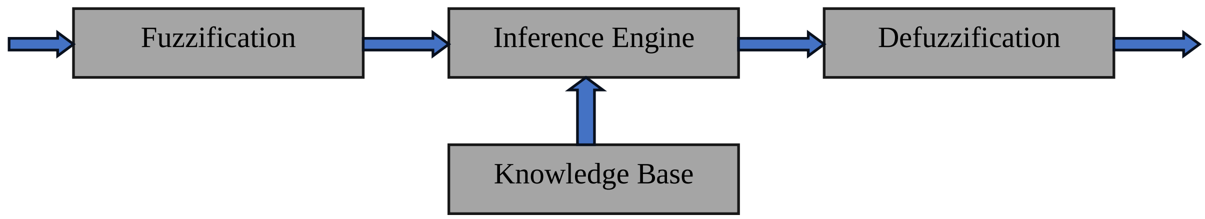

Figure 2. Structure of the Fuzzy Inference System (FIS). Source: Jain and Raheja, own translation.

The most used inference method both in the literature and in implementation is the Mamdani method, developed by Mamdani and Assilian in 1975, it considers several rules with several input variables and a single output variable. As an example, a collection of r inference rules composed of 2 input variables x_1, x_2 in the antecedent with a unique consequent is shown:

$$\text{IF } x_1 \text{ is } A_1^k \text{ and } x_2 \text{ is } A_2^k \text{ THEN } y^k \text{ is } B^k k = 1,2,\ldots,r \qquad (2)$$

where A_1^k and A_2^k are fuzzy sets representing the antecedent of the k-th rule and B^k is the fuzzy set representing the k-th consequent.

Generally the min-max process is used: For each of the facts x_1 is A_1^k and x_2 is A_2^k, the intersection operator is applied using the minimum of the membership values, this will be the value at which the output function B^k is cut, this process is repeated for all r rules of the system. Finally, the union is obtained with the maximum of all the membership functions of the consequents B^k, this last process is called aggregation, because it integrates all the values to the output of all the rules of the system [14]. This technique is shown graphically in Figure 3 and can be expressed as:

$$f_{B^k}(y) = \max_k \{\min [f_{A_k}(\text{input}(i)), f_{A_k}(\text{input}(j))]\}, k = 1,2,\ldots,r \qquad (3)$$

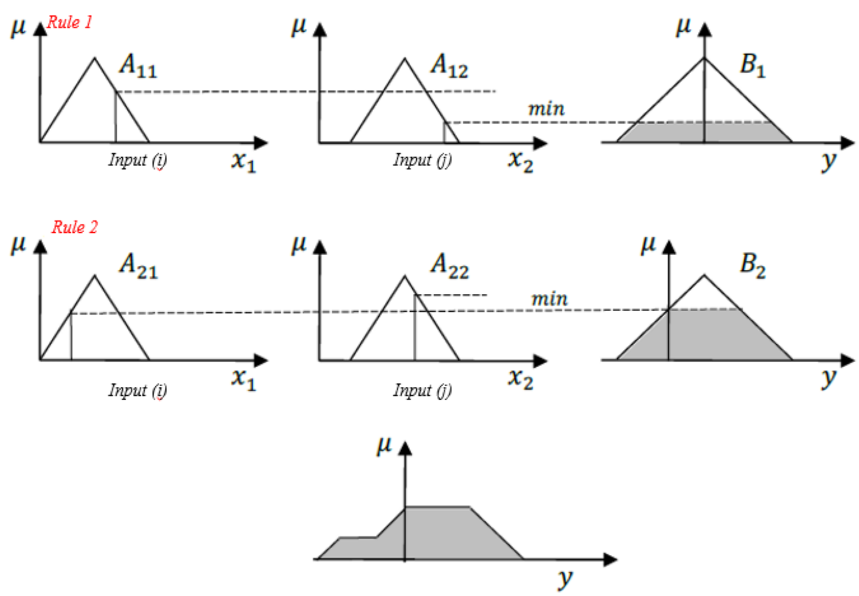

Figure 3. Min-max inference for the Mamdani method.

3.2. Simulated Annealing

Optimization problems have a wide number of potential solutions, the objective is to find the appropriate values for the decision variables involved that allow obtaining the maximum or minimum value of an objective function, various problems have high algorithmic complexity, even so, they can be solved efficiently. For this, procedures are generated that can find acceptable solutions without necessarily being optimal, an exact method will always generate an optimal solution, but a heuristic method simply seeks to provide an approximate solution to the problem that may often not be optimal [15].

Heuristic techniques are usually used when there is no exact method to find the solution to the problem, or, there is an exact method, but it is computationally very expensive, they are also applied when the problem does not require the exact solution or if there are conditions difficult to model. Heuristic methods are used in a wide range of problems and some of their advantages are: having a potentially good solution from the starting point, being able to be used to solve only a part of the problem and being very simple to understand.

Simulated Annealing was designed for combinatorial optimization problems for routing and traveling salesman (TSP) in 1983 by Kirkpatrick, Gellat and Vecchi[16]. Zhang [17] describes it as an algorithm that tries to imitate the annealing process of metallic materials. By cooling them to a state of minimum energy, larger crystals are obtained that reduce the defects of their structures. Annealing is a procedure that requires utmost care of temperature, both when heating the metal and in its cooling rate, one of its advantages is the ability to evade local minima and be able to converge to the local optimum under appropriate conditions, that is, if good random steps are used with an adequate cooling rate.

The way of operation of annealing consists of iteratively applying a random search and accepting both points that improve the solution and some others that do not, any movement that improves the solution is automatically accepted, however, any point that does not improve it, can be accepted with a probability p, known as transition probability, given by:

$$p = e^{-\frac{\Delta f}{T}} \qquad (4)$$

Where Δf is the difference between the current solution and the best of the objective function up to that moment and T is the current temperature.

By automatically accepting a better solution, the current region is being exploited in search of a local optimum, while by accepting with a low probability a solution that does not improve the result, an exploration task is carried out looking for a global optimum. As the temperature decreases, the probability of diversifying solutions tends to 0, so local search is intensified. The system cools gradually from a high temperature to sufficient cooling, which is normally programmed geometrically, in this process an initial temperature T_0 is established, in addition to a temperature conservation factor α such that $0 < \alpha < 1$, in each iteration t the temperature is updated by Equation (5):

$$T_t = T_0 \alpha^t \qquad (5)$$

This technique prevents reaching $T = 0$ because this only occurs when $t \to \infty$ without the need to establish a number of iterations. The slow descent of temperature requires multiple repetitions to generate acceptable solutions, because a small amount will cause the system not to converge to the global optimum, in addition, a too large amount will consume excessive computation time, a problem that worsens when working in too many dimensions. The general Simulated Annealing algorithm is shown in Figure 4.

Simulated Annealing Algorithm

Objective function $f(x)$, $x = (x_1, \ldots, x_d)^T$

Set initial temperature T_0 and initial solution x_0

Set final temperature T_f and maximum number of iterations N

Define cooling schedule $T \mapsto \alpha T$, $(0 < \alpha < 1)$

while $(T > T_f \ \& \ t < N)$

  Choose ϵ from a Gaussian distribution

  Move randomly to a new location: $x_{t+1} = x_t + \epsilon$ (random walk)

  Calculate $\Delta f = f_{t+1}(x_{t+1}) - f_\epsilon(x_t)$

  Accept the new solution if it is better

  if **not** improved

    Generate a random number r

    Accept the new solution if $p = \exp\left[-\Delta f / T\right] > r$

  end if

  Update the best x_* and f_*

  $t = t + 1$

end while

Figure 4. Simulated Annealing Algorithm [18].

3.3. FINDRISC Test

The Finnish Diabetes Risk Score (FINDRISC), is a screening instrument used to assess an individual's risk of developing type 2 diabetes [19] within the next 10 years, it is widely applied around the world for its simplicity of use as it is based on an easy-to-apply questionnaire. The FINDRISC test was presented in 2003 by Lindström and Tuomilehto, with the aim of having a non-invasive and easy-to-apply tool in family medicine units to measure the risk of suffering from diabetes mellitus type 2 for people in Finland.

The study is based on the FINRISK studies that originally monitored patients for 10 years in the development and treatment of diabetes if they were affected. From 4746 test individuals, descriptive data that do not require special laboratory studies were obtained, in addition, binary questions are included, subsequently logistic regression was applied determining the coefficients that are used for the calculation of the probability of suffering from diabetes. The product was a 7-question model where risk is calculated using a logistic function, however, this procedure would be inadequate to apply in clinics, so a scoring system assigned to each item depending on the response was determined, there is a maximum of 20 points and the test result is strictly categorical, so, regardless of the specific value of a data, if it is in some interval, the same score of the entire category will be used, which prevents establishing a fully personalized risk percentage. The model was validated with a sensitivity and specificity of 0.78 and 0.77 for the original FINRISK group and with a second group that obtains 0.81 and 0.76 respectively.

The authors indicate that a question about family history of diabetes can be integrated, however, it does not have the required scalar for the calculation of the logistic function and only the score for the item is indicated. The Clinical Practice Guide of the Mexican Institute of Social Security (IMSS), does take into account the question about family history in addition to adding an additional category for age, this establishes a maximum score of 26 points, the questionnaire applied at IMSS is shown in Table 1.

Table 1. Questionnaire and scores of the IMSS FINDRISC test.

Variable	Score
AGE <45	0
AGE 45-54	2
AGE 55-64	3
AGE >64	4
BMI <25	0
BMI 25-30	1
BMI >30	3
ABDOMINAL CIRCUMFERENCE MALE <94	0
FEMALE <80	
ABDOMINAL CIRCUMFERENCE MALE 94-101	3
FEMALE 80-87	
ABDOMINAL CIRCUMFERENCE MALE >101	4
FEMALE >87	
Have you ever been treated with medication for high blood pressure?	2
Have you ever been detected with high glucose levels?	5
Do you perform less than 4 hours of physical activity per week?	2
Does your diet lack fruits, vegetables or berries?	1
Has there been any diagnosis of DM in your family? No	0
Has there been any diagnosis of DM in your family? Yes: Grandparents, uncles or first cousins	3
Has there been any diagnosis of DM in your family? Yes: Parents, sibling or children	5

The risk of suffering from type 2 diabetes according to the questionnaire score is shown in Table 2:

Table 2. Possible results of the FINDRISC test.

Score	Interpretation	Risk of developing diabetes in the next 10 years
$P < 7$	Low risk	1%
$7 \leq P \leq 11$	Slightly elevated risk	4%
$12 \leq P \leq 14$	Moderate risk	17%
$15 \leq P \leq 20$	High risk	33%
$P > 20$	Very high risk	50%

3.4. Tools for the interpretation of diagnostic accuracy studies

To describe the usefulness of systems or tests for disease diagnosis, the contingency table is taken into account, see Figure 5.

Diagnostic Test		Reference Standard (—)
+	**True Positives (TP)** The patient has the disease and the test is positive.	**False Positives (FP** The patient hast dot have the disease, but the test is positive.
—	**FN Negatives (FN)** The patient has the disease, but but the test is negative.	**True Negatives (TN)** The patient doet the disease and test is negative.

Figure 5. Contingency table for evaluation of a diagnostic test.

From which the following metrics are obtained:

- Sensitivity: Proportion of individuals correctly diagnosed with the disease by the diagnostic test with respect to a reference standard.

$$\text{sensitivity} = \frac{VP}{VP + FN} \qquad (6)$$

- Specificity: Proportion of individuals correctly diagnosed with absence of the disease by the diagnostic test with respect to a reference standard.

$$\text{specificity} = \frac{VN}{VN + FP} \qquad (7)$$

- Positive Predictive Value (PPV): Conditional probability that the patient has the disease given that the test was positive, that is, the proportion of patients with a positive diagnostic test who actually suffer from the disease.

$$\text{PPV} = \frac{VP}{VP + FP} \qquad (8)$$

- Negative Predictive Value (NPV): Conditional probability that the patient does not have the disease given that the test was negative, that is, the proportion of patients with a negative diagnostic test and who do not suffer from the disease.

$$\text{NPV} = \frac{VN}{VN + FN} \qquad (9)$$

Predictive values are estimates of the probability that the diagnostic test delivers a correct result given that it is negative or positive, as the case may be. Since the mentioned proportions are estimates obtained with studies carried out with population samples, they are subject to variability, thus, to be able to use them properly it is necessary to calculate their confidence intervals, in this case, the 95% confidence interval (CI 95%) is chosen. In other words, the interval in which 95% of subsequent tests of the system will concentrate their values of the mentioned metrics will be determined. A standard method based on the binomial proportion is used:

$$p \pm Z_{0.95}\sqrt{\frac{p(1-p)}{N}} \qquad (10)$$

Where p is the proportion for which the confidence interval is being estimated, N the sample size and $Z_{0.95}$ is obtained from the normal function tables, for a two-tailed bell, $Z_{0.95} = 1.96$. It should be noted that confidence intervals must be taken into account when analyzing the validity of the test, a sample size N too small, less than 30 runs the risk of showing extremely wide confidence intervals, leaving the validity of the test limited. The optimal size of the interval is not written by any rule, it remains subject to the type of study and related conditions. The concept of accuracy is added, which indicates how much a result deviates from the reference value, the closer to the real value, the greater the accuracy of the results.

3.5. Data used

The investigation of Pesaro et al. in 2021 aimed to evaluate the performance of the FINDRISC test, with patients free of type 2 diabetes assigned to Family Medicine. 295 participants were randomly selected, 205 female and 90 males to apply the questionnaire, as well as fasting oral glucose tests to determine if they suffered from diabetes or not. Among the collected data are age in years, body mass index (BMI), measurement in centimeters of abdominal circumference rounded to the nearest integer, in addition to some binary data such as performing at least 30 minutes of physical activity per day, daily consumption of fruits and vegetables, previous medication for high blood pressure, previous positive tests for high glucose, as well as a tertiary item where the patient is asked if they have close or distant relatives with detected diabetes, with the option to respond negatively if they do not have any diagnosed relatives, same data required by the FINDRISC test, also, the score obtained in the test and the categorical result are recorded, as well as the result of the laboratory tests necessary for diagnosis. After data collection, the number of patients scored with high and low risk according to the FINDRISC test was recorded, and the diagnosis after consultation after laboratory glucose test according to the American Diabetes Association, which classifies patients as normal glucose <(100mg/dl), prediabetes (100 to 125mg/dl) and type 2 diabetes (>125mg/dl), in addition patients with low risk were classified as individuals with 14 points or less in the FINDRISC test, and high risk those with 15 or more points.

The results showed that the FINDRISC test has adequate performance for screening type 2 diabetes in the Mexican population, with sensitivity greater than 80%, patients with undiagnosed type 2 diabetes, to whom the questionnaire is applied will have 15 points or more. While it detects a large number of false positives, it has the ability to discriminate those who are not sick. The FINDRISC test proved to be adequate and useful as a screening test in addition to being easy to use and non-invasive, the results are detailed in section 4.

3.6. *Implemented system*

As can be seen in Table 2, the risk of suffering from type 2 diabetes yielded by the FINDRISC test, can only adopt 5 possible results, so all evaluated patients will belong to one of these categories, however, this classification may not be the most descriptive for some individuals. Consider the cases of two people with scores on the FINDRISC test of 11 and 12 points respectively, the first corresponds to a risk of 4%, slightly elevated, while the second obtains a moderate risk of 17% even though both patients could show identical characteristics in all items except in one, for example, age, where 64 and 65 years yield a point difference when applying the test. It is for cases like this that the construction of a system that can indicate to a patient their risk of suffering with a non-categorical result and that reflects their current state is proposed, and thus, the required measures for the care of their health can be taken.

Using the data from, the subset required by the FINDRISC test is considered, subsequently a fuzzy logic system based on the Mamdani inference method capable of predicting the risk of suffering from diabetes of a patient based on the selected data was developed, since the abdominal circumferences of each gender consider different intervals, a system was developed for each gender. The FINDRISC test grants a certain amount of points on a scale from 0 to 5 to the response of each question, so each of the possibilities is used as a linguistic variable, this is shown in Table 3:

Table 3. Assignment of linguistic variables depending on the FINDRISC score.

Score	Linguistic Variable
0	Very low risk factor
1	Low risk factor
2	Slightly elevated risk factor
3	Moderate risk factor
4	High risk factor
5	Very high-risk factor

Note that not all linguistic variables are used for each input data, because only those that are present in the FINDRISC questionnaire are used, for example, consider the input variable age, from Table 1, it is known that only the linguistic variables Age of very low risk, Age of slightly elevated risk, Age of moderate risk and Age of high risk will be used. The universe of discourse comprises age from 18 to 90 years, this interval is used to cover almost the entire population, the Age of very low risk, is described by a Z-shaped function whose maximum is at the value 45 and its minimum at the value of 50, Age of slightly elevated risk is represented by a generalized bell with center at 50, which is the midpoint of the age interval comprised by the FINDRISC item, the width of the bell and its slope were selected visually, so that the function approached its minimum when reaching the maximums of the neighboring membership functions, the linguistic variable Age of moderate risk, is also a generalized bell with center at 60, where the same criteria were applied to select the center, width and slope, finally, Age of high risk is visualized through an S function, whose maximum is at 65 and its minimum at 60, this configuration can be seen in Figure 6.

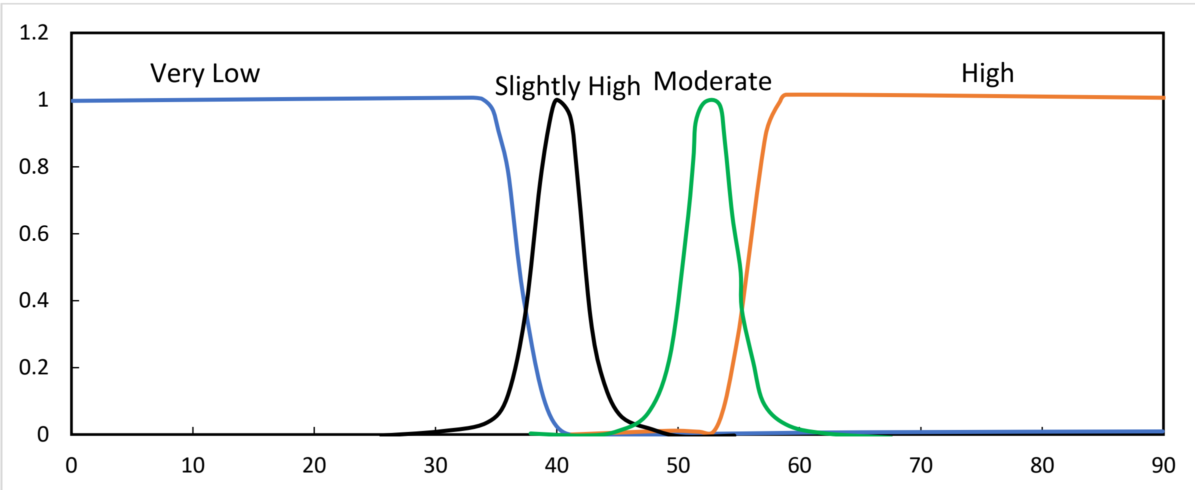

Figure 6. Membership functions associated with the age of patients.

In general, when an input variable has more than two linguistic variables, the heuristic is responsible for adjusting the width and slope of the central membership functions, so, for binary variables, no optimization is required. The results obtained by this system are shown in detail in section 4.

As mentioned in section 3.2, simulated annealing accepts non-better solutions at high temperatures with the objective of taking advantage of the exploration stage in the solution space, as a consequence, a global optimum is being sought, however, this approach is not the most suitable for the problem addressed in this research, because a configuration attached to the theory is already available, so it is only necessary to refine these membership functions to improve the result, this is equivalent to exploiting the region close to this configuration in search of a local optimum, then, simulated annealing should be used with low temperatures and a considerable number of iterations. The width and slope of 4 membership functions were optimized, generating an 8-dimensional optimization problem, the best result obtained alters the membership functions of the age variable as shown in Figure 7 and discussed in section 4.

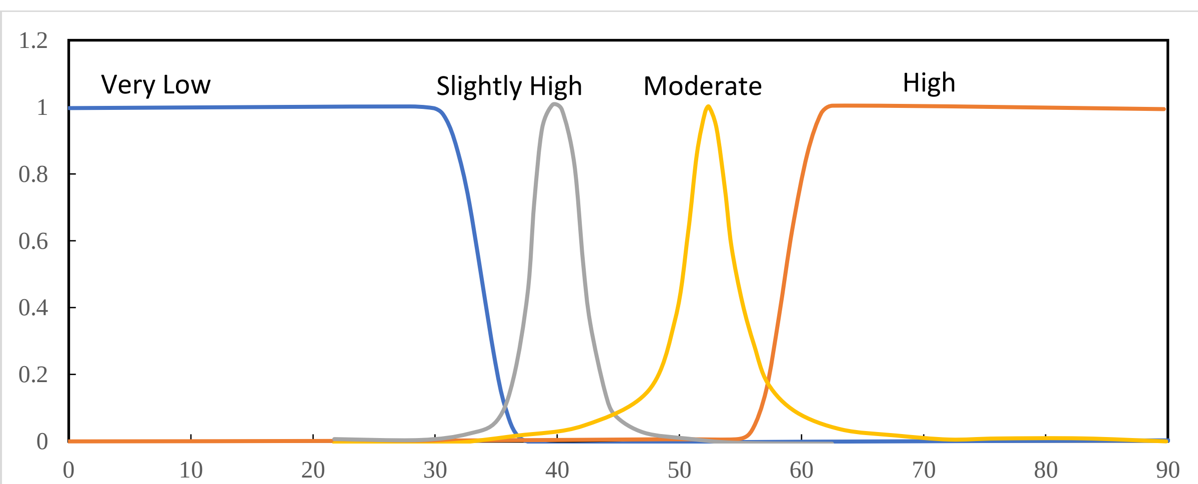

Figure 7. Optimized membership functions for patient age.

On the other hand, the inference engine is composed of 102 fuzzy rules obtained by analyzing each of the individuals within the database, the reasoning used for this task is explained below.

The 6 linguistic variables mentioned above are used, for each of the 295 cases within the database, the score of each question dictated by the FINDRISC test and its result are obtained, generating a rule whose antecedent is composed of the risk factors contained in the database and the consequent is the output of the FINDRISC test, as an example consider the female case from Table 4 with risk of suffering according to the FINDRISC test of 4%, that is Slightly elevated risk:

Table 4. Analysed female case.

Risk Factor	Value	Score
Age	55 years	3
Abdominal Circumference	87 cm	3
Body Mass Index	26.75	1
Lack of Physical Activity	True	2
Low Consumption of Fruits and Vegetables	True	1
Previous Treatment for Blood Pressure	True	2
Previous Study of High Glucose	False	0
Family History of Diabetes	False	0

Whose fuzzy rule is:

IF age is of moderate risk and abdominal circumference is of moderate risk and body mass index is of low risk and physical activity is of slightly elevated risk and consumption of fruits and vegetables is of low risk and treatment for blood pressure is off slightly elevated risk and previous glucose study is of very low risk and family history of diabetes is of very low risk, THEN risk of suffering is slightly elevated.

If an antecedent already exists in the system, the patient is omitted. The systems of both genders share the fuzzy rules. The implementation of the optimization was carried out in MATLAB R2021a, the design of the fuzzy system and the evaluation was performed with the MATLAB Fuzzy Logic Designer extension. The general scheme of the system can be seen in Figure 8.

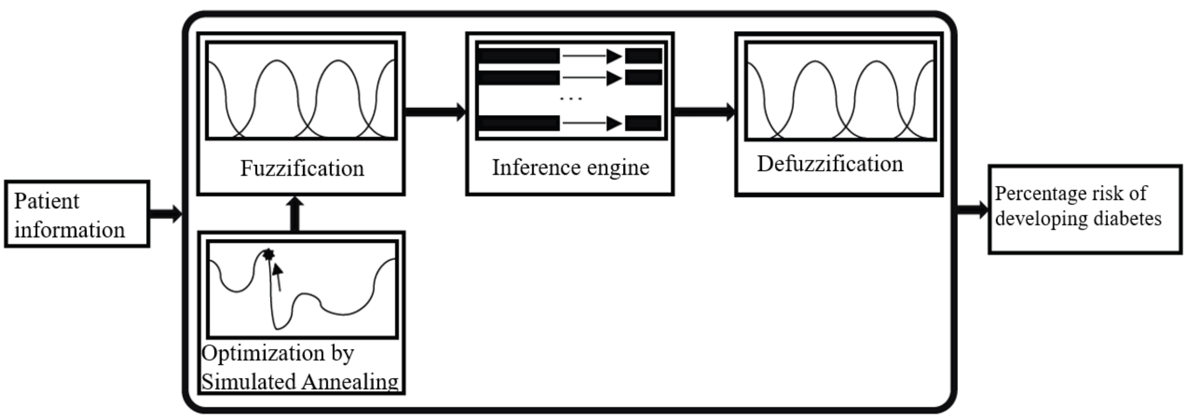

Figure 8. Diagram of the fuzzy system.

4. Results & Discussion

Here are recorded the results obtained by the implemented fuzzy system optimized and unoptimized, and contrasted with those obtained by Mendiola et al. The optimization algorithm was executed 40 times for each fuzzy system and the best result was used for the comparison, Tables 5 and 6 show the results obtained by the unoptimized fuzzy systems for female and male patients respectively, while Tables 7 and 8 refer to the optimized systems.

Table 5. Results obtained by the unoptimized fuzzy system for female patients.

	NPV	PPV	Sensitivity	Specificity
Result	0.9562	0.3382	0.7931	0.7443
Start of CI 95%	0.9219	0.2258	0.6457	0.6799
End of CI 95%	0.9905	0.4507	0.9405	0.8088
Size of CI 95%	0.0685	0.2249	0.2949	0.1289

Table 6. Results obtained by the unoptimized fuzzy system for male patients.

	NPV	PPV	Sensitivity	Specificity
Result	0.9464	0.2353	0.7273	0.6709
Start of CI 95%	0.8875	0.0927	0.4641	0.5673
End of CI 95%	1.0054	0.3779	0.9905	0.7745
Size of CI 95%	0.1180	0.2852	0.5264	0.2072

Table 7. Results obtained by the optimized fuzzy system for female patients.

	NPV	PPV	Sensitivity	Specificity
Result	0.9687	0.3246	0.8620	0.7045
Start of CI 95%	0.9386	0.2200	0.7365	0.6371
End of CI 95%	0.9988	0.4292	0.9875	0.7719
Size of CI 95%	0.0602	0.2092	0.2510	0.1348

Table 8. Results obtained by the optimized fuzzy system for male patients.

	NPV	PPV	Sensitivity	Specificity
Result	0.9814	0.2777	0.9090	0.6709
Start of CI 95%	0.9455	0.1314	0.7392	0.5672
End of CI 95%	1.0000	0.4240	1.0789	0.7745
Size of CI 95%	0.0545	0.2926	0.3397	0.2073

The results of the optimized fuzzy systems combined from both genders are compared with those obtained by the study of Mendiola et al., the results of the FINDRISC test are taken directly from that publication, the comparison can be seen in Table 9.

Table 9. Comparison of results of both genders of FINDRICS and the fuzzy system.

	NPV FINDRISC	NPV Fuzzy	PPV FINDRISC	PPV Fuzzy	Sensitivity FINDRISC	Sensitivity Fuzzy	Specificity FINDRISC	Specificity Fuzzy
Result	0.9640	0.9725	0.2244	0.3097	0.8750	0.8750	0.5255	0.6941
Start of CI 95%	0.9181	0.9488	0.1615	0.2245	0.732	0.7725	0.4623	0.6376
End of CI 95%	0.9882	0.9963	0.2908	0.3950	0.9591	0.9775	0.5881	0.7507
Size of CI 95%	0.0701	0.0475	0.1293	0.1705	0.2271	0.2050	0.1258	0.1131

5. Conclusions

Unoptimized fuzzy systems show compared to optimized systems, lower negative predictive values, and in general, higher positive predictive value for female gender but lower for male, in addition to showing lower test sensitivity, but with equal or higher specificities, it is also observed that the sizes of the confidence intervals are in general smaller. A lower specificity in optimized systems does not mean that the system is obtaining worse results, sensitivity considers the validity of the test among sick individuals, while specificity considers the validity among healthy individuals, when detection tests for conditions that do not necessarily show symptoms are applied, highly sensitive models are of greater interest to reduce the amount of false negatives, so this metric turns out to be the most important for our purpose, however, specificity should not be neglected, because when confirming a diagnosis high specificity is required to evade false positives, then, the search for maximum sensitivity should be prioritized without neglecting specificity values.

Observing the optimized systems, for both genders the proportion of patients classified as high risk who actually suffer from the disease is high close to 100%, while the proportion of patients classified as low risk and who do not suffer from the disease is low, in addition, sensitivity is acceptable in both cases, above 85% so it adequately detects true positive cases, considering specificity, it is within acceptable margins, greater than 67%, indicating that slightly more than two thirds of true negatives are adequately detected.

From this point, the observations focus on Table 9, it is notable that the positive predictive value delivered by the fuzzy system is slightly higher with a smaller CI95%, the positive predictive value is almost 0.08 units higher, at the cost of having a slightly larger CI95%. Sensitivity is the most important parameter in studies of this type, both methods deliver the same efficacy of 87.5%, however, the fuzzy system has a slightly reduced CI95% compared to that of FINDRISC, finally, specificity is higher in the fuzzy system reaching almost 70% compared to the almost 53% of the FINDRISC test, in addition, the CI95% is slightly smaller, although a difference of this magnitude is not particularly significant.

Although the sensitivity criterion yielded by the fuzzy system is identical to that obtained by the FINDRISC test and the improvement in the confidence interval may not be significant, the increase in specificity suggests that the fuzzy system is capable of detecting to a good extent non-sick patients and assigning them risks of suffering attached to reality based on the patient's description, that is, assign low risks to patients without diabetes and with healthy lifestyles, while assigning high risks to people with prediabetes or diabetes and unhealthy lifestyles.

Furthermore, the positive and negative predictive values in the fuzzy system show significant improvements so the use of the fuzzy system as an aid in the prevention of diabetes mellitus 2 can be of great use by providing results that adequately describe reality compared against a gold standard. The possibility of placing the system through a web or desktop application that allows any person to know the risk of suffering with a non-categorical value is considered, and if necessary, timely go to a specialist for studies and specialized treatment

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

References

[1] Abusaib, M., Ahmed, M., Nwayyir, H. A., Alidrisi, H. A., Al-Abbood, M., Al-Bayati, A., Al-Ibrahimi, S., Al-Kharasani, A., Al-Rubaye, H., Mahwi, T., Ashor, A., Howlett, H., Shakir, M., Al-Naqshbandi, M., & Mansour, A. (2020). Iraqi experts consensus on the management of type 2 diabetes/prediabetes in adults. Clinical Medicine Insights: Endocrinology and Diabetes, 13, 1179551420942232. https://doi.org/10.1177/1179551420942232

[2] El-Sappagh, S., Elmogy, M., & Riad, A. (2015). A fuzzy-ontology-oriented case-based reasoning framework for semantic diabetes diagnosis. Artificial Intelligence in Medicine, 65(3), 179–208. https://doi.org/10.1016/j.artmed.2015.08.003

[3] Aamir, K. M., Sarfraz, L., Ramzan, M., Bilal, M., Shafi, J., & Attique, M. (2021). A fuzzy rule-based system for classification of diabetes. Sensors, 21(23), 8095. https://doi.org/10.3390/s21238095

[4] Grande-Ramírez, J., Palacios, R., Lasserre, A., Flores Asis, R., & Vázquez-Rodríguez, C. (2024). Intelligent fuzzy system to assess the risk of type 2 diabetes and diagnosis in marginalized regions. IAES International Journal of Artificial Intelligence, 13, 1935–1944. https://doi.org/10.11591/ijai.v13.i2.pp1935-1944

[5] Ganie, S. M., & Malik, M. B. (2025). A lifestyle-based fuzzy-enhanced ANN model for early prediction of type 2 diabetes and personalized management in the North Indian population. Diagnostics, 15(24), 3139. https://doi.org/10.3390/diagnostics15243139

[6] Tašić, J., Nagy-Perjési, Z., & Takács, M. (2024). Multilevel fuzzy inference system for estimating risk of type 2 diabetes. Mathematics, 12(8), 1167. https://doi.org/10.3390/math12081167

[7] Jølle, A., Midthjell, K., Holmen, J., Carlsen, S. M., Tuomilehto, J., Bjørngaard, J. H., & Åsvold, B. O. (2019). Validity of the FINDRISC as a prediction tool for diabetes in a contemporary Norwegian population: A 10-year follow-up of the HUNT study. BMJ Open Diabetes Research & Care, 7(1), e000769. https://doi.org/10.1136/bmjdrc-2019-000769

[8] Reddy Gadekallu, T., & Khare, N. (2017). Cuckoo search optimized reduction and fuzzy logic classifier for heart disease and diabetes prediction. International Journal of Fuzzy System Applications, 6(2), 25–42. https://doi.org/10.4018/IJFSA.2017040102

[9] Sahu, N., Verma, T., & Reddy, G. T. (2017). Diabetes classification using fuzzy logic and adaptive cuckoo search optimization techniques. International Journal on Future Revolution in Computer Science & Communication Engineering, 3(9), 252–255.

[10] Bressan, G. M., Flamia Azevedo, B. C., & Molina de Souza, R. (2020). A fuzzy approach for diabetes mellitus type 2 classification. Brazilian Archives of Biology and Technology, 63, 1–11. https://doi.org/10.1590/1678-4324-20201

[11] Pradini, R. S., Previana, C. N., & Bachtiar, F. A. (2020). Fuzzy Tsukamoto membership function optimization using PSO to predict diabetes mellitus risk level. In Proceedings of the 5th International Conference on Sustainable Information Engineering and Technology (SIET '20) (pp. 101–106). ACM. https://doi.org/10.1145/3427423.3427451

[12] Vijayalakshmi, G., Vikram, R., Akgül, A., & Hassani, M. K. (2025). Fuzzy mathematical modelling on diabetic and non-diabetic cases after vaccination. Results in Engineering, 27, 105888. https://doi.org/10.1016/j.rineng.2025.105888

[13] Novák, V., & Lehmke, S. (2006). Logical structure of fuzzy IF–THEN rules. Fuzzy Sets and Systems, 157(15), 2003–2029. https://doi.org/10.1016/j.fss.2006.02.011

[14] Yan, S.-R., Alattas, K. A., Bakouri, M., Alanazi, A. K., Mohammadzadeh, A., Mobayen, S., Zhilenkov, A., & Guo, W. (2022). Generalized type-2 fuzzy control for type-I diabetes: Analytical robust system. Mathematics, 10(5), 690. https://doi.org/10.3390/math10050690
[15] Mohammadian, M. (2009). Supervised learning of fuzzy logic systems. In IGI Global eBooks (pp. 1510–1517). https://doi.org/10.4018/978-1-59904-849-9.ch221
[16] Alnowibet, K. A., Mahdi, S., El-Alem, M., Abdelawwad, M., & Mohamed, A. W. (2022). Guided hybrid modified simulated annealing algorithm for solving constrained global optimization problems. Mathematics, 10(8), 1312. https://doi.org/10.3390/math10081312
[17] Zhang, W., Zhang, R., Shang, R., Li, J., & Jiao, L. (2018). Application of natural computation inspired method in community detection. Physica A: Statistical Mechanics and Its Applications, 515, 130–150. https://doi.org/10.1016/j.physa.2018.09.186
[18] Nature-inspired optimization algorithms. (2014). Elsevier. https://doi.org/10.1016/C2013-0-01368-0
[19] Vandersmissen, G. J., & Godderis, L. (2015). Evaluation of the Finnish Diabetes Risk Score (FINDRISC) for diabetes screening in occupational health care. International Journal of Occupational Medicine and Environmental Health, 28(3), 587–591. https://doi.org/10.13075/ijomeh.1896.00407
[20] Pesaro, A. E., Bittencourt, M. S., Franken, M., Carvalho, J. A., Bernardes, D., Tuomilehto, J., & Santos, R. D. (2021). The Finnish Diabetes Risk Score (FINDRISC), incident diabetes and low-grade inflammation. Diabetes Research and Clinical Practice, 171, 108558. https://doi.org/10.1016/j.diabres.2020.108558