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OPTIMIZATION OF FUZZY SYSTEMS FOR RISK FACTORS IN THE PREVENTION OF CARDIOVASCULAR DISEASES

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ABSTRACT

Obesity and overweight are the most common cardiovascular risk factors in people who have suffered myocardial infarction. They are also considered a threat to health worldwide. People with obesity have twice the risk of suffering heart failure than people with a normal body mass index. In this paper, fuzzy logic models which are optimized are proposed to detect risk factors for heart disease according to age and body mass index.

Keywords: system, diseases, classification, risk, setting, health, BMI, fuzzy logic, optimization.

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1. INTRODUCTION

On a global scale, there is a high rate of death from cardiovascular diseases, particularly ischemic heart disease and cerebrovascular accidents [1].

The risk of cardiovascular disease and cerebrovascular accidents has increased as a result of unhealthy diets, particularly those high in salt, fats, flour, and refined sugars, as well as low levels of physical activity [1-9].

On the other hand, Body Mass Index (BMI) may have a positive linear association with the risk of incidence of Cardiovascular Diseases (CVD), which are defined by the World Health Organization (WHO) as a group of heart disorders and blood vessels, including arterial hypertension and coronary heart disease [2-9].

Expert systems play an important role in the diagnosis of any medical condition. The primary goal of these systems is to classify various diseases or states. The collection of data obtained by each doctor or specialist and stored in a database is critical in the expert system. An expert system is considered precise if the result of the system given is identical to the result given by a doctor for a specific disease or problem. It is critical to obtain expert advice when developing a medical alarm system as the rules generated by the system are directly proportional to the information collected [8].

The result delivered by an expert system allows to have an approach to the prediction of human diseases in a certain way as well as to verify the models using machine learning [6].

Fuzzy logic systems are a suitable option to build expert systems since they allow to relate inputs and outputs in a linguistic way using fuzzy sets that represent concepts [10, 11].

Regarding this, there are numerous references where classification algorithms [3, 4], detection and treatment systems [3], and depression indicators [5] can be found.

The attributes of age, blood pressure, cholesterol, electrocardiogram, blood sugar, heart rate, and gamma graph with talio are commonly used in the diagnosis of cardiovascular diseases [7].

The diagnostic system proposed in this article seeks to contribute to the quality of life of people with poor health habits in order to improve their quality of life and prevent cardiovascular disease. A balanced diet is beneficial for maintaining health and preventing various diseases, as is regular physical activity and regular medical checkups [12].

The rest of the article is organized as follows: Section 2 shows the models of the fuzzy logic system, and the description of how the optimization of fuzzy systems is implemented and performed. Subsequently, in Section 3 the results are presented, being first the obtained value of the performance and then the simulation for the best configuration of the fuzzy logic system. Finally, Section 4 presents the conclusions of the work carried out.

2. FUZZY SYSTEM MODEL

A system is proposed to determine a person's risk factor for cardiovascular disease according to age and BMI, which corresponds to a person's weight in kilograms divided by the square of height in meters. BMI is an easy and inexpensive assessment method for weight categories: underweight, healthy weight, overweight, and obesity. BMI does not measure body fat directly, but BMI correlates moderately with more direct measures of body fat. Furthermore, BMI appears to be as strongly correlated with various metabolic and disease outcomes as these more direct measures of body fat.

For this purpose, the input variables and their respective ranges are proposed in Table-1.

Table-1. Input variables.

Input variables	
BMI (Kg/m^2)	AGE (years)
Range	
18.5 - 50	20 - 100

Considering the above, a total of five fuzzy sets are assigned to the consequent (output). Table-2 displays the output variable and the respective fuzzy sets.

Table-2. Output variable and fuzzy sets.

Fuzzy sets	Classification
Very low risk	0-1
Low risk	1-2
Moderate	2-3
High risk	3-4
Very high risk	4-5

For the system described above, the implementation was carried out in MATLAB using the instruction ‘‘fminunc’’ which implements a Quasi-Newton optimization method. The fuzzy logic system is built using the ‘‘generafis’’ function. The performance index corresponding to the Mean Squared Error (MSE) that is calculated in a function called ‘‘fitness’’, where the difference between the data calculated by the fuzzy logic system and the real data is determined.

For the training and testing of the different classifier configurations, 158 data representing the behavior of the system as described above are available. The data used were taken from the Bogotá open database [13].

2.1 Design Considerations

In the implementation of the system, Gaussian type membership functions are used where the values to be optimized correspond to the parameters of each of these membership functions. In order to observe the effect of the number of membership functions, different configurations are considered as shown in Table-3. It is also worth noting that systems with a different number of rules are considered.

Table-3. Configurations considered.

Setting	BMI	Age	Rules
C1	5 Gaussian membership functions	4 Gaussian membership functions	20
C2	5 Gaussian membership functions	4 Gaussian membership functions	15
C3	3 Gaussian membership functions	2 Gaussian membership functions	6
C4	3 Gaussian membership functions	4 Gaussian membership functions	12

2.1.1 Setting 1 (C1)

For this system, there are 20 rules where the following sets are proposed for the input variables:

- **BMI:** five sets are proposed:
  - Normal
  - Overweight
  - Obese (Class I)
  - Obese (Class II)
  - Obese (Class III)
- **Age:** four sets are proposed:
  - Between 20 and 30 years old
  - Between 31 and 46 years old
  - Between 47 and 55 years old
  - Over 56 years old

Considering the characteristics associated with the input variables, for each set, Gaussian membership functions are used, thus, the aim is to cover the entire range of the input and output variable data. Finally, the system rules are defined as follows:

- If BMI is normal and the age is between 20 and 30 years then the risk factor classification is very low risk.
- If BMI is normal and age is between 31 and 46 years then the risk factor classification is low risk.
- If BMI is normal and age is between 47 and 55 years then the risk factor classification is low risk.
- If BMI is normal and age is greater than 56 years then the risk factor classification is low risk.
- If BMI is overweight and age is between 20 and 30 years then the risk factor classification is low risk.
- If BMI is overweight and age is between 31 and 46 then the risk factor classification is moderate.
- If BMI is overweight and age is between 47 and 55 then the risk factor classification is moderate.
- If the BMI is overweight and the age is greater than 56 years then the risk factor classification is moderate.
- If the BMI is obese (class I) and the age is between 20 and 30 years then the risk factor classification is moderate.
- If the BMI is obese (class I) and the age is between 31 and 46 years then the risk factor classification is moderate.
- If the BMI is obese (class I) and the age is between 47 and 55 then the risk factor classification is high risk.
- If BMI is obese (class I) and age is greater than 56 years then the risk factor classification is moderate.
- If the BMI is obese (class II) and the age is between 20 and 30 years then the risk factor classification is moderate.
- If the BMI is obese (class II) and the age is between 31 and 46 years then the risk factor classification is moderate.
- If the BMI is obese (class II) and the age is between 47 and 55 then the risk factor classification is high risk.
- If the BMI is obese (class II) and the age is greater than 56 years then the risk factor classification is high risk.

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- If the BMI is obese (class III) and the age is between 20 and 30 years then the risk factor classification is moderate.
- If the BMI is obese (class III) and the age is between 31 and 46 years then the risk factor classification is high risk.
- If the BMI is obese (class III) and the age is between 47 and 55 then the risk factor classification is very high risk.
- If the BMI is obese (class III) and the age is greater than 56 years then the risk factor classification is very high risk.

The fuzzy logic system shown in Figure-1 is obtained when considering the above group of rules.

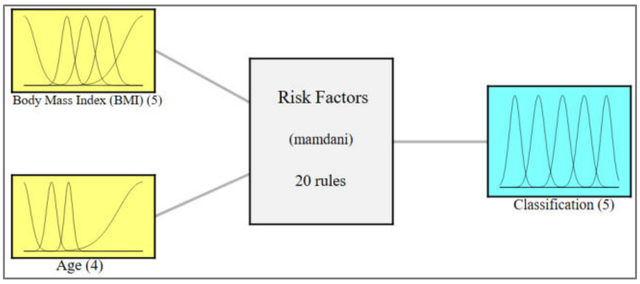

Figure-1. Fuzzy logic system of C1.

2.1.2 Setting 2 (C2)

In addition to the considerations used in configuration 1, the following was taken into account for configuration 2:

- The membership functions used in configuration C1 are maintained.
- The number of rules is reduced to 15.
- The same configuration is used for the membership functions associated with the output.

As can be seen, in this case, the same settings are used for the input and output membership functions, so the system rules are defined as follows:

- If the BMI is normal and the age is between 20 and 30 years then the risk factor classification is very low risk.
- If BMI is normal and age is between 47 and 55 years then the risk factor classification is low risk.
- If BMI is normal and age is greater than 56 years then the risk factor classification is low risk.
- If BMI is overweight and age is between 20 and 30 years then the risk factor classification is low risk.
- If BMI is overweight and age is between 47 and 55 then the risk factor classification is moderate.
- If BMI is overweight and age is greater than 56 years then the risk factor classification is moderate.
- If BMI is obese (class I) and age is between 31 and 46 years then the risk factor classification is moderate.
- If the BMI obese (class I) and the age is between 47 and 55 then the risk factor classification is high risk.
- If BMI is obese (class I) and age is greater than 56 years then the risk factor classification is moderate.
- If the BMI is obese (class II) and the age is between 31 and 46 years then the risk factor classification is moderate.
- If the BMI is obese (class II) and the age is between 47 and 55 then the risk factor classification is high risk.
- If the BMI is obese (class II) and the age is greater than 56 years then the risk factor classification is high risk.
- If the BMI is obese (class III) and the age is between 31 and 46 years then the risk factor classification is high risk.
- If the BMI is obese (class III) and the age is between 47 and 55 then the risk factor classification is very high risk.
- If the BMI is obese (class III) and the age is greater than 56 years then the risk factor classification is very high risk.

Figure-2 shows the graphical description of the fuzzy logic system for this setting.

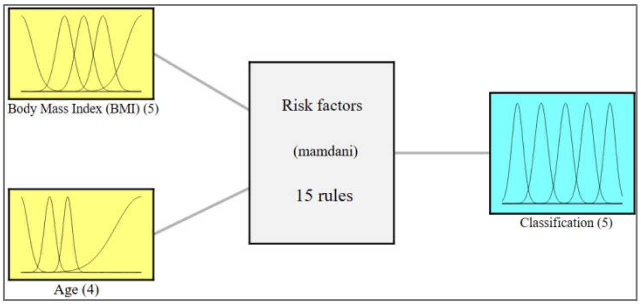

Figure-2. Fuzzy logic system of C2.

2.1.3 Setting 3 (C3)

The following factors were considered for the fuzzy system Setting 3:

- A change was made to the BMI membership functions, decreasing the number of possible sets.
- A change was made to the age membership functions, decreasing the number of possible sets.
- Number of rules equal to 6.
- The same configuration is used for the membership functions associated with the output.

– **BMI:** three sets are proposed:
- Normal
- Overweight
- Obese

– **Age:** two sets are proposed:
- Between 20 and 50 years old
- Between 50 and 100 years old

As in the previous cases, Gaussian membership functions are used in the respective universes of discourse in order to cover them in the best possible way. Finally, the set of rules for this system is as follows:

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- If BMI is normal and age is between 20 and 50 years then the risk factor classification is very low risk.
- If BMI is normal and age is between 51 and 100 years then the risk factor classification is low risk.
- If BMI is overweight and age is between 20 and 50 years then the risk factor classification is moderate.
- If BMI is overweight and age is between 51 and 100 years then the risk factor classification is moderate.
- If the BMI is obese and the age is between 20 and 50 years then the risk factor classification is high risk.
- If the BMI is obese and the age is between 51 and 100 years then the risk factor classification is very high risk.

As a result, Figure-3 presents the configuration when generating the fuzzy logic system for this case.

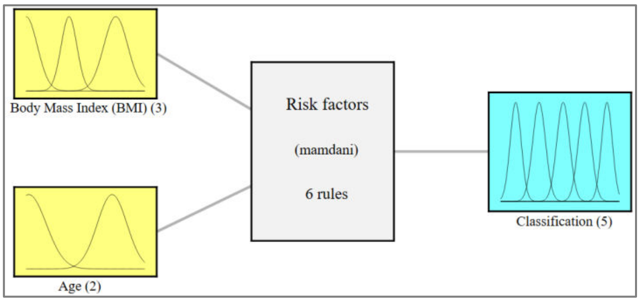

Figure-3. Fuzzy logic system of C3.

2.1.4 Setting 4 (C4)

In this case, it is sought to combine configurations 1 and 3, so that the following is taken into account:

- Three fuzzy sets are used for the input associated with BMI.
- Four membership functions are used for the entry associated with age.
- Number of rules: 12.
- The same configuration is used for the output membership functions.

– **BMI:** three sets are proposed:
- Normal
- Overweight
- Obese

– **Age:** four sets are proposed:
- Between 20 and 35 years old
- Between 36 and 49 years old
- Between 50 and 65 years old
- Over 66 years old

Considering the above aspects, the rules of the system are defined as follows:

- If the BMI is normal and the age is between 20 and 35 years then the risk factor classification is very low risk.
- If BMI is normal and age is between 36 and 49 years then the risk factor classification is very low risk.
- If BMI is normal and age is between 50 and 65 years then the risk factor classification is low risk.
- If BMI is normal and age is greater than 66 years then the risk factor classification is low risk.
- If BMI is overweight and age is between 20 and 35 then the risk factor classification is low risk.
- If BMI is overweight and age is between 36 and 49 then the risk factor classification is moderate.
- If BMI is overweight and age is between 50 and 65 then the risk factor classification is moderate.
- If BMI is overweight and age is greater than 66 years then the risk factor classification is moderate.
- If BMI is obese and age is between 20 and 35 then the risk factor classification is moderate.
- If the BMI is obese and the age is between 36 and 49 then the risk factor classification is high risk.
- If the BMI is obese and the age is between 50 and 65 years then the risk factor classification is high risk.
- If the BMI is obese and the age is greater than 66 years then the risk factor classification is very high risk.

Using the fuzzy sets and the rule base, the graphical description of the fuzzy logic system for this configuration is presented in Figure-4.

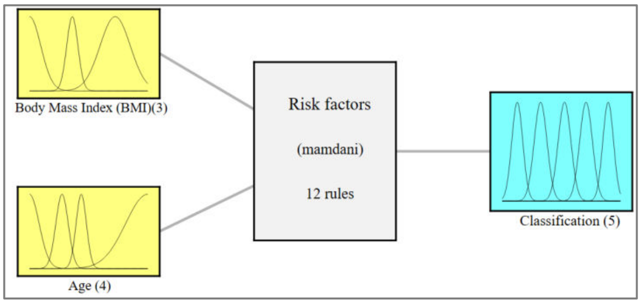

Figure-4. Fuzzy logic system of C4.

3. RESULTS

By implementing the Quasi-Newton optimization algorithm, where the parameters of the fuzzy sets are modified, the adjustment of the considered systems is achieved.

In this section, it is first presented the value of the MSE obtained for each configuration and then for the best configuration is presented the simulation with the real data as well as the configuration of the fuzzy system before and after being optimized.

3.1 Quantitative Results

Table-4 shows the MSE values obtained for each of the settings after performing the optimization process.

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Table-4. MSE for each setting.

	BMI	Age	Iterations	MSE
C1	5 Gaussian functions	4 Gaussian functions	22	0.0576
C2	5 Gaussian functions	4 Gaussian functions	21	0.0733
C3	3 Gaussian functions	2 Gaussian functions	21	0.1263
C4	3 Gaussian functions	4 Gaussian functions	6	0.1827

In Table-4 it can be seen that the best result is obtained for C1 followed by C2 and C3 and finally having the worst performance for C4. It is noteworthy that the algorithm stops for C1 at 22 iterations, C2 and C3 at 21, and for C4 with six iterations.

4. QUALITATIVE RESULTS

Taking into account the results obtained in Table-4, configuration C1is taken to observe the system configuration as well as the simulation obtained with real data. The initial configuration of the fuzzy sets used for this system can be appreciated in Figures 5, 6, and 7.

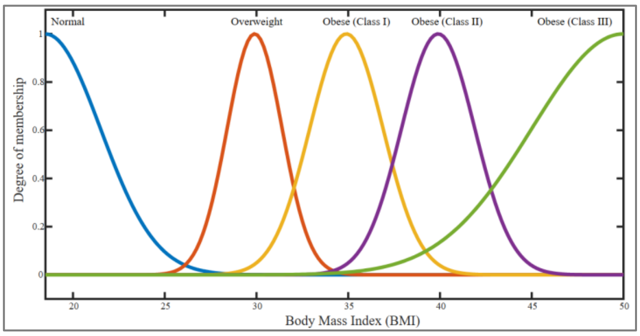

Figure-5. BMI membership functions of C1.

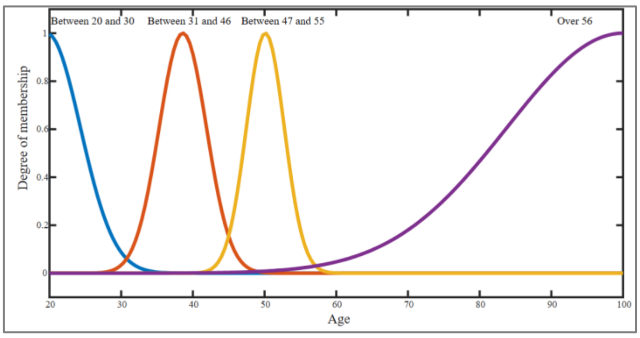

Figure-6. Age membership functions of C1.

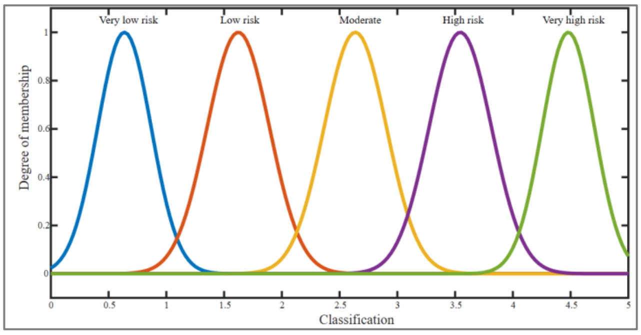

Figure-7. Membership functions of the output of C1.

After 22 iterations of the optimization algorithm, the configuration of the sets of the fuzzy system shown in Figures 8, 9 and 10 was obtained.

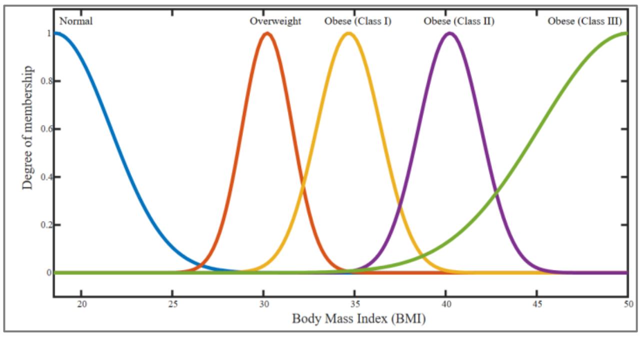

Figure-8. Optimized BMI of C1.

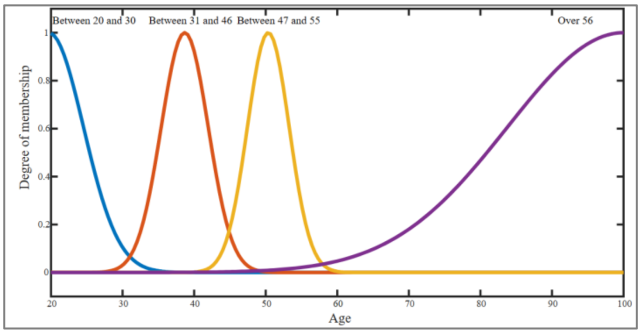

Figure-9. Optimized age of C1.

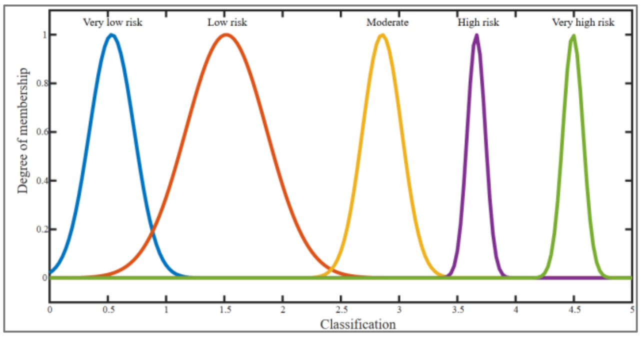

Figure-10. Optimized output of C1.

In this group of figures, it can be seen that the best fit is presented in the fuzzy sets associated with the output variable.

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On the other hand, the response of the optimized system and the desired response can be seen in Figure-11, where it is noticeable that the data estimated by the fuzzy system are close to the reference values.

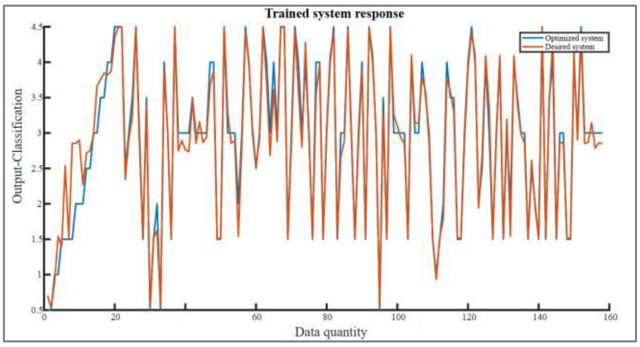

Figure-11. System vs. expected response C1.

Additionally, for the amount of data supplied, in Figure-12 the error graph of the system response is shown. This figure shows the error value obtained for each case, where both positive and negative errors are presented.

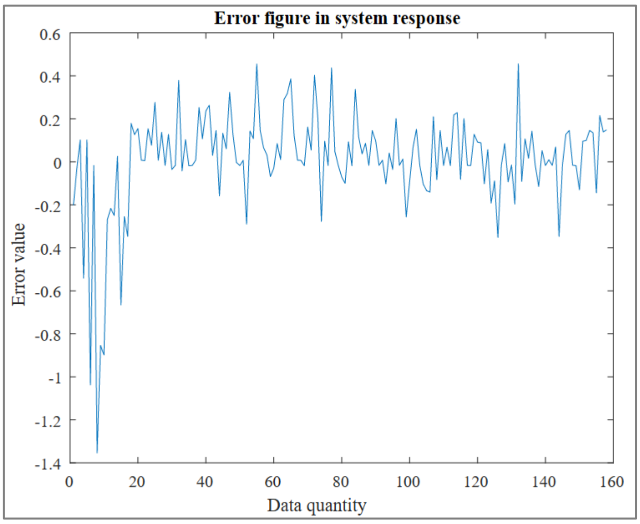

Figure-12. Response error for C1.

5. CONCLUSIONS

The proposed fuzzy inference system was designed considering a collection of fuzzy sets and fuzzy rules, which define the relationships between input and output variables.

Considering the results obtained in the settings with less membership functions in the input (C3 and C4) a higher result (MSE) is obtained compared to the settings C1-C2, which shows that the membership functions used in the inputs are an important factor to consider in the design of the system.

Another relevant aspect to consider is the number of rules used, which allows observing the difference of configurations C1 and C2 with respect to configurations C3 and C4.

Additionally, in the C4 configuration, it is observed that the algorithm stops with six iterations, which shows that the configuration of the fuzzy sets and the number of rules prevent to achieve a suitable performance of this system after being optimized.

The best-performing configurations are C1 and C2. In this order, C1 presents the most suitable performance using 20 rules and five membership functions for each input.

It is expected that future research will allow for the application of this system in a real-world setting to achieve the goal of raising awareness of the significance of weight control in reducing the risk of cardiovascular diseases.

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