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Classification of Iraqi Children According to Nutritional Status Using Fuzzy Decision Tree

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Abstract

The classification is one of the essential tools used in medical statistics to classify the nutritional status of children under five years. A good nutritional status is necessary for children's health and has a sicnificant role in the child's normal development. Likewise, poor nutritional status is considered a serious disease for this age group and needs attention from child health specialists. Doctors face great difficulty in determining the nutritional status due to the state of uncertainty in the incidence of this disease or the ambiguity in the variables and characteristics of that phenomenon. The fuzzy sets theory was applied to classify the nutritional status of children under the age of five years using fuzzy logic, where the fuzzy decision tree method was employed, and a tree was created for each age group (male, female) based on the linguistic variables (weight, height), and body mass index for the classification categories .In this study, the nutritional status of children was classified and the groups were identified more accurately to reduce the chances of misdiagnosis and provide them with more accurate appropriate treatment to improve the health level of children to build a more immune society with a good health level.

The study dealt with a sample of (16487) Iraqi children under 5 years of age, the number of males (8427) and the number of females (8060), divided according to age into 12 categories or groups. The results showed the age groups She was of normal weight in varying proportions.

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Introduction

The state of nutrition in children has attracted the attention of many researchers in the world and different societies to show the growth of those societies with regard to the category of children, which is the basic foundation for building society. The state of malnutrition is represented as a problem that some of these societies suffer from, while other societies do not suffer from that problem, and this happens as a result of the political, economic and social conditions that those societies are going through. Great on the social and health level, so we study the nutritional status of Iraqi children for the year 2018.

Due to the importance of this topic, many researchers presented various studies such as the study (Suca, 2016) which developed a new fuzzy model to predict obesity in children between the ages of (6-17) years using a fuzzy decision tree based on indicators of weight, age, and the index of fat percentage. In the f body fat (BF) and then used as measures of obesity cases. A fuzzy model was developed to be used as an indicator of obesity in the medical field [11]. (Permatasari, 2017) classified the nutritional status of children using the fuzzy inference system (FIS), where the Mamdani method was applied, and he developed nine rules that were deduced and produced the classification of nutritional status [8]. (Wulandari, 2018) assessed the nutritional status of children and used the fuzzy inference system for decision-making and determining the nutritional status of children. Two methods were used in fuzziness, which are the (Mamdani) method and the (Tsukamoto) method, and a comparison was made between the two methods [14]. The study of Muhammad (2020) focused on evaluating the nutritional status of children in Iraq under 5 years of age for the year 2018 and compared the results with the results of 2006 and concluded that there was an improvement in the nutritional status of children [10]. (Irmalia, 2022) built a system that can automatically determine the BMI value and category using fuzzy logic to maintain nutritional status, and tested Body mass index BMI where 5 adjectives were taken into the system (very lean, lean, normal, heavy, obese) were identical to manual calculations [3]. (Hussein & Mohammad, 2023) build a fuzzy classification system for classifying the nutritional status of children under 5 years old in Iraq using the Mamdani method based on input variables such as weight and height to determine the nutritional status of the child.[4] In this research which differs from previous studies, children under 5 years old in Iraq were classified using fuzzy decision tree,

Malnutrition is one of the main problems in developed countries. Several factors explain why malnutrition is widespread in children with low birth weight, inadequate nutrients, the prevalence of infectious diseases, lack of breastfeeding, and inadequate child care. Malnutrition is known to be a contributing factor to disease and death. In the developing world, malnutrition affects nearly 800 million people, more than 340 million children under five years of age. More than six million of these children die each year due to malnutrition. The majority of the world's population lives in countries where overweight and obesity kill more lives than underweight.

The segment of children under 5 years is considered an important segment of society, as it is considered the nucleus of society because in the future it will be one of the important pillars society.

Our study of this segment through the nutritional status and classification of children under 5 years of age to determine the categories or categories accurately, so we used classification techniques using fuzzy groups to classify Iraqi children according to their nutritional status to set limits and distinguish between categories according to the nutritional status of the child and the levels of those who suffer from malnutrition.

The study aims to conduct a classification of children according to nutritional status in order to identify those who are at risk and need assistance to meet the nutritional needs of children according to the World Food Program. It is necessary to have organizations that can provide nutritional needs to supply them with the provide nutritional needs in order to provide them with the appropriate type of assistance.

In this research, we build a fuzzy decision tree for each age group and males and females to derive classification rules from the fuzzy decision tree in order to classify Iraqi children under 5 years of age according to nutritional status based on linguistic variables (weight and height) as input variables, while classification categories (outputs) are indicators.

Theoretical Concepts

Fuzzy Set Theory

In 1965, Professor Lutfi Zadeh presented the theory of fuzzy sets, which is a method for dealing with cases of uncertainty or ambiguity, and applied (Zadeh) multi-valued logic and put the term fuzzy logic, where the fuzzy group is characterized by the affiliation function, which takes values between [0, 1]. The general formula for expressing fuzzy sets is to represent them in the form of ordered pairs.

$$A = \{x, M\_A\ (x)\} \tag{1}$$

Where the first term represents the element in the group, and the second term represents the degree of belonging of the element to the group [1].

Decision Tree Fuzzy

Decision tree definition: They are tree-like structures whose aim is to create a mathematical model that contains branches that lead to the best decision-making. The decision tree simulates human thinking, making it easy to understand.[17] As for the FDT Fuzzy Decision Tree, it represents the decision tree that was employed in the Fuzzy Set Theory to deal with uncertainty,[12] Each FDT node is characterized by a fuzzy group instead of a deterministic group i.e.,[7] the deterministic values used to divide the decision nodes are replaced by fuzzy values.[2]

The following is the theoretical basis of a fuzzy decision tree algorithm based on classification fuzziness. With fuzzy sets, they provide the basic mathematical framework for dealing with ambiguity and uncertainty.[5]

Suppose that A represents a fuzzy set defined on the universal set U with affiliation functions $\mu_{\mathrm{A}}(u)$ for u ∈ U. So, the measure of the group affiliation function is There was a normal distribution of the variable Y defined on $\mathrm{X} = \{\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{n}\}$ The ambiguity of the variable Y is defined as the following:

Definition 1: Ambiguity arises in circumstances in which there are two or more choices so that the choosing between them is left undetermined. Ambiguity can be measured as follows:[5]

$$\mathrm{E_a(Y)} = \mathrm{g}(\mathcal{P}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathcal{P}_\mathrm{i}^* - \mathcal{P}_{\mathrm{i}+1}^*) \ln (\mathrm{i}) \tag{2}$$

Where: $\mathcal{P}^* = \{\mathcal{P}_1^*, \mathcal{P}_2^*, \ldots, \mathcal{P}_\mathrm{n}^*\}$represent permutations of the probability distribution $\mathcal{P} = \{\mathcal{P}(\mathrm{x}_1), \mathcal{P}(\mathrm{x}_2), \ldots, \mathcal{P}(\mathrm{x}_\mathrm{n})\}$ And $\mathcal{P}_\mathrm{i}^* \geq \mathcal{P}_{\mathrm{i}+1}^*$ From above $\mathrm{E_a(Y)} \geq 0$ If $\mathrm{E_a(Y)} = 0$ then $\mathcal{P}_2^* = 0$ Indicates that there is no ambiguity because only one value is possible for Y if $\mathcal{P}_\mathrm{n}^* = 1$, $\mathrm{E_a(Y)} = \ln(\mathrm{n})$ Which indicates that all values are perfectly possible for Y, and also represents the largest available ambiguity.

In order to measure the fuzzy A value of the affiliation function is set $\{\mu_{\mathrm{T}_1}(\mathrm{u_i}), \mu_{\mathrm{T}_2}(\mathrm{u_i}), \ldots, \mu_{\mathrm{T_s}}(\mathrm{u_i})\}$ For any variable in the fuzzy set $\mathrm{T(A)} = \mathrm{T}_1, \ldots, \mathrm{T_s}$, the fuzzy distribution probability of A can be obtained as shown in the following formula:[15]

$$\mathcal{P}_{\mathrm{T_s}}(\mathrm{u_i}) = \mu_{\mathrm{T_s}}(\mathrm{u_i}) / \max_{1 \leq \mathrm{j} \leq \mathrm{s}} \{\mu_{\mathrm{T_j}}(\mathrm{u_i})\}\ ,\ \mathrm{s} = 1, \ldots, \mathrm{S} \tag{3}$$

Thus, fuzziness can be measured for each $\mathrm{u_i}$ view as follows [15]

$$\mathrm{E_a}(A(\mathrm{u_i})) = g(\mathcal{P}_T(u_i)) \tag{4}$$

The blur measurement formula can be obtained according to the following formula:[15]

$$\mathrm{E_a}(A) = \frac{1}{m} \sum_{i=1}^{m} \mathrm{E_a}(A(\mathrm{u_i})) \tag{5}$$

The concept of the fuzziness rule and the level of confidence takes the following form: “IF A THEN B” where the fuzziness relationship is defined from the fuzzy conditional group (A) to the conclusion of the fuzzy group B[1]. So we need to determine the validity of the rule using the concept of confidence level and it can be measured by definition 2.

Definition 2: The degree of truth or the level of reality of the fuzzy rule is measured by the following S (A, B) law, in which A is a fuzzy subset and B is a part of it.[16]

$$S(A, B) = \frac{M\ (A \cap B)}{M(A)} = \frac{\sum_{u \in U} min(\mu_A(u), \mu_B(u))}{\sum_{u \in U} \mu_A(u)} \tag{6}$$

In a classification problem the fuzzy evidence is a conditional fuzzy subset defined on the superset, which represents the linguistic values that one or more adjectives take on.[13]

Definition 3: Depending on the fuzzy evidence E, the probability of classifying things into classes or classes can be defined according to [9]

$$\mathcal{P}(C_i|E) = S(E,C_i) \,/\, \max_j S(E,C_j) \tag{7}$$

Where $S(E,C_i)$ is degree of realism

By knowing the set of fuzzy evidence, classification fuzziness with fuzzy parts can be defined as follows:

Definition 4: The fuzziness of the classification with the fuzzy parts $\mathrm{P} = \{\mathrm{E}_1, \dots, \mathrm{E}_\mathrm{k}\}$ The fuzzy index F is denoted by G(P|F) and is called the weighted average of the classification fuzziness with each subset of the parts which define as [16]

$$\mathrm{G(P|F)} = \sum_{\mathrm{i=1}}^{\mathrm{k}} \mathrm{w(E_i|F)\, G(E_i \cap F)} \tag{8}$$

Where $\mathrm{G(E_i \cap F)}$ Classification is ambiguous with hazy evidence $\mathrm{E_i \cap F}$, and $\mathrm{w(E_i|F)}$ The weight represents the relative size of the subgroup and is given by the following relation [16]

$$\mathrm{w(E_i|F)} = \mathrm{M(E_i \cap F)} / \sum_{\mathrm{j=1}}^{\mathrm{k}} \mathrm{M(E_i \cap F)} \tag{9}$$

Overlapping of linguistic boundaries may lead to high classification ambiguities. Ambiguity in the classification of objects depends on the values of the affiliation function with respect to the evidence. Here the evidence is strong if the affiliation function exceeds a certain significant level.[9]

Definition 5: Given the values of the affiliation functions of the fuzzy index observations E, the fuzzy index E_α can be defined at the level of significance α with the affiliation functions as:[13]

$$\mu_{E_\alpha}(u) = \begin{cases} \mu_E(u) & if \;\; \mu_E(u) \geq \alpha \\ 0 & if \;\; \mu_E(u) < \alpha \end{cases} \tag{10}$$

Classification ambiguity with fuzzy partitioning is calculated at the level of significance α, as it provides the level of significance α that is imposed, to reduce the ambiguity in the parts. The steps of the process of creating a decision tree will be mentioned on the practical side with the data.

Case Study

The applied side is concerned with classifying the nutritional status of Iraqi children under 5 years of age, based on the data obtained through the Multiple Indicator Statistical Survey, which is MICS6, which was conducted in 2018 by the Central Statistical Organization in Iraq, in cooperation with the Ministry of Health and the World Health Organization. Data was collected on (16689) children under the age of 5 years, including (8532) males and (8157) females. Table (1) shows the data divided into (12) age groups according to the age variable.[4] The variables studied to classify the nutritional status are the weight of the child as a linguistic variable and symbolized by the symbol (X) and its linguistic limits (x_1 represents Scrawny, x_2 represents Light, x_3 represents normal, x_4 represents Obese, x_5 represents very Obese), and the variable of child height as a linguistic variable and symbolizes it By the symbol (Y) and its categorical boundaries (y_1 represents Stunting, y_2 represents short, y_3 represents normal, y_4 represents tall, y_5 represents very tall) (input variables) and classification categories BMI and its categorical boundaries (Z_1 malnutrition, Z_2 underweight, Z_3 normal, Z_4 is overweight, Z_5 is obese) (Output variable).

Table 1: It represents a description of the 2018 Iraq Children data

Set	Age	Female	Male	Sum
Set1	Less than 2 Months	228	239	467
Set2	Less than 4 Months	296	320	616
Set3	Less than 6 Months	314	272	586
Set4	Less than 8 Months	268	292	560
Set5	Less than 10 Months	268	292	560
Set6	Less than 12 Months	203	247	450
Set7	Less than 16 Months	554	546	1100
Set8	Less than 20 Months	524	579	1103
Set9	Less than 24 Months	477	507	984
Set10	Less than 3 years	1498	1610	3108
Set11	Less than 4 years	1786	1809	3595
Set12	Less than 5 years	1644	1714	3358
Sum		8060	8427	16487
Missing observations and recording errors		97	105	202
Sum		8157	8532	16689

The fuzzy decision tree method for classifying the nutritional status of children is carried out in four main steps sequentially, as follows:

Step1: Fuzzification

In fact, fuzzifying is a conceptual process that people often use to reduce information overload in the decision-making process [13].

The construction of affiliation functions is according to the age groups, where in the first year it is every two months (6 functions), in the second year every four months (3 functions), the third, fourth and fifth years for each year is indicative. And fuzzing the data (inputs and outputs) using the trigonometric affiliation function, the L function, and the R function. In our current study, the criteria for classifying children will be chosen according to nutritional status based on the tables of the World Health Organization [6]. The fuzzing functions of the Y variable for the age group less than two months for males are as follows:

$$\boldsymbol{\mu_A y_1}(y\,;\ 50.8, 52.8) = \begin{cases} 1 & y \le 50.8 \\ \frac{52.8-y}{52.8-50.8} & 50.8 \le y \le 52.8 \\ 0 & y \ge 52.8 \end{cases}$$

$$\boldsymbol{\mu_A y_2}(y\,;\ 50.8, 52.8, 54.7) = \begin{cases} 0 & y \le 50.8 \\ \frac{y-50.8}{52.8-50.8} & 50.8 \le y \le 52.8 \\ \frac{54.7-y}{54.7-52.8} & 52.8 \le y \le 54.7 \\ 0 & y \ge 54.7 \end{cases}$$

$$\boldsymbol{\mu_A y_3}(y\,;\ 52.8, 54.7, 56.7) = \begin{cases} 0 & y \le 52.8 \\ \frac{y-52.8}{54.7-52.8} & 52.8 \le y \le 54.7 \\ \frac{56.7-y}{56.7-54.7} & 54.7 \le y \le 56.7 \\ 0 & y \ge 56.7 \end{cases}$$

$$\boldsymbol{\mu_A y_4}(y\,;\ 54.7, 56.7, 58.6) = \begin{cases} 0 & y \le 54.7 \\ \frac{y-54.7}{56.7-54.7} & 54.7 \le y \le 56.7 \\ \frac{58.6-y}{58.6-56.7} & 56.7 \le y \le 58.6 \\ 0 & y \ge 58.6 \end{cases}$$

$$\boldsymbol{\mu_A y_5}(y\,;\ 56.7, 58.6) = \begin{cases} 0 & y \le 56.7 \\ \frac{y-56.7}{58.6-56.7} & 56.7 \le y \le 58.6 \\ 1 & y \ge 58.6 \end{cases}$$

Figure (1) represents the function of belonging to the variable of height according to the data of the nutritional status of Iraqi children of less than two months of age :

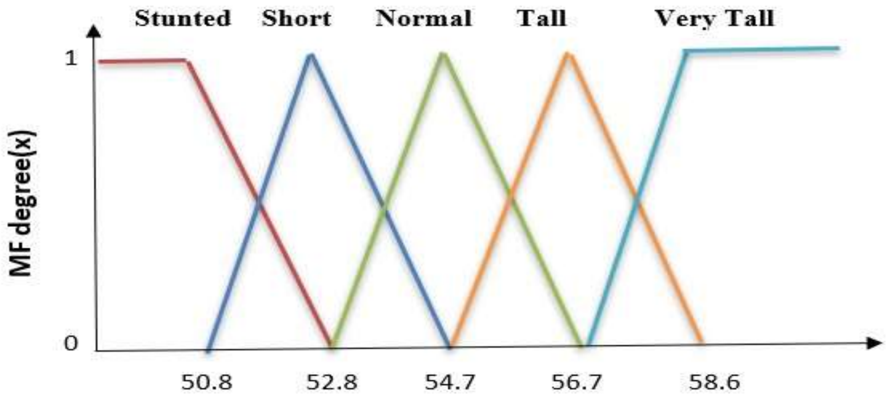

Figure 1. represents the affiliation functions of the length variable.

Where the horizontal axis is the input value that is the length variable, while the vertical axis is the degree of belonging to the input value of the length variable, and in order to apply fuzzy functions to the X variable for the age group less than two months for males, the following:

$$\mu_A \boldsymbol{x_1}(x\,;3.4,3.9) = \begin{cases} 1 & x \le 3.4 \\ \frac{3.9 - x}{3.9 - 3.4} & 3.4 < x < 3.9 \\ 0 & x \ge 3.9 \end{cases}$$

$$\mu_A \mathbf{x_2}(x\,;\ 3.4,3.9\,,4.5\ ) = \begin{cases} 0 & x \le 3.4 \\ \frac{x - 3.4}{3.9 - 3.4} & 3.4 < x \le 3.9 \\ \frac{4.5 - x}{4.5 - 3.9} & 3.9 < x < 4.5 \\ 0 & x \ge 4.5 \end{cases}$$

$$\mu_A x_3(x\,;\ 3.9\,,4.5\,,5.1\,) = \begin{cases} 0 & x \le 3.9 \\ \frac{x - 3.9}{4.5 - 3.9} & 3.9 < x \le 4.5 \\ \frac{5.1 - x}{5.1 - 4.5} & 4.5 < x < 5.1 \\ 0 & x \ge 5.1 \end{cases}$$

$$\mu_A x_4(x\,;\ 4.5\,,5.1,5.8\,) = \begin{cases} 0 & x \le 4.5 \\ \frac{x - 4.5}{5.1 - 4.5} & 4.5 < x \le 5.1 \\ \frac{5.8 - x}{5.8 - 5.1} & 5.1 < x < 5.8 \\ 0 & x \ge 5.8 \end{cases}$$

$$\mu_A x_5\,(x;\ 5.1,5.8\,) = \begin{cases} 0 & x \le 5.1 \\ \frac{x - 5.1}{5.8 - 5.1} & 5.1 < x < 5.8 \\ 1 & x \ge 5.8 \end{cases}$$

Figure (2) represents the function of belonging to the weight variable according to the nutritional status data of children in Iraq for less than two months of age:

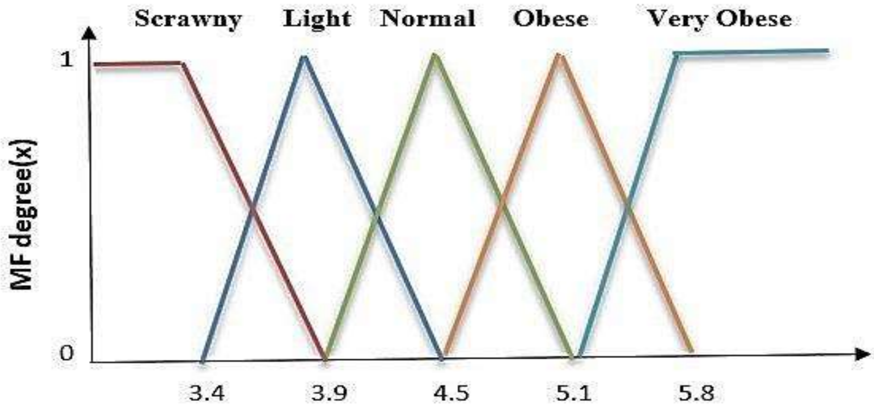

Figure 2. represents the affiliation functions of the weight variable.

Where the horizontal axis is the input value that is the weight variable, while the vertical axis is the degree of belonging to the input value of the weight variable, to apply fuzzing functions to the Z variable, which represents the body mass index (classification categories) for the age group less than two months for males, as follows:

$$\mu_A z_1(z\ 12.4, 13.6) = \begin{cases} 1 & z \le 12.4 \\ \frac{13.6 - x}{13.6 - 12.4} & 12.4 \le z \le 13.6 \\ 0 & z \ge 13.6 \end{cases}$$

$$\mu_A z_2(z\,; 12.4, 13.6, 14.9) = \begin{cases} 0 & z \le 12.4 \\ \frac{x - 12.4}{13.6 - 12.4} & 12.4 \le z \le 13.6 \\ \frac{14.9 - x}{14.9 - 13.6} & 13.6 \le z \le 14.9 \\ 0 & z \ge 14.9 \end{cases}$$

$$\mu_A z_3(z\,;\ 13.6, 14.9, 16.3) = \begin{cases} 0 & z \le 13.6 \\ \frac{x - 13.6}{14.9 - 13.6} & 13.6 \le z \le 14.9 \\ \frac{16.3 - x}{16.3 - 14.9} & 14.9 \le z \le 16.3 \\ 0 & z \ge 16.3 \end{cases}$$

$$\mu_A z_4(z\,; 14.9, 16.3, 17.8) = \begin{cases} 0 & z \le 14.9 \\ \frac{x - 14.9}{16.3 - 14.9} & 14.9 \le z \le 16.3 \\ \frac{17.8 - x}{17.8 - 16.3} & 16.3 \le z \le 17.8 \\ 0 & z \ge 17.8 \end{cases}$$

$$\mu_A z_5(z\,; 16.3, 17.8) = \begin{cases} 0 & z \le 16.3 \\ \frac{x - 16.3}{17.8 - 16.3} & 16.3 \le z \le 17.8 \\ 1 & z \ge 17.8 \end{cases}$$

Figure (3) represents the function of belonging to the body mass index variable according to the nutritional status data of Iraqi children less than two months old:

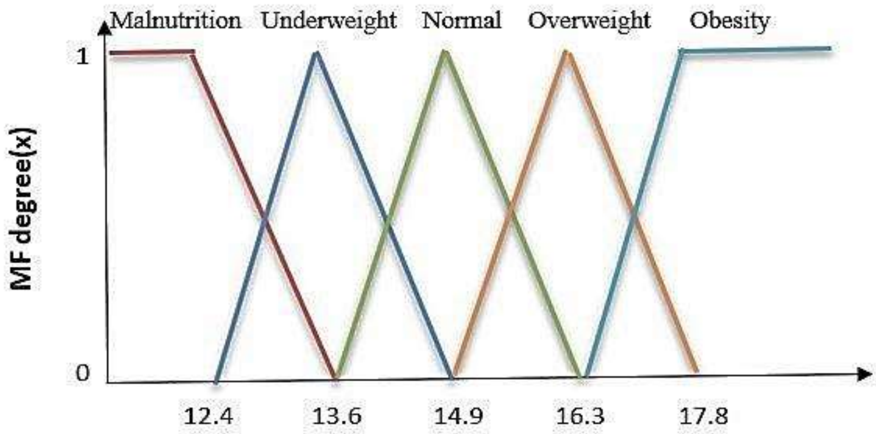

Figure 3. represents the functions of belonging to the BMI variable.

Where the horizontal axis is the input value that is the BMI variable, while the vertical axis is the degree of belonging to the input value of the BMI variable, in the same way the rest of the age groups, males and females, are fuzzed based on the tables of the World Health Organization [6].

Before starting the stimulation process, the values of the significant level of fuzzy evidence α and a threshold for the level of realism β should be assumed [13]. In our study, a significant level of fuzzy evidence (α = 0.1) was chosen to filter out the unimportant fuzzy evidence, i.e. affiliations less than 0.1 are neglected and replaced with zero. This is because our study is concerned with the nutritional status of children, i.e. it is concerned with human and child health in a special case, and the threshold parameter was chosen for the level of realism (β = 0.9) for a larger decision tree and higher classification accuracy. The process of triggering a decision tree consists of the following steps:

Step A: Measuring the classification ambiguity associated with each trait and identifying the trait that has the smallest classification ambiguity and is treated as the root node [17]. The results are shown in Table (2), it was found that weight X is the least ambiguity for all age groups and for males and females, in this case Weight X is a root node in the fuzzy decision tree for all age groups, males and females, and has five Branches namely (X_1, X_2, X_3, X_4, X_5).

Table 2: represents the classification ambiguity values for the variable weight (X) and height (Y) for males and females and according to age groups.

Age	Male		Female	
	X	Y	X	Y
Less than 2 Months	0.74398	1.12042	0.78040	0.88056
Less than 4 Months	0.73098	1.15944	0.70596	0.96728
Less than 6 Months	0.72003	1.07460	0.75386	0.91906
Less than 8 Months	0.79809	1.04243	0.73331	0.88716
Less than 10 Months	0.80296	1.04300	0.76206	0.88353
Less than 12 Months	0.75900	1.00817	0.63647	0.88068
Less than 16 Months	0.85502	1.02771	0.84087	1.04562
Less than 20 Months	0.83614	1.00789	0.81854	1.01880
Less than 24 Months	0.82116	1.05092	0.83240	0.96961
Less than 3 years	0.86747	0.92820	0.83934	0.93769
Less than 4 years	0.76374	0.88287	0.74611	0.82109
Less than 5 years	0.71288	0.73785	0.67693	0.72358

Step B: We calculate the level of realism of the classification for all views within the branch and for all categories. If the Reality level of the classification in a unit of the computed classes gives greater than the Reality level threshold parameter β, then we terminate the branch as a Node Leaf [17] But if it is less than the threshold parameter, the level of realism β, then we go to step c. Table (3) shows the results obtained when calculating the level of realism in the first branch, X1, for males and for all age groups. It is less than the threshold for the level of realism β = 0.9. In the same way, the rest of the branches are calculated for males and females. From the results obtained, it became clear that the results of the level of realism for all branches of the root node X (X_1, X_2, X_3, X_4, X_5) do not end with a leaf because it is less than the threshold level parameter β = 0.9, except for the last branch X5 less than five years at the classification category Z_5 score was 0.911 from the threshold level parameter 0.9, in which case the branch in this category ends with a paper titled (Obesity) Z_5.

Table 3: represents the values of the level of realism for the first branch X1 for males and for all age groups.

Male	S (x_1, z_1)	S (x_1, z_2)	S (x_1, z_3)	S (x_1, z_4)	S (x_1, z_5)
Less than 2 Months	0.62403	0.22376	0.08960	0.07645	0.06396
Less than 4 Months	0.57824	0.30169	0.13838	0.07269	0.04163
Less than 6 Months	0.56635	0.37820	0.14521	0.02920	0.03856
Less than 8 Months	0.56238	0.32669	0.20599	0.02578	0.02574
Less than 10 Months	0.50376	0.28848	0.23256	0.10857	0.01878
Less than 12 Months	0.25887	0.39976	0.31128	0.14352	0.07071
Less than 16 Months	0.37538	0.30308	0.32402	0.12687	0.02734
Less than 20 Months	0.25078	0.37207	0.39208	0.18929	0.02920
Less than 24 Months	0.28930	0.32621	0.36704	0.13607	0.07187
Less than 3 years	0.13568	0.26889	0.42444	0.27528	0.07613
Less than 4 years	0.16516	0.37671	0.44994	0.18655	0.03539
Less than 5 years	0.19044	0.43741	0.42763	0.13438	0.02320

Step C: If the level of realism computed in step b is less than the threshold parameter level of realism β in this case, we check if the added variable will increase subdivision and further reduce classification ambiguity. In this case, we compute the classification ambiguity for each branch of the root node and then we install it as a fuzzy index and compute the classification ambiguity with the other fuzzy parts (the language boundary of the length variable Y) to define a decision node [17]. Table (4) shows the measurement of ambiguity in the first branch $x_1$and the measurement of classification ambiguity for the added variable Y after that if x_1 is installed as a fuzzy guide for comparison between them in order to choose the added variable of length as a decision node or install the branch x_1 as a corridor for all age groups and for males and females. In the same way, ambiguity is measured for the rest of the branches (x_2, x_3, x_4, x_5).

Table 4: represents the results of measuring the ambiguity of the branch x_1 and measuring the ambiguity of the added variable classification Y.

Age	Male		Female	
	$G(X_1)$	**$G(Y/X_1)$**	**$G(X_1)$**	$G(Y/X_1)$
Less than 2 Months	0.3649	0.4533	0.4991	0.7424
Less than 4 Months	0.5109	0.7088	0.4101	0.5172
Less than 6 Months	0.5979	0.6318	0.8190	0.7068
Less than 8 Months	0.5746	0.7137	0.4192	0.6129
Less than 10 Months	0.6544	0.6990	0.5647	0.5909
Less than 12 Months	0.9451	0.7270	0.8689	0.7746
Less than 16 Months	1.0392	0.7345	0.9787	0.8439
Less than 20 Months	1.0726	0.7246	1.1366	0.7793
Less than 24 Months	1.0860	0.7792	1.0429	0.7490
Less than 3 years	0.8384	0.7373	0.8499	0.7576
Less than 4 years	0.8716	0.6970	0.8605	0.7231
Less than 5 years	0.9544	0.7982	0.7711	0.7289

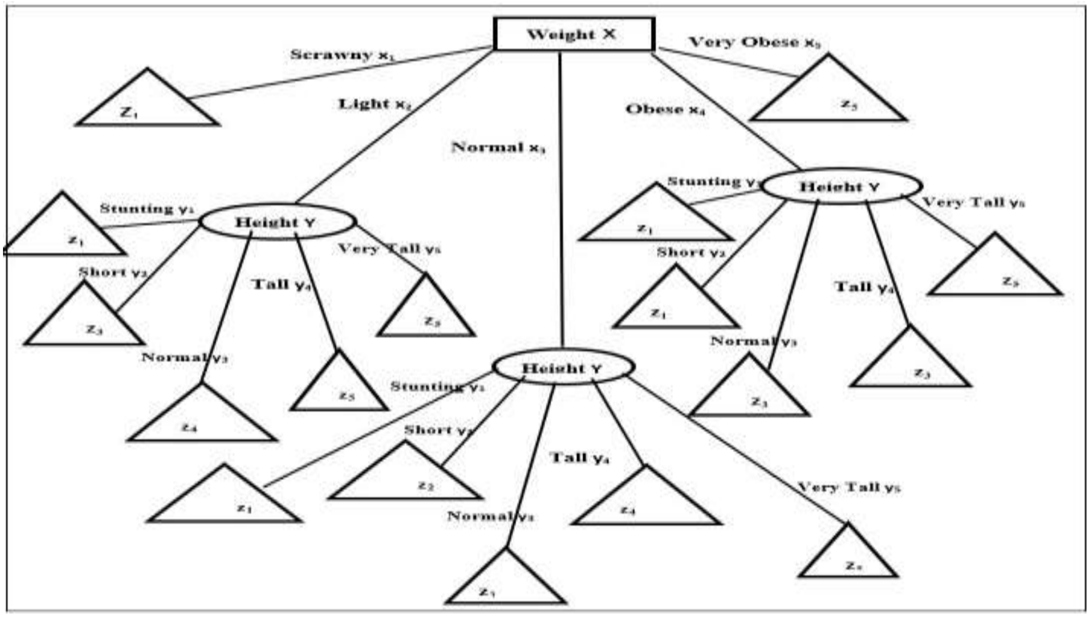

Figure 4. shows the fuzzy decision tree of the age group less than two months for males.

We compare the classification ambiguity of the branch G(x) and the classification ambiguity of the added variable G(Y/x). With the classification categories according to equation (6) and we choose the largest level of realism, (for example in Table (4) at the age group less than 12 months for males, we note that $G(Y/x_1)$ is less than $G(X_1)$ at branch x_1 in this case the length becomes Y decision node and it has five branches $(Y_1, Y_2, Y_3, Y_4, Y_5)$. We calculate the level of realism at each branch according to equation (6) with the classification categories, and we choose the highest level of realism even if it is less than the threshold of the level of realism $\beta = 0.9$ and it is the title of the paper But if the opposite is G(Y/x) greater than G(x), then we end this section as a paper that is titled according to one category with the highest level of realism calculated in Table (4) (for example in Table (4) When the age group is less than 2 months for males, we note that $G(x_1)$ is less than $G(Y/x_1)$. In this case, the added variable does not reduce the ambiguity of the classification. We return to Table (3) and choose the highest level of realism. From the results, we note that the highest A level of realism at the first category. In this case, the section ends with a paper entitled

Malnutrition (Z_1). In the same way, calculations are made for all branches until a fuzzy decision tree is created for all age groups of males and females,Figure (4) shows the fuzzy decision tree after making calculations for all branches of the age group less than two months for males.

Step3: Converting the decision tree into a set of rules

Each branch path from the root node to the leaf node can be transformed into a rule with a condition part representing the traits on the branches passing from the root to the leaf and the conclusion part representing the category in the leaf with the highest level of truth in the taxonomy [13]. To clarify this, the following fuzzy rules for the fuzzy decision tree were created for males for the age group less than two months (as shown in Figure (1)). In the same way for all age groups, males and females.

$$R1: \; IF \;\; X \;\; is \;\; x_1 THEN \;\; Z \;\; is \;\; z_1$$

$$R2: \; IF \;\; X \;\; is \;\; x_2 \;\; AND \;\; Y \;\; is \;\; y_1 THEN \;\; Z \;\; is \;\; z_1$$

$$\vdots$$

$$R17: \; IF \;\; X \;\; is \;\; x_5 THEN \;\; Z \;\; is \;\; z_5$$

Step 4: Applying fuzzy rules for classification

In the Fuzzy Decision Tree (FDT), several paths (rules) can be applied to one individual at the same time, and thus the individual can be classified into different categories to different degrees. The following steps must be performed [9]

1: We calculate the affiliation for each individual based on his characteristics for the conditional part of each track (rule). The affiliation of the conclusion (classification to a class) will be associated equal to the affiliation of the condition.

2: When applying two or more rules to classify an individual in the same category with different affiliations, we take the maximum as affiliation in the category.

3: The individual can be classified into several categories with different degrees, based on the affiliation computed in Step 2.

After performing the step Applying fuzzy rules for classification 4, the results were obtained in Table (5).

Table 5. Results of classification of the nutritional status of Iraqi male children for the age group less than 2 months

S.	X	Y	Result of class.	
1	4.80	36.00	Z1	Malnutrition
2	9.30	52.40	Z5	Obesity
3	5.40	41.20	Z1	Malnutrition
⋮	⋮	⋮	⋮	⋮
237	3.90	60.70	Z5	Obesity
238	2.50	50.10	Z1	Malnutrition
239	2.60	51.80	Z1	Malnutrition

Table (5) shows the weight and height of the child less than 2 months old, and the nutritional status classification using the fuzzy decision tree method, and so on for the rest of the age groups, males and females.

Discussion of Results

After applying the fuzzy decision tree method to all age groups of males and females, the final results shown in two tables (6,7) were reached.

Table 6: Results of preparing children classified according to nutritional status for all age groups of males.

Age	Malnutrition		Underweight		Normal		Overweight		Obesity	
	N	Per%	N	Per%	N	Per%	N	Per%	N	Per%
Less than 2 Months	78	32.6	30	12.6	62	25.9	25	10.4	44	18.4
Less than 4 Months	101	31.6	64	20.0	81	25.3	43	13.4	31	9.7
Less than 6 Months	68	25.0	63	23.2	83	30.5	33	12.1	25	9.2
Less than 8 Months	50	17.1	48	16.4	84	28.8	54	18.5	56	19.2
Less than 10 Months	73	25.0	62	21.2	57	19.5	80	27.4	20	6.8
Less than 12 Months	22	8.9	75	30.4	62	25.1	70	28.3	18	7.3
Less than 16 Months	152	27.8	64	11.7	219	40.1	82	15.0	29	5.3
Less than 20 Months	84	14.5	184	31.8	221	38.2	33	5.7	57	9.8
Less than 24 Months	99	19.5	105	20.7	222	43.8	37	7.3	44	8.7
Less than 3 years	212	13.2	589	36.6	690	42.9	71	4.4	48	3.0
Less than 4 years	227	12.5	438	24.2	844	46.7	261	14.4	39	2.2
Less than 5 years	156	9.1	492	28.7	941	54.9	94	5.5	31	1.8

Table (6) shows the number of male children for each category of nutritional status and the percentage of each category in relation to each age group. Respectively, as for most children in the age groups less than (10, 12) months, they were suffering from weight gain by rates (27.4%, 28.3%), respectively, and most children in the age groups less than (6, 8, 16, 20, (24) months and less than (3, 4, 5) years old, they were of normal weight with rates of (30.5%, 28.8%, 40.1%, 38.2%, 43.8%, 42.9%, 46.7%, 54.9%), respectively.

Table 7: Results of preparing children classified according to nutritional status for all age groups of females.

Age	Malnutrition		Underweight		Normal		Overweight		Obesity	
	N	Per%	N	Per%	N	Per%	N	Per%	N	Per%
Less than 2 Months	79	34.6	16	7.0	75	32.9	35	15.4	23	10.1
Less than 4 Months	83	28.0	59	19.9	97	32.8	21	7.1	36	12.2
Less than 6 Months	11	3.5	142	45.2	98	31.2	19	6.1	44	14.0
Less than 8 Months	55	20.5	36	13.4	81	30.2	66	24.6	30	11.2
Less than 10 Months	58	21.6	33	12.3	96	35.8	43	16.0	38	14.2
Less than 12 Months	13	6.4	34	16.7	86	42.4	35	17.2	35	17.2
Less than 16 Months	95	17.1	145	26.2	192	34.7	86	15.5	36	6.5
Less than 20 Months	147	28.1	94	17.9	170	32.4	71	13.5	42	8.0
Less than 24 Months	50	10.5	165	34.6	170	35.6	62	13.0	30	6.3
Less than 3 years	16	1.1	554	37.0	718	47.9	153	10.2	57	3.8
Less than 4 years	238	13.3	435	24.4	1017	56.9	60	3.4	36	2.0
Less than 5 years	160	9.7	952	57.9	448	27.3	61	3.7	23	1.4

Table (7) shows the number of female children for each category of nutritional status and the percentage of each category in relation to each age group. The results showed that most children in the age group less than 2 months suffer from malnutrition by (34.6%), while most children in the younger age groups From 6 months to less than 5 years old, they were suffering from weight loss with rates of (45.2%, 57.9%), respectively, and most children in the age groups less than (4, 8, 10, 12, 16, 20, 24) months and less than (3, 4) years old, they were of normal weight (32.8%, 30.2%, 35.8%, 42.4%, 34.7%, 32.4%, 35.6%, 47.9%, 56.9%), respectively.

Conclusion

We introduced the fuzzy decision tree method to classify the nutritional status of children under 5 years old through application. It turned out to be a good and efficient method and gave very close results compared to research conducted in this field. In this research, we used child weight and height as input variables in the fuzzy decision tree, as well as using an indicator variable. Body mass as an output variable in the classification of nutritional status. Through the results, we found that most children under the age of 6 months suffer from malnutrition in the being form of underweight in Iraq, and this may be due to the presence of conditions in below the poverty level or perhaps vulnerable groups, while most children in the rest of the age groups were in the normal weight category.

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تصنيف الأطفال العراق حسب الحالة التغذوية باستعمال شجرة القرار الضبابي

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المستخلص

يعد التصنيف أحد الادوات المهمة المستعملة في الاحصاء الطبي لتصنيف حالات التغذية لدى الاطفال دون الخمس سنوات وتعتبر حالة التغذية الجيدة مهمة لصحة الاطفال ولها دور كبير في نمو الطفل بالشكل الطبيعي وحالة التغذية غير الجيدة تعتبر مرض لهذه الفئة العمرية وتحتاج الى اهتمام من قبل المختصين بصحة الاطفال، ويواجها الاطباء صعوبة في تحديد الحالة التغذوية بسبب حالة عدم اليقين في الاصابة بهذا المرض او الغموض في متغيرات وصفات تلك المتغيرات.

طبقنا نظرية المجموعات الضبابية (Fuzzy Sets) لتصنيف الحالة التغذوية للأطفال دون خمس سنوات باستخدام المنطق الضبابي حيث تم توظيف طريق شجرة القرار الضبابية وتم انشاء شجرة لكل فئة عمرية (ذكور، الاناث) بالاعتماد على المتغيرات اللغوية (الوزن، الطول)، ومؤشر كتلة الجسم لفئات التصنيف. وفي هذا البحث تم تصنيف الحالة التغذوية للأطفال وتحديد المجموعات بشكل أكثر دقة لكي نقلل من فرص التشخيص الخاطئ وتقديم العلاج الملائم لهم بدقة أكثر للارتقاء بالمستوى الصحي للأطفال لبناء مجتمع أكثر مناعة وذات مستوى صحي جيد.

اعتمدت الدراسة حجم عينة 16487 فرد من الأطفال العراق دون 5 سنوات، 8427 ذكور، 8060 اناث، قسمت حسب العمر الى 12 فئة او مجموعة. واظهرت النتائج اغلب الفئات العمرية كانت ذات وزن طبيعي بنسب متفاوتة.

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