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Research Article

Design of a Fuzzy System Based on Lookup Table for Diagnosis and Predicting of Metabolic Syndrome in Preschoolers, Children, and Adolescents

Mohammad Dehghandar[1*], **Ghasem Ahmadi**[2], **Heydar Aghebatbin Monfared**[3]

[1,2,3]Department of Mathematics, Payame Noor University (PNU),
P.O. Box. 19395-4697, Tehran, Iran.

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Abstract. The purpose of this study was to provide a fuzzy system for predicting and diagnosing metabolic syndrome (MetS) in preschoolers, children, and adolescents. In this study, previous research on the factors affecting metabolic syndrome, especially in children, and adolescents, has been considered. After integrating the initial variables, a fuzzy system has been designed with 8 data on age, waist size, systole blood pressure, diastole blood pressure, body mass index (BMI), waist-to-height ratio, nutrition, and abdominal obesity. Ultimately, the system gives us an output that diagnoses the health status of a child or adolescent with MetS or predicts the possibility of a person contracting the disease in the future. The system is designed based on the data of 1300 persons participating in the fifth study of the program for monitoring and prevention of non-communicable diseases of children, and Adolescents in Tehran and Isfahan provinces that 1050 data were used as training data and 250 data as test data that used to test the rules and output of the system. After reviewing the rules and eliminating similar or contradictory rules using their degree calculation, finally, the system was designed with 45 rules, a multiplication inference engine, a single fuzzifier, and a centroid defuzzifier. Then the system was evaluated using the confusion matrix accuracy, sensitivity, and specificity. Our analysis shows that this method, with an error rate of less than 4 percent more accurate than other methods, can predict and diagnose MetS in children.

Keywords. Metabolic syndrome, Children and adolescents, Fuzzy expert system, Lookup table, Accuracy.

MSC. 90C34; 90C40.

* Corresponding author
m_dehghandar@pnu.ac.ir, g.ahmadi@pnu.ac.ir, mr.aghebatbeen@gmail.com
http://mathco.journals.pnu.ac.ir

1 Introduction

Non-communicable diseases are rapidly spreading around the world. Various studies have estimated that 75 percent of deaths worldwide are due to non-communicable diseases, especially in low- and middle-income countries. Metabolic syndrome (MetS) is one of the most common metabolic disorders leading to non-communicable diseases, including cardiovascular disease, diabetes mellitus, some cancers, kidney disease, and mental disorders [8, 7, 29, 33]. 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 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 MetS, but can be considered as a warning sign for this disease and other serious diseases [24].

Raven et al. first defined the current form of MetS in 1988. About a year later, Kaplan added the most critical 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) [10].

In recent years, according to global statistics, the prevalence of metabolic syndrome has increased significantly, especially among preschoolers, children, and adolescents. Weight gain and obesity are the most critical health issues in the world in the 21st century. According to the World Health Organization, the prevalence of obesity doubled from 1980 to 2014. Body mass index (BMI) is usually used to estimate obesity, obtained by dividing a person's weight in kilograms by his or her height squared in meters. By definition, when a BMI exceeds 25, that person is considered overweight, and when a BMI exceeds 30, that person is considered obese.

The trend of exacerbation of obesity in children and adolescents in recent decades due to various factors such as gene interactions, epidemiological transmission, nutritional disorders, and inactivity of this age group has caused great concern [16, 33]. Children and adolescents are among the age groups vulnerable to this disease, and the incidence of people at this age will lead to a decrease in their efficiency in adulthood will lead to a decrease in social productivity. For MetS, in addition to its two main consequences, 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 the treatment of its components, namely high blood pressure, dyslipidemia, and obesity. It can also be considered the front line of treatment of MetS, lifestyle modification, i.e., a healthy diet and regular physical activity. Due to the time-consuming treatment of this disease, its early diagnosis can increase the probability of successful treatment and reduce its complications [21].

Since the pathological process and risk factors for this syndrome are formed in childhood, 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 [32].

In general, medicine can be defined as the relationship between the symptoms of a disease and the diagnosis that a physician makes from reference books. Sometimes a symptom may be attributed to various diseases. On the other hand, a disease may occur in the patient so that it is 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 based on personal judgments, relying on colleagues' experience 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 based on 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. On the other hand, due to the empirical nature of medical sciences, complete reliance on reference books can't provide a good source for decisions. A fuzzy system, due to its fuzzy nature, can sufficiently 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 could 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 [4].

The probability of successful prediction and treatment of MetS is significantly increased if artificial intelligence is used. Early detection of MetS can effectively treat this disease, which causes many other diseases that pose a serious challenge to human life. The main goal of MetS treatment is to reduce the risk of ischemic heart disease. Another goal of treatment is to lower LDL cholesterol and high blood pressure and manage 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 various aspects, treating MetS is a complex process. However, early detection of the disease is essential in reducing its complications and helping to treat better and save lives. Using this system is more critical in helping to diagnose the disease in some areas. In many societies, including ours, 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 time for various reasons, including lack of access to medical facilities, specialized laboratories, and inexperienced physicians, and may experience a variety of complications. Many of these problems can be prevented by early detection of the disease using the recommended system used as a physician's assistant.

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 system have fuzzy values. Much research has been done on the FES and its applications [15].

Various researches have been done under the title of designing medical expert systems, including FES for diagnosis of chronic kidney disease, FES for diagnosis of hypertension, FES for diagnosis of coronary heart disease, and FES for diagnosis of Bacterial meningitis than other meningitis in children [5, 10, 29, 33]. In addition, much research has been done on analyzing 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 the use of fuzzy logic inpatient classification for medical diagnosis in expert systems is a practical approach [19].

In a study by Khosravi et al., fuzzy systems have been used to diagnose diabetes [13]. In a study, 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 the response. Despite the value of this research, an error of more than 10 percent, sometimes up to 30 percent, was one of its weaknesses [20]. Khosravanian and Ayat have also introduced a medical system using an artificial neural network to diagnose diabetes [30]. In another study, Zabah diagnosed diabetes using artificial and neural-fuzzy neural networks [12].

There has also been much 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 foods in treating 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. Ebrahimpour et al. have investigated the relationship between MetS and insulin levels in obese children in a school in Tehran [9]. Mehrdad et al. have studied the prevalence of MetS among children aged 3 to 9 years by studying glucose and lipids [22]. In another study by Qarqarachi et al., the prevalence of MetS in obese children and adolescents was investigated. Klishadi et al. examined the pattern of nutrition and physical activity in 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 [14]. In another study, Dehghandar et al. introduced a fuzzy system for the diagnosis of metabolic syndrome in children and adolescents [6].

In this study, our purpose is to design a fuzzy physician assistant system that can diagnose and predict MetS in preschoolers, children, and adolescents aged 4 to 18 years with a higher number of input variables and, therefore, higher accuracy compared to previous studies. In this system, various input variables such as age, waist circumference, systolic blood pressure, diastolic blood pressure, BMI index, waist to height ratio, nutrition, and abdominal obesity have been selected as system input variables, all of which play a role based on previous studies. It has been identified in the diagnosis and development of MetS. At the end of the system, it gives us an output with four values of healthy, patient 1, patient 2, and patient 3, which respectively indicate the amount of healthy output indicating the health of the person, the value of patient output 1 indicates the appearance of signs of disease and risk. If there is no positive change in lifestyle, the amount of discharge of patient 2 indicates a person's illness and the need to take necessary measures to improve health and the amount of discharge of patient 3 indicates a severe threat to health and the urgent need to see a doctor and take medication and supplemental instructions to immediately reduce the symptoms of the disease. The innovation of this system is from the perspective that it uses 1300 standard data collected from Tehran and Isfahan provinces, enters several variables into the system simultaneously as input variables, and as a result, provides comprehensive information about the individual. The evaluation uses a fuzzy system to do so, which sufficiently covers the uncertainties that exist like medical science, in addition to diagnosing the predictability of future infections based on the patient's current information. The error of the method is less than 4 percent and it is more accurate compared to other methods.

2 Estimation of System Accuracy

In this study, we use the confusion matrix to evaluate the accuracy, sensitivity, and efficiency of the system [1]. 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 appropriately diagnosed as healthy.
- FN: All healthy people who have been misdiagnosed as sick.

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

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{1}$$

The performance evaluation of the algorithms described above uses 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:

$$Sensitivity = \frac{TP}{TP + FN}. \tag{2}$$

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:

$$Specificity = \frac{TN}{TN + FP}. \tag{3}$$

3 The Proposed Fuzzy System

In this diagnostic study, an expert system based on fuzzy logic is presented to diagnose and predict MetS in preschoolers, children, and adolescents. In this system, using the diagnosis of doctors and specialists, first, 14 variables of age, gender, height, waist circumference, waist to height ratio, abdominal obesity, weight, BMI, systolic blood pressure, diastolic blood pressure, consumption of fruits and vegetables, daily milk consumption and fast food consumption are considered as input variables. MetS is also considered as an output variable that has four values healthy, patient 1 (observing the signs of disease symptoms and risk of future if there is no positive change in lifestyle), patient 2 (sign is the cause of the person's illness, and the need to take the necessary measures to improve the health condition) and the patient 3 (serious threat to the person's health and the urgent need to see a doctor and take medication and supplemental instructions to reduce the symptoms of the disease immediately). The system is designed based on the data of 1300 preschoolers, children, and adolescents participating in the fifth study of the program for monitoring and prevention of non-communicable diseases of children and adolescents in Tehran and Isfahan provinces. Table 1 shows the general status of the data.

Table 1: General status of input data

Datal	Average
N	1300
Age (year)	10.62
Gender (girl = 1 and boy = 0)	0.52
Systolic blood pressure	92.76
Diastolic blood pressure	63.10
Waist	57.22
Height	135.66
Waist-to-height	0.47
Weight	34.3
BMI (kg/m^2)	17.83
Abdominal obesity	0.38
Consumption of fruits and vegetables (yes = 1 and no = 0)	0.71
Daily milk consumption (yes = 1 and no = 0)	0.51
Fast food consumption (yes = 0 and no = 1)	0.42

Membership functions related to different variables were defined using the opinion of experts and previous relevant related research. Then the system was designed using the fuzzy toolbox of MATLAB software. The total number of data used in this study is 1300 data, of which 1050 data were used as educational data to design the system and formulate rules, and the remaining 250 pieces of data were used to test the system and investigate possible errors. Then the system was evaluated using the accuracy confusion matrix, sensitivity index, and characteristic index.

4 Findings

First, using the latest scientific findings and the opinion of experts, the limits of each variable and membership functions were defined. We also use language variables.

4.1 The input variables

1. Age: This language variable has three values: preschoolers, children, and adolescences. The membership functions of these variables respectively are as follows:

$$\mu_{preschoolers} = \begin{cases} 1, & x \leq 6, \\ \frac{8-x}{2}, & 6 < x \leq 8, \end{cases} \tag{4}$$

$$\mu_{children} = \begin{cases} \frac{x-6}{4}, & 6 \leq x < 10, \\ 1, & x = 10, \\ \frac{13-x}{3}, & 10 < x \leq 13, \end{cases} \tag{5}$$

$$\mu_{adolescence} = \begin{cases} \frac{x-11}{6}, & 11 \leq x < 17, \\ 1, & 17 \leq x. \end{cases} \tag{6}$$

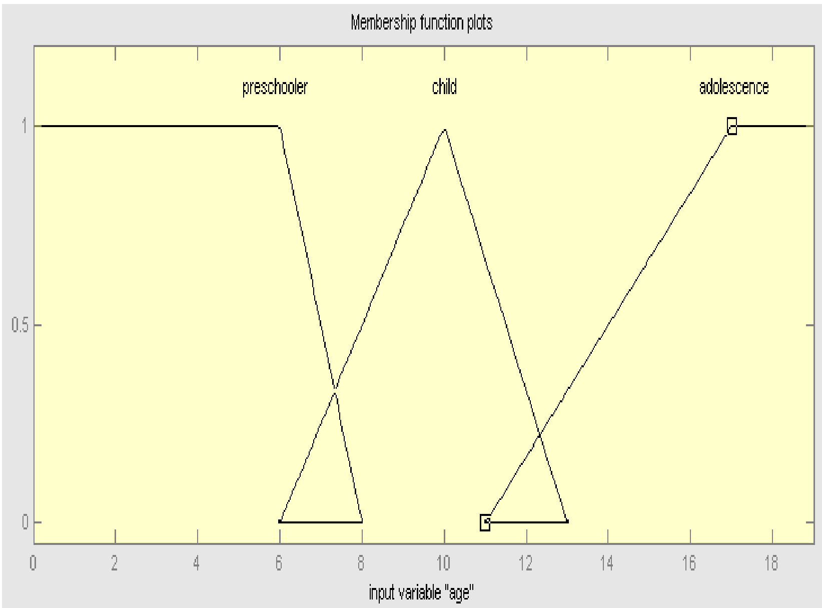

Figure 1: Membership function of the age input variable.

In this article, the limits of the intervals have been determined using the opinions of physicians and experts.

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 calculate these numbers separately for preschoolers, children, and adolescents. Membership functions corresponding to these values in different age ranges are as follows. Preschoolers:

$$\mu_{low} = \begin{cases} 1, & x \leq 74, \\ \frac{82-x}{8}, & 74 < x \leq 82, \end{cases} \tag{7}$$

$$\mu_{normal} = \begin{cases} \frac{x-78}{8}, & 78 \leq x < 86, \\ 1, & x = 86, \\ \frac{93-x}{7}, & 86 < x \leq 93, \end{cases} \tag{8}$$

$$\mu_{high} = \begin{cases} \frac{x-88}{9}, & 88 \leq x < 97, \\ 1, & x = 97, \\ \frac{105-x}{8}, & 97 < x \leq 105, \end{cases} \tag{9}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-102}{7}, & 102 \leq x < 109, \\ 1, & 109 \leq x, \end{cases} \tag{10}$$

Children:

$$\mu_{low} = \begin{cases} 1, & x \leq 83, \\ \frac{85-x}{2}, & 83 < x \leq 85, \end{cases} \tag{11}$$

$$\mu_{normal} = \begin{cases} \frac{x-83}{7}, & 83 \leq x < 90, \\ 1, & x = 90, \\ \frac{99-x}{9}, & 90 < x \leq 99, \end{cases} \tag{12}$$

$$\mu_{high} = \begin{cases} \frac{x-92}{14}, & 92 \leq x < 106, \\ 1, & x = 106, \\ \frac{115-x}{9}, & 106 < x \leq 115, \end{cases} \tag{13}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-105}{10}, & 105 \leq x < 115, \\ 1, & 115 \leq x. \end{cases} \tag{14}$$

Adolescents:

$$\mu_{low} = \begin{cases} 1, & x \leq 86, \\ \frac{92-x}{6}, & 86 < x \leq 92, \end{cases} \tag{15}$$

$$\mu_{normal} = \begin{cases} \frac{x-86}{9}, & 86 \leq x < 95, \\ 1, & x = 95, \\ \frac{105-x}{10}, & 95 < x \leq 105, \end{cases} \tag{16}$$

$$\mu_{high} = \begin{cases} \frac{x-95}{13}, & 95 \leq x < 108, \\ 1, & x = 108, \\ \frac{115-x}{7}, & 108 < x \leq 115, \end{cases} \tag{17}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-110}{8}, & 110 \leq x < 118, \\ 1, & 118 \leq x. \end{cases} \tag{18}$$

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 calculate these numbers separately for preschoolers, children, and adolescents. Membership functions corresponding to these values in different age ranges are as follows. Preschoolers:

$$\mu_{low} = \begin{cases} 1, & x \leq 40, \\ \frac{50-x}{10}, & 40 < x \leq 50, \end{cases} \tag{19}$$

$$\mu_{normal} = \begin{cases} \frac{x-43}{9}, & 43 \leq x < 52, \\ 1, & x = 52, \\ \frac{60-x}{8}, & 52 < x \leq 60, \end{cases} \tag{20}$$

$$\mu_{high} = \begin{cases} \frac{x-54}{7}, & 54 \leq x < 65, \\ 1, & x = 65, \\ \frac{75-x}{9}, & 65 < x \leq 75, \end{cases} \tag{21}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-71}{8}, & 71 \leq x < 79, \\ 1, & 79 \leq x. \end{cases} \tag{22}$$

Children:

$$\mu_{low} = \begin{cases} 1, & x \leq 44, \\ \frac{52-x}{8}, & 44 < x \leq 52, \end{cases} \tag{23}$$

$$\mu_{normal} = \begin{cases} \frac{x-44}{11}, & 44 \leq x < 55, \\ 1, & x = 55, \\ \frac{61-x}{6}, & 55 < x \leq 61, \end{cases} \tag{24}$$

$$\mu_{high} = \begin{cases} \frac{x-65}{7}, & 58 \leq x < 65, \\ 1, & x = 65, \\ \frac{70-x}{5}, & 65 < x \leq 70, \end{cases} \tag{25}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-67}{5}, & 67 \leq x < 72, \\ 1, & 72 \leq x. \end{cases} \tag{26}$$

Adolescents:

$$\mu_{low} = \begin{cases} 1, & x \leq 54, \\ \frac{64-x}{10}, & 54 < x \leq 64, \end{cases} \tag{27}$$

$$\mu_{normal} = \begin{cases} \frac{x-54}{11}, & 54 \leq x < 65, \\ 1, & x = 65, \\ \frac{73-x}{8}, & 65 < x \leq 73, \end{cases} \tag{28}$$

$$\mu_{high} = \begin{cases} \frac{x-67}{8}, & 67 \le x < 75, \\ 1, & x = 75, \\ \frac{85-x}{10}, & 75 < x \le 85, \end{cases} \tag{29}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-72}{14}, & 72 \le x < 86, \\ 1, & 86 \le x. \end{cases} \tag{30}$$

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 adolescences. This variable has three values: normal, borderline, and obese. Membership functions corresponding to these values in different age ranges are as follows.

   Preschoolers:

$$\mu_{normal} = \begin{cases} 1, & x \le 52, \\ \frac{56-x}{4}, & 52 < x \le 56, \end{cases} \tag{31}$$

$$\mu_{border} = \begin{cases} \frac{x-52}{4}, & 52 \le x < 56, \\ 1, & x = 56, \\ \frac{61-x}{5}, & 56 < x \le 61, \end{cases} \tag{32}$$

$$\mu_{fat} = \begin{cases} \frac{x-57}{4}, & 57 \le x < 61, \\ 1, & 61 \le x. \end{cases} \tag{33}$$

   Children:

$$\mu_{normal} = \begin{cases} 1, & x \le 59, \\ \frac{64-x}{5}, & 59 < x \le 64, \end{cases} \tag{34}$$

$$\mu_{border} = \begin{cases} \frac{x-59}{3}, & 59 \le x < 62, \\ 1, & x = 62, \\ \frac{68-x}{6}, & 62 < x \le 68, \end{cases} \tag{35}$$

$$\mu_{fat} = \begin{cases} \frac{x-65}{5}, & 65 \le x < 70, \\ 1, & 70 \le x, \end{cases} \tag{36}$$

   Adolescences:

$$\mu_{normal} = \begin{cases} 1, & x \le 64, \\ \frac{71-x}{7}, & 64 < x \le 71, \end{cases} \tag{37}$$

$$\mu_{border} = \begin{cases} \frac{x-68}{5}, & 68 \le x < 73, \\ 1, & x = 73, \\ \frac{79-x}{6}, & 73 < x \le 79, \end{cases} \tag{38}$$

$$\mu_{fat} = \begin{cases} \frac{x-77}{5}, & 77 \le x < 82, \\ 1, & 82 \le x. \end{cases} \tag{39}$$

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 functions corresponding to these values in different age ranges are as follows. Preschoolers:

$$\mu_{normal} = \begin{cases} 1, & x \leq 13.5, \\ \frac{15-x}{1.5}, & 13.5 < x \leq 15, \end{cases} \tag{40}$$

$$\mu_{border} = \begin{cases} \frac{x-14}{1}, & 14 \leq x < 15, \\ 1, & x = 15, \\ \frac{16.6-x}{1.6}, & 15 < x \leq 16.6, \end{cases} \tag{41}$$

$$\mu_{high} = \begin{cases} \frac{x-16}{1}, & 16 \leq x < 17, \\ 1, & x = 17, \\ \frac{19-x}{2}, & 17 < x \leq 19, \end{cases} \tag{42}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-17}{2}, & 17 \leq x < 19, \\ 1, & 19 \leq x. \end{cases} \tag{43}$$

Children:

$$\mu_{normal} = \begin{cases} 1, & x \leq 14.2, \\ \frac{16.5-x}{2.3}, & 14.2 < x \leq 16.5, \end{cases} \tag{44}$$

$$\mu_{border} = \begin{cases} \frac{x-14.2}{1.4}, & 14.2 \leq x < 15.6, \\ 1, & x = 15.6, \\ \frac{18-x}{1.9}, & 15.6 < x \leq 17.5, \end{cases} \tag{45}$$

$$\mu_{high} = \begin{cases} \frac{x-16}{2}, & 16 \leq x < 18, \\ 1, & x = 18, \\ \frac{19.5-x}{1.5}, & 18 < x \leq 19.5, \end{cases} \tag{46}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-18.5}{1.5}, & 18.5 \leq x < 20, \\ 1, & 20 \leq x. \end{cases} \tag{47}$$

Adolescences:

$$\mu_{normal} = \begin{cases} 1, & x \leq 15.5, \\ \frac{20-x}{4.5}, & 15.5 < x \leq 20, \end{cases} \tag{48}$$

$$\mu_{border} = \begin{cases} \frac{x-17.5}{3}, & 17.5 \leq x < 20.5, \\ 1, & x = 20.5, \\ \frac{24.5-x}{4}, & 20.5 < x \leq 24.5, \end{cases} \tag{49}$$

$$\mu_{high} = \begin{cases} \frac{x-24}{3}, & 20.7 \leq x < 23.7, \\ 1, & x = 23.7, \\ \frac{29-x}{2}, & 23.7 < x \leq 26.7, \end{cases} \tag{50}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-24.5}{2.5}, & 24.5 \leq x < 27, \\ 1, & 27 \leq x. \end{cases} \tag{51}$$

6. Waist-to-height: The waist to height ratio is also an important indicator, especially in preschoolers, children, and adolescents, and this index can be used to determine the growth and health of this age group. This variable has four values: appropriate, borderline, high, and very high. Membership functions corresponding to these values in different age ranges are as follows.

$$\mu_{appropriate} = \begin{cases} 1, & x \leq 0.46, \\ \frac{0.51-x}{0.05}, & 0.46 < x \leq 0.51, \end{cases} \tag{52}$$

$$\mu_{border} = \begin{cases} \frac{x-0.48}{0.02}, & 0.48 \leq x < 0.5, \\ 1, & x = 0.5, \\ \frac{0.55-x}{0.05}, & 0.5 < x \leq 0.55, \end{cases} \tag{53}$$

$$\mu_{high} = \begin{cases} \frac{x-0.53}{0.03}, & 0.53 \leq x < 0.56, \\ 1, & x = 0.56, \\ \frac{0.59-x}{0.03}, & 0.56 < x \leq 0.59, \end{cases} \tag{54}$$

$$\mu_{very\ high} = \begin{cases} \frac{x-0.58}{0.06}, & 0.56 \leq x < 0.59, \\ 1, & 0.59 \leq x. \end{cases} \tag{55}$$

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 preschoolers, children, and adolescents, and their lack of metabolic syndrome is accepted in the world today. Especially the consumption of nutrients such as fruits and vegetables, daily drinking of milk, not consuming sugary drinks, not consuming sweets and salty snacks, and not consuming ready meals and fast food are significant in the health of preschoolers, 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.

4.2 The output variable

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

$$\mu_{healthy} = \begin{cases} 1, & x \leq 1, \\ \frac{1.25-x}{0.25}, & 1 < x \leq 1.25, \end{cases} \tag{56}$$

$$\mu_{patient\,1} = \begin{cases} \frac{x-1.15}{0.85}, & 1.15 \leq x < 2, \\ 1, & x = 2, \\ \frac{2.75-x}{0.75}, & 2 < x \leq 2.75, \end{cases} \tag{57}$$

$$\mu_{patient\,2} = \begin{cases} \frac{x-2.5}{1.25}, & 2.5 \leq x < 3.75, \\ 1, & x = 3.75, \\ \frac{4.2-x}{0.45}, & 3.75 < x \leq 4.2, \end{cases} \tag{58}$$

$$\mu_{patient\,3} = \begin{cases} \frac{x-3.5}{0.6}, & 3.5 \leq x < 4.1, \\ 1, & 4.1 \leq x. \end{cases} \tag{59}$$

According to experts, to reduce or increase the effect of some variables on the output of the system to realize and adapt to scientific findings, some variables were combined. For example, due to the role of height input variable in the variables of the waist to height ratio and BMI, this variable was removed from the system. For similar reasons, the weight variable, together with the height of the BMI index, was removed. Also, the input variables of daily milk consumption, fruit and vegetable consumption, and fast food consumption were combined as a suitable nutritional variable. Then, with the help of MATLAB software fuzzy toolbox and fuzzy system membership were designed using these functions. Suppose that the fuzzy set B^l in the if-then rules is a natural setting with center $\overline{y}^l$.

4.3 The base of rules

The rule set is called the fuzzy "if-then" set, which forms the basis of the fuzzy inference system. To determine the fuzzy rules, we have used the knowledge of experts directly and indirectly (using valid scientific articles).

4.4 Fuzzy Iinference engine

The fuzzy inference engine works similarly to the human reasoning process in that it is applied to inputs and rules to determine output. The implication process is implemented for each rule. Consider a fuzzy system with a base of fuzzy rules with an inference engine (60):

$$\mu_B(y) = \max_{L=1}^{M}\left[\sup_{x\in U}\left(\mu_A(x)\prod_{i=1}^{n}\mu_{A_i^l}(x)\mu_{B^l}(y)\right)\right]. \tag{60}$$

4.5 Fuzzifier

For a fuzzy system, we use a unique fuzzifier (61):

$$\mu_A(x) = \begin{cases} 1, & X = X^\star, \\ 0, & X \neq X^\star. \end{cases} \tag{61}$$

4.6 Defuzzifier

There are different defuzzifiers such as the center of gravity, bisector, half maximum (average value of maximum fuzzy set), greatest maximum, and smallest maximum. After testing different modes, we use the average centers defuzzifier (62):

$$y^\star = \frac{\sum_{l=1}^{M}\overline{y}^l w^l}{\sum_{l=1}^{M} w^l}. \tag{62}$$

4.7 Degree of rules

A fuzzy system with a base of fuzzy rules with inference engine (60) and unique fuzzifier (61) and defuzzifier of average centers (62) is displayed as follow:

$$f(x) = \frac{\sum_{l=1}^{M}\overline{y}^l\left(\prod_{i=1}^{n}\mu_{A_i^l}(x)\right)}{\sum_{l=1}^{M}\left(\prod_{i=1}^{n}\mu_{A_i^l}(x)\right)}, \tag{63}$$

where $x \in U \subset \mathbf{R}^n$ is the input of the fuzzy system, and $f(x) \in V \subset \mathbf{R}$ is its output. Also, we use the relationship

$$D(rule) = \prod_{i=1}^{n}\mu_{A_i^l}\left(x_{oi}^p\right)\mu_{B^l}\left(y_o^p\right), \tag{64}$$

to calculate the degree of each rule, and to use the calculated degrees, we remove the same and contradict the rules with lower degrees [27]. Using the lookup table method, the membership function value was first calculated for each of 1050 preschoolers, children, and adolescents. Then the degree of each rule was calculated. For example, consider a 10-year-old child with a systolic blood pressure of 80, a diastolic blood pressure of 60, a waist circumference of 72, a BMI of 22.9, and a waist-to-height ratio of 0.54, who is obese and malnourished. The rule of thumb for this person is 0.00000216. Thus, rules were formulated using the information of individuals. Then similar and

Table 2: Input data for three people (W/H shows the "Waist to height")

Age	Systol	Diastole	Waist	BMI	W/H	obesity	Nutr.	Output
16	120	80	84	24.51	0.51	0	0	3.1
10	80	60	72	22.90	0.54	1	0	3.6
7	80	50	55	12.29	0.45	0	1	1.15

contradictory rules were removed using the calculated degree of rules and their comparison. Table 2 shows information about the three patients and how to remove the rules.

For example, rules 5 and 69 are two similar rules:

- Rule 5: If the age is child and waist size is obese, and BMI index is high, the result is patient 2.
- Rule 69: If the age is child and abdominal obesity is yes and BMI index is high, the result is patient 2.

According to the second degree of the rule obtained from (64), which shows that rule 69 is more vigorous, rule 5 was deleted.

$$D(5) = 216.65 \times 10^{-5} \quad < \quad D(69) = 218.8 \times 10^{-4}$$

Rules 12 and 54 are also contradictory, removed by calculating the second degree of rule 54. With the continuation of this process for all 1050 patients and the elimination of contradictory and similar rules, 45 rules remained at the end, and the knowledge base of the fuzzy inference system was formed using these 45 rules. After designing the system, using the remaining 250 data, which are test data, possible errors were investigated and fixed, and this system was designed with eight input variables and one output variable, multiplication inference engine, single fuzzifier, and centroid defuzzifier [8].

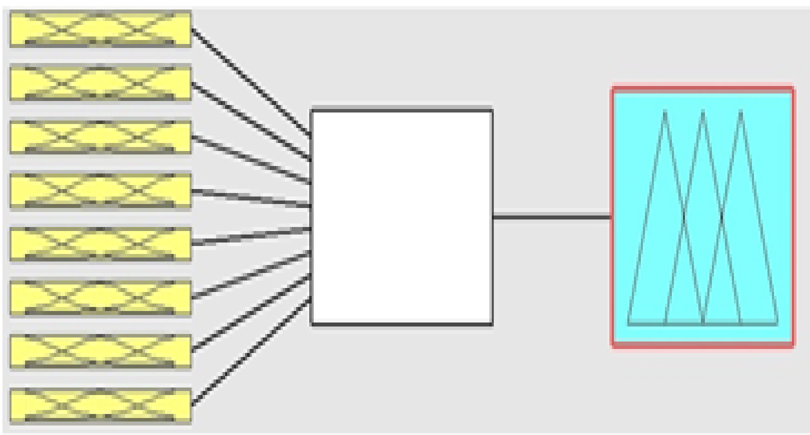

Figure 2: The proposed system with eight input variables and one output variable.

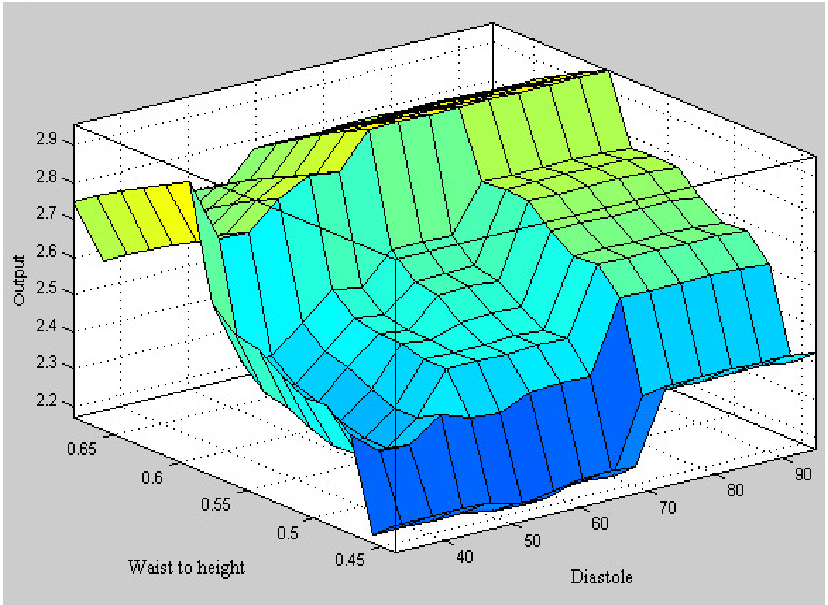

Figure 3: The effect of two input variables diastole and waist to height together on the output variable.

5 System Accuracy

The confusion matrix for the fuzzy system training data used with healthy output is shown in Table 3.

Table 3: Data confusion matrix using the fuzzy system for healthy output

System	Healthy	Other
Healthy	71	3
Other	3	173

As shown in Table 3, out of a total of 74 healthy individuals, 71 were diagnosed by the system, and among the other 176, 173 were correctly diagnosed. Other cases are similar.

Table 4: Results of sensitivity, specificity, and accuracy of the system designed for each output

System	Sensitivity	Specificity	Accuracy
Healthy	0.983	0.96	0.976
Patient 1	0.97	0.932	0.96
Patient 2	0.97	0.971	0.968
Patient 3	0.975	0.942	0.968

It can be seen that the designed system has accurately detected more than 96 percent 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.

6 Discussion and Conclusion

In this study, it was observed that each of the factors of increasing systolic blood pressure and diastolic blood pressure, abdominal obesity, malnutrition, and increasing BMI on the incidence of preschoolers, children, and adolescents has a positive effect on MetS. This is consistent [18, 23]. 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 [17]. In this system, the capacity of fuzzy mathematics is used. We have already seen the successful use of fuzzy mathematics in medical matters [15, 16, 29, 33]. Given the characteristics of fuzzy mathematics, the uncertainty in medical knowledge can be well overcome.

The system was based on the data of 1300 preschoolers, children, and adolescents participating in the fifth study of the program for monitoring and prevention of non-communicable diseases in children and adolescents in Tehran and Isfahan provinces, 1050 were used as education data and 250 data as test data were used to test the rules and output system. The minimum age of people in this study was four years, and the maximum age was 18 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 in with real-world problems, it provides more accurate results with system error estimated at less than 4 percent. Of course, although there is not much difference in the accuracy of the performance of different models, because of the issue 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 study conducted in 2006, 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 percent accuracy [26]. Of course, this method was not used to predict a person's future infection using current information. In another study conducted in 2010, Barakat et al. increased the accuracy of diagnosis by up to 94 percent using the support vector machine method. However, the number of input variables in this study, including blood pressure, blood sugar, and BMI, was less than our study [3]. In another study in 2010, Thai researchers were able to diagnose MetS with 90 percent accuracy using the decision tree method [28]. Of course, this method was not used to predict the disease in the future 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 [2] that was more accurate than all three methods alone. Of course, this method was also used only for disease. 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 diagnose the disease with 76 percent accuracy [25].

Compared to other methods, this method can be considered a new method in two ways. First, there is no method with all the input variables that, according to previous research, all of them affect the incidence of MetS, and 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 also used to predict the development of MetS in the future using the current information. As a result, from the point of view of using a fuzzy system for this purpose, which sufficiently covers the uncertainties that exist like 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 in Tehran and Isfahan provinces, in addition to the ability to diagnose the disease is also used in the field of disease prediction with less than 4% error, it is a new system. This system can serve as an assistant to a specialist doctor to diagnose the disease.

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