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Designing a Fuzzy Expert System for Diagnosis and Prediction of Metabolic Syndrome in Children and Adolescents

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Abstract

Introduction: Metabolic Syndrome (MetS) is one of the most common metabolic disorders seen in children and adolescents. In this study, the prevalence of MetS and its related factors are evaluated using a fuzzy expert system (FES) in a national representative sample of age groups.

Methods: The FES is designed based on the data of 800 participants of the fifth study of the program for monitoring and prevention of non-communicable diseases among children and adolescents in Iran in 2015. The data of 560 participants were used as training data and 240 as test data were used to test the rules and output of the system. The fuzzy system that has been designed includes input data (age, waist, systolic blood pressure, diastolic blood pressure, BMI, waist-to-height ratio, nutrition, and abdominal obesity), and at the end gives us an output that diagnoses the health status with MetS or predicts the disease.

Results: The analysis shows that this method, with an accuracy of more than 98%, can predict and diagnose MetS among children and adolescents better than other methods.

Conclusion: The fuzzy system is designed to accept multiple variables simultaneously as input variables and also use more people information than similar research as primary data. In addition, its accuracy is more than 98%. Preliminary data were collected from children and adolescents with different lifestyles across the country. This system can act as an assistant in the service of a specialist doctor to diagnose the disease.

Keywords: Metabolic syndrome(MetS), Children, adolescents, Fuzzy expert.

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Introduction

The rapidly increasing prevalence of non-communicable diseases around the world has raised concerns in developing societies. Non-communicable diseases are estimated to comprise 75% of the world's mortality, especially in low- and middle-income countries. Metabolic syndrome (MetS) is one of the most common metabolic disorders leading to many non-communicable diseases including cardiovascular disease, diabetes, some kinds of cancers, kidney disease and mental disorders (1-3). MetS is a set of conditions such as high blood pressure, high blood insulin, excess fat accumulated around the abdomen and increased levels of hyperlipidemia, high blood pressure, high blood sugar, high triglycerides and low HDL that usually occur together and increase the risk of heart disease, stroke and diabetes. Having only one of the mentioned conditions does not indicate having MetS, but can be considered as a warning sign for this disease and other serious diseases (4).

The current form of MetS was first introduced by Reaven et al. in the Journal of Diabetes in 1988. About a year later, Kaplan added the most important component of the complex, abdominal obesity, meaning the deposition of fat in the splanchnic and subcutaneous tissues of the abdomen, and named it as the fourfold death (hypertriglyceridemia, impaired glucose tolerance, central obesity, and hypertension) (5).

Statistics show that the prevalence of MetS has increased significantly in recent years, especially among children and adolescents. The increase in weight and obesity as the most important health issue in the world has been raised in the 21st century and as a serious disease requires immediate global prevention. According to the World Health Organization (WHO), the prevalence of obesity in the world doubled from 1980 to 2014. A common method for estimating obesity is to use body mass index (BMI); the index that is obtained by dividing a person's weight in kilograms by the square of his height in meters. By definition, when a BMI exceeds 30, that person is considered obese (6, 7).

In the children's and adolescent groups in the past decades due to various factors such as gene interactions, epidemiological transmission, eating disorders and inactivity, the trend of exacerbation of obesity in this age group has caused great concern (3, 8). Children and adolescents are among the age groups vulnerable to this disease and the incidence of the population at this age will lead to a decrease in their efficiency in adulthood and a decrease in social productivity. For MetS, in addition to its two main consequences namely diabetes and cardiovascular disease, other complications have been listed including fatty liver, hepatic steatosis, liver cirrhosis, chronic renal failure, albuminuria, hyperuricemia and gout, polycystic ovary syndrome and sleep apnea. The treatment of MetS is actually the treatment of its components, namely high blood pressure, dyslipidemia and obesity. lifestyle modification, i.e. a healthy diet and regular physical activity can also be considered as the front line of the treatment of MetS. Due to the time consuming treatment of this disease, its early diagnosis can increase the chances of successful treatment and reduces its complications (9).

Because the pathological process and risk factors for this syndrome are formed in children, diagnosing this syndrome in children and adolescence and modifying lifestyle with medication can lead to the prevention of dangerous diseases such as diabetes and heart disease in adulthood (10).

Medical knowledge refers to the relationship between the symptoms of a disease and the diagnosis that a doctor makes from reference books. Sometimes a symptom may be attributed to many diseases. On the other hand, a disease may be confused with other diseases. MetS means the association of a group of risk factors for cardiovascular disease and diabetes in a person. Various researches on doctors' decision-making methods have shown that most decisions are based on reference books first and then on the basis of personal judgments, relying on the experiences of colleagues or what is done routinely in clinical wards. These experiences are not necessarily based on scientific and reasonable methods and may have become commonplace solely on the basis of repetition. This is particularly important because the medical field is always fraught with uncertainty due to the complexity, urgency, and ambiguity that arises in clinical cases, and there is potentially a tendency to make decisions based on subjective judgment. Moreover, due to the empirical nature of medical sciences, complete reliance on reference books can not provide a sufficient source for decision making. A fuzzy system due to its nature can well cover the uncertainty that is an integral part of the nature of medical science (11).

In the second half of the 20th century, more than half of medical knowledge was stored in computer systems, which can be used to access expert decision-making systems for diagnosis. Due to the inherent ambiguity in the definition of medical concepts, it is better to store the instructions for symptomatic diagnosis with fuzzy rules and use fuzzy rules to deduce these instructions (12).

Predicting and diagnosing MetS using artificial intelligence increases the likelihood of successful treatment in individuals. Early diagnosis of MetS is helpful to early treatment of this disease, which is the cause of many other diseases that pose a serious challenge to human life. The main goal of treating MetS is to reduce the risk of ischemic heart disease and to lower LDL cholesterol and high blood pressure and manage diabetes. The next goal of treatment is to prevent type 2 diabetes. Long-term complications of diabetes often include heart and kidney disease, decreased vision, and amputation of limbs, including the feet and toes. Unfortunately, due to its various aspects, the treatment of this disease is a complex process. However, early detection of this disease is very important in reducing its complications and helping to better treat and save lives. This system is even more important in helping to diagnose the disease in some areas. In many countries, including Iran, the level of access to all medical facilities and skilled physicians is not the same everywhere. Many people may not be aware of their condition in a timely manner for a variety of reasons, including lack of access to medical facilities, specialized laboratories, and inexperienced physicians, and may experience various complications. Many of these problems can be prevented by timely diagnosis of the disease using the recommended physician's system.

Artificial intelligence was created in 1956 when two Caroline Polytechnic researchers in the United States, Alan Neville and Herbert Simon, wrote a computer program. In a fuzzy expert system (FES), the rules of the expert system have fuzzy values. Much research has been done on the FES and its applications (12). Various researches have been done under the title of designing medical expert systems, including: FES for the diagnosis of chronic kidney disease, hypertension, coronary heart disease and bacterial meningitis than other meningitis in children (2, 3, 8, 13). In addition, much research has been done on the analysis of risk factors for coronary heart disease, and several diagnostic methods have been used to screen for the disease. Also, in a study by Kornowski, the application of fuzzy logic in the design of medical expert systems was examined and it was found that using fuzzy logic in patient classification for medical diagnosis in expert systems is an effective approach (14).

In a study by Khosravi et al., Fuzzy systems have been used to diagnose diabetes (15). Sedehi et al. used artificial neural networks and logistic regression to diagnose MetS. In this study, in which 347 people participated, several variables were recorded together and after three years, the onset of MetS was considered as the response. Despite the value of this research, an error of more than 10%, sometimes up to 30%, was one of its weaknesses (16). Khosravanian and Ayat have also introduced a medical system using an artificial neural network to diagnose diabetes (17). In another study, Zabah diagnosed diabetes using artificial and neural-fuzzy neural networks (18).

There has also been a lot of research on MetS, most of which has focused on its side effects or ways to treat it and the effect of exercise, medication or certain food in the treatment of this disease. Ghasemi and Afzalaghaei in a study entitled "MetS in overweight children" have studied the prevalence of MetS among obese children referred to Imam Reza (AS) Hospital in Mashhad using statistical methods (19). Ebrahimpour et al. investigated the relationship between MetS and insulin levels in obese children in a school in Tehran (20). Mehrdad et al. studied the prevalence of MetS among children aged 3 to 9 years by investigating glucose and lipid levels (21). In another study by Qarqarachi et al., the prevalence of MetS in obese children and adolescents was investigated (22). Klishadi et al. examined the pattern of nutrition and physical activity among obese children and adolescents with and without MetS. Also in another study, Klishadi examined the effect of vitamin D and placebo on the components of MetS in children and adolescents aged 10 to 16 years (23).

In this study, our purpose is to design a fuzzy physician assistant system that can diagnose and predict MetS in children and adolescents aged 7 to 18 years with a higher number of input variables and therefore higher accuracy than previous studies. In this study, after the introduction that contains information about is the definition of MetS, explanations of the status of this disease in today's society, especially in children and adolescents, our goals of this study and how it differs from previous studies, the background of research and studies that have been done in this field, in the second part, the introduction of fuzzy sets is introduced. The third section will describe the proposed system, how it works, and the details about input variables, output variables, and the rules governing the system. In the fourth section, estimating system accuracy is stated. In the fifth part, the system argument and conclusion and in the sixth part, the sources used in this study are given.

Fuzzy Expert System (FES)

As can be seen in the various fields of medical knowledge, the nature of medical science is in many cases uncertain. Therefore, fuzzy theory can be used to cover this feature of medical science. A fuzzy set is defined based on the membership function, in which the set image is in the interval of zero and one. The membership function allows the experts to quantify a language word and display a fuzzy set graphically. Each member has a membership rank. In the theory of classical collections, a member either belongs to the collection or does not. While in fuzzy theory the relative degrees of membership of the members in the set is allowed (7). Membership function is a function of the total set to the closed interval [0,1]. The number that the function values for each member determines the degree of membership of that member in that set. The membership function ranges from {0,1} for sets to closed intervals [0,1] for fuzzy sets (24).

Suppose that X is a reference set. The fuzzy set $\tilde{A}$ defined on X is the members of X and the membership of $\mu_A(x)$. The membership function $\mu_A(x)$ is from X to [0,1] and determines the membership of the X elements in set A. In other words:

$$\tilde{A} = \{(x, \mu_A(x)) : \ \mu_A(x) : X \to [0,1]\} \quad (1)$$

In this system, we used triangular and trapezoidal membership functions.

$$\mu_A(x) = \begin{cases} \dfrac{x-a}{m-a} & a < x \le m \\ \dfrac{b-x}{b-m} & m < x \le b \end{cases} \quad (2)$$

The triangular membership function is used only for fuzzy sets where the maximum membership rate occurs at only one point, and the trapezoidal membership function is used for sets that have a maximum membership of one interval.

$$\mu_A(x) = \begin{cases} \dfrac{x-a}{m-a} & a < x \le m \\ 1 & m < x \le n \\ \dfrac{b-x}{b-n} & n < x \le b \end{cases} . \quad (3)$$

A non-membership function v_A,

$$\nu_A(x) = \begin{cases} 1 & if\ x < a \\ \frac{s-x}{s-a} & if\ a \le x \le s \\ 0 & if\ x = s \\ \frac{x-s}{b-s} & if\ s \le x \le b \\ 1 & if\ b < x \end{cases} \quad (4)$$

gives the degree of non-membership of x to A. These functions satisfy the conditions

$$\mu_A(x), \nu_A(x) \in [0,1], \quad \mu_A(x) + \nu_A(x) \le 1, \quad (5)$$

for every $x \in E$ (25).

In the theory of fuzzy sets, the degree of membership of fuzzy numbers is between zero and one, and the degree of non-membership only complements the degree of membership of one. However, when the decision maker expresses his decision in the form of fuzzy sets, he does not consider the degree of non-membership as a complement to the degree of membership of one, and in fact, there may be a degree of doubt. These sets are a good tool for describing vague and inaccurate information and dealing with uncertainty and ambiguity in the decision-making process (26). The fuzzy system has components fuzzifier, fuzzy rule database, fuzzy inference engine and defuzzifier.

Fuzzifier

A mappin s defined from a point $x^* \in U \subset R^n$ to a fuzzy set A' in U.

Due to the simplicity of calculations and elimination of perturbations, we used a triangular fuzzy generator:

$$\mu_{A'}(x) = \begin{cases} \left(1 - \frac{|x_1 - x_1^*|}{b_1}\right) \hat{\times} \ldots \hat{\times} \left(1 - \frac{|x_n - x_n^*|}{b_n}\right) & |x_i - x_i^*| \le b_i \\ 0 & O.W \end{cases} \quad (6)$$

where b_i is a positive parameter and $\hat{X}$ represents t-soft, which is selected here as min.

We converted the definite input to a language variable using the membership functions stored in the fuzzy knowledge base. In this step, for each input variable, we consider membership functions so that the definite inputs become fuzzy and are in the fuzzy inference system.

Rules Base

The rule set is called the fuzzy "if-then" set, which is the main part of the fuzzy inference system. To determine the fuzzy rules, we used the knowledge of experts directly and indirectly.

Fuzzy Inference Engine

The fuzzy inference engine works similarly to the human reasoning process, and by applying it to inputs and rules, the output is determined. The implication process is implemented for each rule. In this study, the Min method, which cuts the output fuzzy set, is used.

Defuzzifier

In designing this system, we use centroid defuzzifier in MATLAB.

Materials and Methods

In this study, an expert system based on fuzzy logic is presented to diagnose and predict MetS in children and adolescents. To create a fuzzy inference system, we used the graphical interface of the fuzzy logic toolbox in MATLAB software. This toolbox has two types of fuzzy inference systems, Sugeno and Mamdani. Due to the fact that Mamdani method is suitable for the inputs defined in this system, Mamdani fuzzy inference system has been used. Our proposed system includes 51 rules of single input-output and dual input-single output types. This system works with 8 variables as input and one variable as output. The system is based on the data of 800 children and adolescents participating in the fifth study of the program for monitoring and prevention of non-communicable diseases in children and adolescents in Iran in 2015, from 560 participants as training data and 240 participants as test data used to test the rules and output of the system.

The first step is to design a system for determining the input and output variables. We also used language variables. A language variable is defined by an ordered five (x, T(x), U, G, M) where x is the name of the variable, T(x) is a set of conditions (set of linguistic variables x), and G is a rule for generating the term name. And M is a semantic rule for relating each expression to its meaning. A language value is defined by its membership function and its non-membership function.

Input variables are:

1- Age

This language variable has three values: preschooler, children and adolescence. The membership and non-membership functions of adolescence are as follows:

$$\mu_{adolescent} = \begin{cases} \frac{x-11}{6} & if\ 11 \le x \le 17 \\ 1 & if\ 17 \le x \end{cases} \quad (7)$$

$$\nu_{\text{adolescent}} = \begin{cases} 1 & if\ x < 13 \\ \dfrac{19 - x}{6} & if\ 13 \le x \le 19 \end{cases} \quad (8)$$

2- Systolic blood pressure

This variable has four values: low, normal, high and very high. Given that the appropriate systolic blood pressure numbers vary at different ages, we calculated these numbers separately for preschoolers, children and adolescents. Membership and non-membership functions corresponding to adolescent in normal case are as follows.

$$\mu_{\text{normal}} = \begin{cases} \dfrac{x - 86}{9} & if\ 86 \le x \le 95 \\ 1 & if\ x = 95 \\ \dfrac{105 - x}{10} & if\ 95 \le x \le 105 \end{cases} \quad (9)$$

$$\nu_{\text{normal}} = \begin{cases} 1 & if\ x < 84 \\ \dfrac{95 - x}{12} & if\ 107 \le x \le 95 \\ 0 & if\ x = 95 \\ \dfrac{x - 95}{8} & if\ 95 \le x \le 103 \\ 1 & if\ 131 < x \end{cases} \quad (10)$$

3- diastolic blood pressure

This variable has four values: low, normal, high and very high. Given that the appropriate diastolic blood pressure numbers vary at different ages, we calculated these numbers separately for preschoolers, children, and adolescents. Membership and non-membership functions corresponding to adolescent in normal case are as follows.

$$\mu_{\text{normal}} = \begin{cases} \dfrac{x - 54}{11} & if\ 54 \le x \le 65 \\ 1 & if\ x = 65 \\ \dfrac{73 - x}{8} & if\ 65 \le x \le 73 \end{cases} \quad (11)$$

$$\nu_{normal} = \begin{cases} 1 & if\ x < 53 \\ \dfrac{65 - x}{12} & if\ 53 \le x \le 65 \\ 0 & if\ x = 65 \\ \dfrac{x - 65}{12} & if\ 65 \le x \le 77 \\ 1 & if\ 77 < x \end{cases} \quad (12)$$

4- Waist

Given that children are of growing age and their physical condition and ossification change with age, this variable has been calculated separately for the age periods of preschoolers, children and adolescence. This variable has three values: normal, borderline and obese. Membership and non-membership functions corresponding to adolescent in normal case are as follows.

$$\mu_{\text{normal}} = \begin{cases} 1 & if\ x \le 64 \\ \dfrac{71 - x}{7} & if\ 64 \le x \le 71 \end{cases} \quad (13)$$

$$\nu_{\text{normal}} = \begin{cases} \dfrac{x - 73}{6} & if\ 67 \le x \le 73 \\ 1 & if\ 73 < x \end{cases} \quad (14)$$

5- Body Mass Index (BMI)

BMI is the product of weight divided by height squared. Given that children are of growing age and their height and weight change with age, this variable has been calculated separately for the age periods of preschoolers, children and adolescence. This variable has four values: normal, border, high and very high. Membership and non-membership functions corresponding to adolescent in normal case are as follows.

$$\mu_{\text{normal}} = \begin{cases} 1 & if\ x \le 15.5 \\ \dfrac{20 - x}{4.5} & if\ 15.5 \le x \le 20 \end{cases} \quad (15)$$

$$\nu_{\text{normal}} = \begin{cases} \dfrac{x - 15}{7} & if\ 15 \le x \le 22 \\ 1 & if\ 22 < x \end{cases} \quad (16)$$

6- Waist-to-height

Waist to height ratio is also an important indicator, especially in children and adolescents, and this index can be used to determine the growth and health of this age group. Given that children are of growing age and their height and skeleton change with age, this variable has been calculated separately for the age periods of preschoolers, children and adolescence. This variable has four values: appropriate, borderline, high, and very high. Membership and non-membership functions corresponding to these values in different ages for appropriate case are as follows:

$$\mu_{\text{appropriate}} = \begin{cases} 1 & if\ x \le 0.46 \\ \dfrac{0.51 - x}{0.05} & if\ 0.46 \le x \le 0.51 \end{cases} \quad (17)$$

$$\nu_{\text{appropriate}} = \begin{cases} \dfrac{x - 0.53}{0.04} & if\ 0.49 \le x \le 0.53 \\ 1 & if\ 0.53 < x \end{cases} \quad (18)$$

7- Abdominal obesity

It has only a certain amount of language, yes, if the patient has abdominal obesity.

8- Nutrition

The role of nutrition in the health of people, especially children and adolescents, and their lack of MetS is accepted in the world today. Especially the consumption of nutrients such as fruits and vegetables, daily drinking of milk, not consuming sugary drinks, sweets and salty snacks and ready meals and fast food are very important in the preservation of the health of children and adolescents. For this reason, a variable called proper nutrition is also included among the problem variables. This variable has only one language value, yes (Figures 1 and 2).

Output Variables

For this system, an output variable with four values is considered, healthy, patient 1, patient 2, and patient 3. Membership and non-membership functions of these values are as follows:

$$\mu_{\text{normal}} = \begin{cases} 1 & if\ x \le 1 \\ \dfrac{1.25 - x}{0.25} & if\ 1 \le x \le 1.25 \end{cases} \quad (19)$$

$$\nu_{\text{normal}} = \begin{cases} \dfrac{x - 1.2}{0.4} & if\ 1.2 \le x \le 1.6 \\ 1 & if\ 1.6 < x \end{cases} \quad (20)$$

$$\mu_{\text{border}} = \begin{cases} \dfrac{x - 1.15}{0.85} & if\ 1.15 \le x \le 2 \\ 1 & if\ x = 2 \\ \dfrac{2.75 - x}{0.75} & if\ 2 \le x \le 2.75 \end{cases} \quad (21)$$

$$\nu_{\text{border}} = \begin{cases} 1 & if\ x < 1.6 \\ \dfrac{2 - x}{0.4} & if\ 1.6 \le x \le 2 \\ 0 & if\ x = 2 \\ \dfrac{x - 2}{0.9} & if\ 2 \le x \le 2.9 \\ 1 & if\ 2.9 < x \end{cases} \quad (22)$$

$$\mu_{\text{high}} = \begin{cases} \dfrac{x - 2.5}{1.25} & if\ 2.5 \le x \le 3.75 \\ 1 & if\ x = 3.75 \\ \dfrac{4.2 - x}{0.45} & if\ 3.75 \le x \le 4.2 \end{cases} \quad (23)$$

$$\nu_{\text{high}} = \begin{cases} 1 & if\ x < 2.3 \\ \dfrac{3.75 - x}{1.45} & if\ 2.3 \le x \le 3.75 \\ 0 & if\ x = 3.75 \\ \dfrac{x - 3.75}{0.55} & if\ 3.75 \le x \le 4.3 \\ 1 & if\ 4.3 < x \end{cases} \quad (24)$$

$$\mu_{\text{very high}} = \begin{cases} \dfrac{x - 3.5}{0.6} & if\ 3.5 \le x \le 4.1 \\ 1 & if\ 4.1 \le x \end{cases} \quad (25)$$

$$\nu_{\text{very high}} = \begin{cases} 1 & if\ x < 3.6 \\ \dfrac{4 - x}{0.4} & if\ 3.6 \le x \le 4 \end{cases} \quad (26)$$

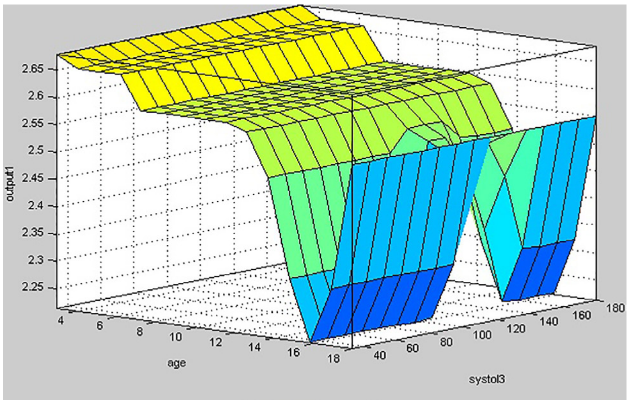

Figure 1: Simultaneous effect of two input variables, age and systolic blood pressure, on the output variable

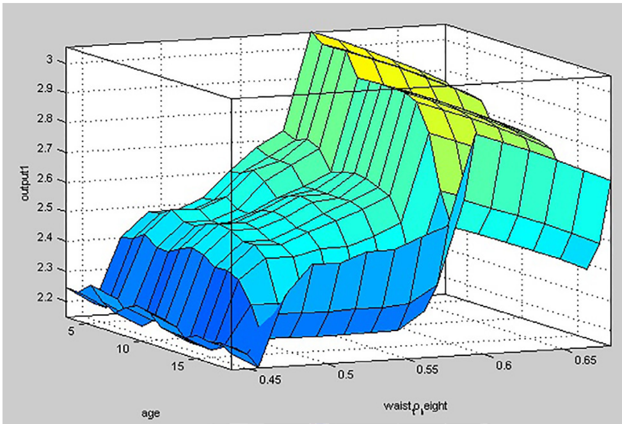

Figure 2: Simultaneous effect of two input variables of age and waist to height ratio on output variable

The main part of a fuzzy system is the rules. Our system contains 51 rules and 8 input variables. The rules are one input-one output and two input-one output. To write these rules, the latest medical findings, academic articles, and expert opinions were used, and then tested using test data.

The Rules

The system rules are as follows:

1- If the age is preschooler and systolic blood pressure is low, the result is healthy.

2- If the age is preschooler and systolic blood pressure is normal, the result is healthy.

3- If the age is preschooler and the systolic blood pressure is high, the result is patient 2.

4- If the age is preschooler and the systolic blood

pressure is very high, the result is patient 3.
5- If the age is child and systolic blood pressure is low, the result is healthy.
6- If the age is child and systolic blood pressure is normal, the result is healthy.
7- If the age is child and the systolic blood pressure is high, the result is patient 2.
8- If the age is child and the systolic blood pressure is very high, the result is patient 3.
9- If the age is adolescent and systolic blood pressure is low, the result is healthy.
10- If the age is adolescent and systolic blood pressure is normal, the result is healthy.
11- If the age is adolescent and systolic blood pressure is high, the result is patient 2.
12- If the age is adolescent and systolic blood pressure is very high, the result is patient 3.
13- If the age is preschooler and diastolic blood pressure is low, the result is healthy.
14- If the age is preschooler and diastolic blood pressure is normal, the result is healthy.
15. If the age is preschooler and diastolic blood pressure is high, the result is patient 2.
16. If the age is preschooler and diastolic blood pressure is too high, the result is patient 3.
17- If the age is child and the diastolic blood pressure is low, the result is healthy.
18- If the age is child and diastolic blood pressure is normal, the result is healthy.
19. If the age is child and diastolic blood pressure is high, the result is patient 2.
20. If the age is child and the diastolic blood pressure is too high, the result is patient 3.
21- If the age is adolescent and the diastolic blood pressure is low, the result is healthy.
22. If the age is adolescent and diastolic blood pressure is normal, the result is healthy.
23. If the age is adolescent and the diastolic blood pressure is high, the result is patient 2.
24- If the age is adolescent and the diastolic blood pressure is very high, the result is patient 3.
25. If the age is preschooler and waist size is normal, the result is healthy.
26. If the age is preschooler and waist size is on the border, the result is patient 1.
27- If the age is preschooler and waist size is obese, the result is patient 2.
28. If the age is child and waist size is normal, the result is healthy.
29- If the age is child and waist size is on the border, the result is patient 1.
30- If the age is child and waist size is obese, the result is patient 2.
31- If the age is adolescent and waist size is normal, the result is healthy.
32- If the age is adolescent and waist size is on the border, the result is patient 1.
33. If the age is adolescent and waist size is obese, the result is patient 3.
34. If the age is preschooler and BMI is normal, the result is healthy.
35- If the age is preschooler and BMI index is on the border, the result is patient 1.
36- If the age is preschooler and BMI index is high, the result is patient 2.
37. If the age is preschooler and BMI index is very high, the result is patient 3.
38. If the age is child and BMI is normal, the result is healthy.
39. If the age is child and BMI is on the border, the result is patient 1.
40- If the age is child and BMI index is high, the result is patient 2.
41. If the age is child and BMI is very high, the result is patient 3.
42. If the age is adolescent and BMI is normal, the result is healthy.
43- If the age is adolescent and BMI index is on the border, the result is patient 1.
44- If the age is adolescent and BMI index is high, the result is patient 2.
45- If the age is adolescent and BMI index is very high, the result is patient 3.
46. If the waist to height ratio is appropriate, the result is healthy.
47- If the waist to height ratio is at the border, the result is patient 1.
48. If the waist to height ratio is high, the result is patient 2.
49. If the waist to height ratio is very high, the result is patient 3.
50- If the abdominal obesity is yes, the result is patient 2.
51. If the nutrition is good, the result is healthy.

Results

In this study, we used the perturbation matrix to evaluate the accuracy, sensitivity and efficiency of the system (27). The variables used are as follows:

TP: All sick people who have been correctly diagnosed.

FP: All sick people who have been misdiagnosed as healthy.

TN: All healthy people who have been properly diagnosed as healthy.

FN: All healthy people who have been

misdiagnosed as sick.

Network accuracy for test data is obtained from the following equation:

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (27)$$

The performance evaluation of the algorithms described above has been done using different criteria based on the sensitivity and detection perspective. Sensitivity index means the number of sick people to the total number of people diagnosed as sick, is calculated from the following equation:

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (28)$$

Also, the characteristic index, which means the ratio of the number of healthy people to the total number of people diagnosed as healthy, is calculated as follows:

$$Specificity = \frac{TN}{(TN + FP)} \quad (29)$$

The perturbation matrix for the fuzzy system training data used with healthy output, patient 1, patient 2 and patient 3 is shown in Tables 1, 2, 3 and 4.

As shown in Table 1, out of a total of 72 healthy individuals, 71 were diagnosed by the system, and 163 were correctly diagnosed among the other 166.

As shown in Table 2, out of a total of 66 patients1, 64 were diagnosed by the system, and among the other 174, 171 were correctly diagnosed.

As shown in Table 3, out of a total of 54 patients 2, 53 were diagnosed by the system and among the other 186 patients, 182 were correctly diagnosed.

As shown in Table 4, out of a total of 47 patients 3, 45 were diagnosed by the system, and among the other 193, 190 were correctly diagnosed.

According to Tables 1, 2, 3, 4 and 5, the designed system has accurately detected more than 98% of the health status or disease of people at different stages. The number specific to the sensitivity and specificity indicators for each value of the system output variable is also significant.

Table 1: Data perturbation matrix using fuzzy system for healthy output

System	Healthy	Other
Healthy	72	1
Other	3	165

Table 2: Data Perturbation Matrix Using Fuzzy System for Patient 1 output

System	Patient 1	Other
Patient 1	64	2
Other	3	171

Table 3: Data perturbation matrix using fuzzy system for patient 3 output

System	Patient 2	Other
Patient 2	53	1
Other	4	182

Table 4: Data perturbation matrix using fuzzy system for patient 3 output

System	Patient 3	Other
Patient 3	45	2
Other	3	190

Discussion

In this study, it was observed that each of the factors increasing systolic blood pressure and diastolic blood pressure, abdominal obesity, malnutrition and body mass index among children and adolescents have a positive effect on MetS. This is consistent with other studies in this field (28, 29). Also in this study, similar to other studies that have been done before, a significant relationship has been observed between abdominal obesity and high blood pressure (30). In the fuzzy system, the capacity of fuzzy mathematics is used. We have already seen the successful use of fuzzy mathematics in medical matters (2, 3, 8, 13). Given the characteristics of fuzzy mathematics, the uncertainty in medical knowledge can be well overcome.

The system is based on the data of 800 children and adolescents participating in the fifth study of the program for monitoring and prevention of non-communicable diseases in children and adolescents in Iran in 2004 and 2005, from 560 data as education data and 240 data as test data used to test the rules and output of the system. The minimum age of people in this study was 4 years and the maximum

Table 5: Results of sensitivity, specificity and accuracy of the system designed for each output

System	Sensitivity	Specificity	Accuracy
Healthy	0.994	0.96	0.983
Patient 1	0.988	0.956	0.98
Patient 2	0.995	0.93	0.98
Patient 3	0.99	0.938	0.98

age was18 years. MATLAB software has also been used to simulate the algorithm and view the results. Given that the logic used in our system works with inconsistent data and fits with the real-world problems, it provides more accurate results with a system error estimated at less than 2%. Of course, there is not much difference in the accuracy of the performance of different models, but because of the value of human life in the diagnosis of the disease, improving the accuracy of the system is even important by as much as one percent.

In a 2006 study, Su et al. used a combination of four methods of artificial neural network data mining, decision tree, regression, and dependency rules to diagnose the disease with 89% accuracy (31). Of course, this method was not used to predict a person's future infection using current information. In another study conducted in 2010, Brakat et al. were able to increase the accuracy of diagnosis by up to 94% using the support vector machine method. However, the level of input variables in this study including blood pressure, blood sugar and BMI was less than our study (32). In another study in 2010, Thai researchers were able to diagnose MetS with 90% accuracy using the decision tree method (33). This method was not used to predict the disease in the future life of people. In another recent study by Bagherzadeh Khiabani et al., a hybrid model of three simple Bayes classification algorithms, a decision tree, and a support vector machine was developed (34) that was more accurate than all three methods alone. The method was estimated to be less than 5%. This method was also used only for the purpose of disease diagnosis. Numerous other studies have been conducted in this field, including a study by Smith et al. who used a neural network to diagnose the disease and was able to diagnose the disease with 76% accuracy (35).

Conclusion

Compared to other methods, our method can be considered a new method in two ways. First, there is no method with all the input variables that affect the incidence of MetS. In other studies mainly the effect of one to a maximum of three input variables, or the effect of a particular drug on the disease has been investigated. Secondly, in addition to diagnosing the disease, this method is used to predict the development of MetS in the future using the current information. As a result, using a fuzzy system for this purpose, which well covers the uncertainties that exist in the nature of medical science, it enters multiple input variables into the system simultaneously, more information from more people. Compared to similar studies as primary data, the standard data of this system is collected from children and adolescents across the country with different lifestyles .In addition to being able to diagnose the disease, it is used to predict the disease, and also because it provides a very accurate output with an error of less than 2%, it is a better system than previous ones. This system can well serve as a doctor›s assistant to diagnose the disease.

Conflict of Interest: None declared.

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