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Diet Recommendation according to Kilocalories and People's Tastes

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Abstract. Malnutrition and eating disorders are a latent problem in our society which are generated by an inadequate combination of foods either by lack of time, money, knowledge or a specialist who can help to properly manage food with the macronutrients necessary for good nutrition. In this research we present an architecture of diet recommendation using fuzzy logic and first-order logic, the research is divided into three phases: first, people's data such as age, weight, height, physical activity level and gender were taken into account to obtain the required daily kilocalories using fuzzy logic; second, we considered as a knowledge base the menu plan for breakfast, mid-morning snack, lunch, mid-afternoon snack and dinner according to the tastes of the person for the first order logic; third, using a selection algorithm, a daily menu plan according to its kilocalories and the list of menus obtained with the first order logic are recommended. To validate the proposed architecture, Kaggle's Cardiovascular Disease Detection dataset has been taken from which 500 people data have been taken for the research, the preferences of each person have been added to the dataset, finally the prototype recommends the diet for the 500 people according to the required kilocalories, the average kilocalories required are 1776 and the average kilocalories of the recommended menus are 1864, being the difference of 88 kilocalories, we conclude that our prototype based on the proposed architecture performs a proper recommendation.

Keywords. Healthy diet, fuzzy logic, first-order logic, diet recommendation.

1 Introduction

Eating disorders due to lack of resources, time, good habits or knowledge are the cause of malnutrition and visiting an expert to properly manage food considering all macronutrients does not seem a viable option. According to [19], it is difficult to modify any prescribed diet without compromising some necessary component if we do not know how to balance it properly, if we do not provide adequate energy and nutrients for good health then we incur in malnutrition.

According to the World Health Organization [23], in 2016, more than 1900 million adults aged 18 or older were overweight, of which, more than 650 million were obese, 39% of adults aged 18 or older (39% men and 40% women) were overweight. Between 1975 and 2016, the global prevalence of obesity has almost tripled. According to the nutrition strategy 2016-2025, the WHO is working with the Member States and partners to achieve universal access to effective nutritional interventions and healthy diets, with sustainable and resilient food systems.

Peru has been implementing programs against the fight against malnutrition, according to [16], it has been successful, reducing malnutrition by 5.2% in the last 5 years.

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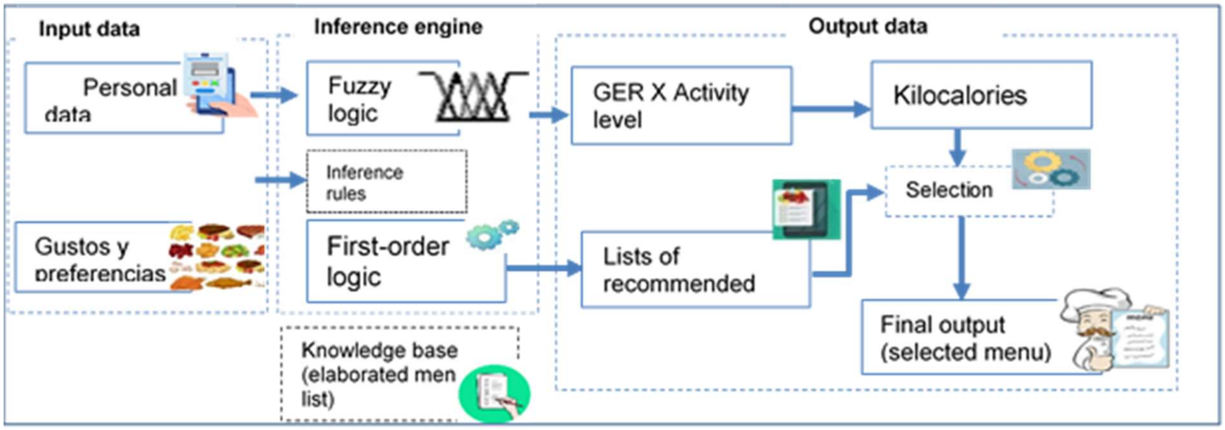

Fig. 1. Diet recommendation architecture

Another major problem of malnutrition affecting children between 6 and 35 months is anemia, which affected 43.6% of the Peruvian population and has decreased by 0.9% in the last 5 years.

According to their type of anemia, mil anemia increased in the last 5 years from 25.4% to 27.8%, moderate anemia decreased from 18.5% to 15.5% and severe anemia showed no variation with respect to 2016 (0.4%) [3], to avoid these diseases, proper nutrition is important, which according to [22] is the intake of food according to the dietary needs of our body, good nutrition is a balanced diet, sufficient and combined with physical exercise.

According to the research by [2], it considers that the distribution of proteins, fat and carbohydrates is 18.30% and 52% of the total caloric value (2000), that is, proteins 360 kcal (90g), fats 600kcal (67g) and carbohydrates 1040 kcal (260g).

On the other hand, artificial intelligence is a science involving various disciplines such as neuroscience, psychology, information technologies, cognitive science, physics, mathematics, expert systems, neural networks, etc. [11], in that sense there is plenty of research where they use expert systems based on knowledge whose operation generates results that mimic the human expert [4].

The objective of this research is to design a healthy diet recommendation architecture using fuzzy logic and first-order logic algorithms.

To obtain the necessary kilocalories by means of the fuzzy logic, the data of people have been taken: age, weight, height and level of physical activity, for the knowledge base the menu plan for breakfast, mid-morning snack, lunch, mid-afternoon snack and dinner according to the tastes of the person has been considered, then subjected to first-order logic for inference, through a selection algorithm the prototype expert system selects the menu plan that best fits the kilocalories of the person according to their tastes.

2 Related Work

There are several investigations that focus on diet recommendation, such as [24] that proposed a food recommendation system in the cloud, based on the pathological reports of patients, they used ant colony optimization algorithms to generate an optimal list of recommended foods and accordingly recommend the appropriate diet.

[12] proposes a nutrition expert system prototype that generates healthy meal recipes for children depending on the age range of the person, looking at criteria such as developmental status.

[6] uses a deep neural network model to be able to categorize products automatically, filtering the categorized products with a model based on the genetic data of the individual.

[28] proposes a fuzzy expert system to provide the user with a list of diets calculating calories according to gender, weight, height, age and activity level, in this way the developed software

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gives nutritional suggestions for obesity and eating problems.

In [5], the authors proposed a prototype of an expert system in the nutrition and diet domain using a rule-based technique.

In [13], it is proposed a fuzzy logic-based diet recommendation system according to their BMI, age, nutrients and economic income, selected suitable foods and divided into low and high-cost categories. In this way, the system presents a list of recommended healthy and nutritious food.

In [9, 8], the authors present a recommendation system using the validated FFQ questionnaire and propose nutritional advice for personalized nutritional care for the specific needs of older adults.

In [10], it is proposed a diet and nutrition expert system, for this they developed an Android-based application which requests people's data for diet recommendation.

According to [26], the authors developed a rule-based expert system that uses sets and lists to manage data and a Maple computer algebraic inference engine for the recommendation of personalized menus for each customer according to the restaurant's recipes and people's data.

According to [25], it is sought to solve specific pathologies under the recommendation of diets with specific high nutrients that help to cure certain diseases, they used graphs to represent each food and applied ant colony optimization algorithms.

In [18], the authors propose an expert system that recommends the amount of each food ingredient for a person in a normal or specific diet using the optimal nearest neighbor method generated as a recommendation solution.

In [17], it is developed an expert system for nutrition and healthy dietetics, classified food products as appropriate and inappropriate for different groups of people.

In [20], the authors performed an expert system to provide a meal plan for a girl, taking into account nutritional requirements, food preferences and lowest food cost, using linear programming models as a rule-based inference engine consisting of goal programming and linear programming modeling models.

In [1], it is proposed to apply reasoning techniques for diabetes expert systems.

Table 1. Fuzzy set as input data for fuzzy logic

Age	Weight	Height	Activity level
Joven 18-28	Thin 39-50	Short 140-156	Low 1.20-1.50
Young adult 24-45	Average 45-75	Average 150-180	Moderate 1.40-1.80
Adult 40-60	Overweight 75-90	Tall 170-190	Vigorous 1.75-2.20

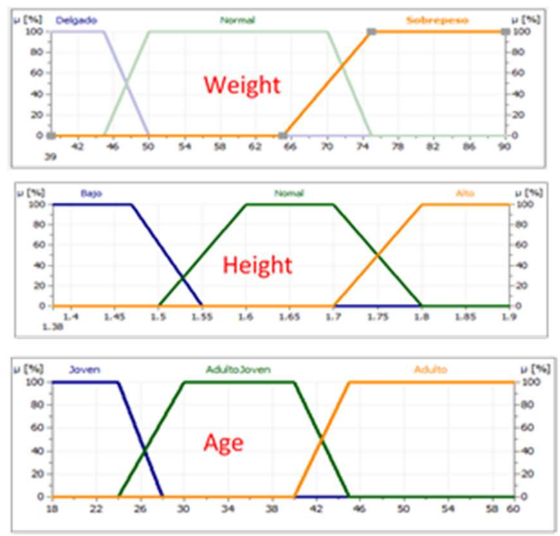

Fig. 2. Membership function for fuzzy logic sets age, weight, height

In [13], the authors built a recommendation system for chronic diseases with expert knowledge and provided more convenient and accurate dietary recommendations.

[15] built an expert system for case-based diet recommendation.

According to [7], the authors proposed a diet recommendation system using the knapsack algorithm for appropriate diet recommendation for people who have diabetes, hypertension or high cholesterol according to the patient's health information. The system infers the daily caloric requirement and recommends the appropriate diet.

However, the reviewed research take into account either people's data, some disease or people's tastes, nonetheless, in this research we will take two algorithms: fuzzy logic and first-order logic taking into account people's data and

Table 2. Fuzzy set as input data for fuzzy logic

C.	Age	Weight	Height	Activity level	Calories
1	Young	Average	Average	Low	Normal
2	Young	Overweight	Average	Moderate	High
…	…	…	…	…	…
80	Young adult	Thin	Tall	Moderate	Low
81	Adult	Thin	Tall	Vigorous	Normal

people's tastes in order to make the recommendation of a suitable menu plan for the whole day.

3 Methodology

3.1 Diet Recommendation Architecture

In this research we present a healthy diet recommendation architecture for people, based on their profiles and tastes.

Personal data (age, weight, height and activity level) are inputs for the fuzzy logic that allows to calculate the amount of kilocalories required, tastes in food and the list of menus are inputs for first-order logic.

As a result, the architecture allows to recommend a menu for each type of meal (breakfast, mid-morning snack, lunch, mid-afternoon snack and dinner).

For the research we considered 50 menus designed by a specialist considering the table of food composition of Peru, also an average of 2000 daily kilocalories was taken according to the WHO, the distribution of protein, fat and carbohydrates were 18,30% and 50% of the total caloric value, taken as reference for the consumption of carbohydrates from the European Food Safety Authority, for proteins it was taken as reference from the Institute of Medicine of the United States of America and for the consumption of fats the recommendations of the WHO, FAO and EFSA.

3.2 Calculation of Required Energy Expenditure by Means of Fuzzy Logic

In order to determine the required energy expenditure using fuzzy logic, fuzzy sets, membership function, design of inference rules and defuzzification using Mamdani have been defined.

3.2.1 Definition of Fuzzy Sets (Input Variables)

Input data for fuzzy logic (age, weight, height and physical activity level) each variable is considered as a fuzzy set, the range design is shown in Table 1.

For the definition of these fuzzy sets age, weight and height, the values established by MINSA [21] were used as a reference; to determine the level of activity, the WHO was used as a reference.

The fuzzy set Age has been classified into three ranges (Young, Young Adult, Adult), the fuzzy set Weight has been divided into 3 groups according to the kilograms of weight (Thin, Average, Overweight), the fuzzy set Height has been divided into 3 groups according to the centimeters of weight (Short, Average, Tall), as for the level of activity the WHO classification has been taken as a reference.

3.2.2 Membership Function for Each Fuzzy Set

For the fuzzy sets age, height, weight and activity level, the same trapezoidal membership function has been generated, whose formula is:

$$Trapezoidal(x, a, b, c, d) = \max\left(min\left(\frac{x-a}{b-a}, \frac{c-x}{d-c}\right), 0\right),$$

where x is the fuzzy set, a is the initial position, b and c are intermediate positions and d is the final position. The graph generated for each fuzzy set is presented.

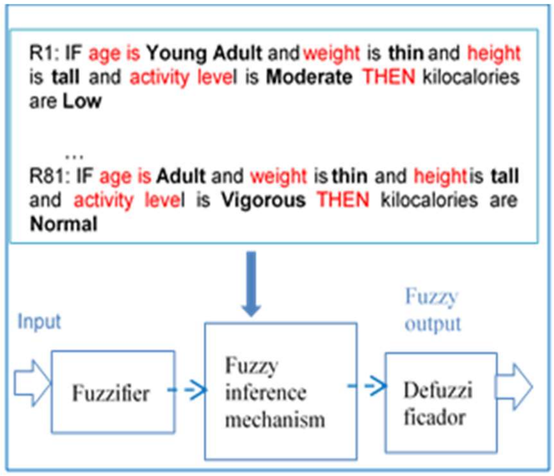

Fig. 3. Application of fuzzy logic to find the GER

As can be seen in Figure 2, the membership function has been defined for the fuzzy set Age, where young age is considered from 18 to 28 years old, young adult is considered from 24 to 45 years old and adult is considered from 40 to 60 years old.

For the fuzzy set Weight where it has been considered as thin from 39 to 50 kilograms of weight, average from 45 to 75 kilograms of weight and overweight from 65 to 90 kilograms of weight. For the fuzzy set Height, it has been considered short from 1.40 to 1.56 centimeters, average from 1.50 to 1.80 and tall from 1.70 to 1.90.

Finally, for the Fuzzy set Activity level, it has been considered low activity from 1.20 to 1.50, Moderate from 1.40 to 1.80 and Vigorous from 1.75 to 2.20.

3.2.3 Design and Construction of Inference Rules

For the design and construction of the rules, a combination (C=nm) of the fuzzy sets Age, Weight, Height and Level of physical activity was made. The fuzzy set Age (young, young adult and adult) combined with the fuzzy set Weight (thin, average, overweight) obtaining a total of 09 combinations, this result has been combined with the fuzzy set Height (short, average and tall) obtaining 27 combinations which have also been combined with the fuzzy set Activity level (low, moderate and vigorous) resulting in 81 rules.

In addition, to establish the rules we have reviewed the sources WHO, MINSA, ANIVES that consider the average daily kilocalories required for a person ranging from 1400 Kcal to 3000Kcal according to age, weight, height, level of physical activity and gender.

3.2.4 Application of Mamdani

According to [14], there are 3 types of fuzzy inference systems: Mamdani, Takagi-Sugeno-Kang and Tsukamoto.

These inference systems differ from each other according to the fuzzy set within the output universes, in this research Mamdani inference was used.

For defuzzification we have considered the membership functions of each fuzzy set which were subjected to the inference rules obtaining as a result the centroid with the formula: $y = \frac{\sum_i b_i \int \mu(i)}{\sum_i \int \mu(i)}$.

Here $\mathbf{b_i}$ is the input value belonging to the fuzzy set and $\mathbf{u_i}$ is the degree of membership expressed as probability in the range from 0 to 1, in this research the centroid found is the GER for each person.

Taking the centroid result in terms of nutrition is the GER, this value is multiplied with the level of physical activity of the person to obtain the kilocalories needed, being the final result of the fuzzy logic process.

Table 3. Kilocalories obtained though fuzzy logic

N°	Age	Weight	Height	Activity Level	Kilocalories through fuzzy logic
1	52	69	170	1.3	1546
2	54	76	152	1.6	2168
3	57	53	157	1.76	2093
…	…	…	…	…	…
498	59	77	157	1.4	1996
499	44	85	180	1.4	2000
500	56	75	158	1.3	1857

Table 4. Recommended menus according to tastes with first-order logic

N°	Breakf.	Mid Mor.	Lunch	Mid-aft.	Dinner	Kcal per menu
1	D4 (448)	MM1 (183)	A7 (631)	MT (183)	C2 (363)	1808
2	D1 (506)	MM8 (212)	A2 (768)	MT5 (199)	C1 (408)	2093
…	…	…	…	…	..	…
79	D9 (493)	MM9 (184)	A7 (631)	MT4 (187)	C10 (403)	1898
80	D7 (516)	MM7 (195)	A3 (704)	MT1 (185)	C7 (400)	2000

3.3 Diet Recommendation Using First-Order Logic

For the design and construction of the inference rules of the first-order logic, the knowledge base was built for the type of menu, the ingredients of each dish and their respective nutritional values with their respective kilocalories and macronutrients.

3.3.1 Knowledge Base

For the development of the research, in this stage the 10 menu plans were considered. These included breakfast, mid-morning snack, lunch, mid-afternoon snack and dinner which have been prepared by the specialist making a total of 50 menus.

This knowledge base corresponds to three relationships.

– Taste relationship (ingrediente,tipo_alimento).

– Ingredient Relationship (tipo_alimento,menu).

– Meal_plan relationship (menu, plan_alimento).

3.3.2 Design of Inference Rules

The knowledge base and taste of people were taken according to food group: (1) Milk and dairy products, (2) Meat, eggs (3) Tubers, legumes and dried fruit, (4) Vegetables, (5) Fruit, (6) Bread, pasta, cereals and sugar, (7) Fats, oils and butter and (8) Fish.

Rule design to recommend breakfast:

Quantifiers**:**

$$\forall I, \exists GD, \forall M, \forall P, \exists M, \exists K$$

$$\mathbf{Rule1}: [\mathrm{taste}(\mathrm{I}, \mathrm{GD} \wedge \mathrm{ingredient}(\mathrm{I}, \mathrm{M}), \mathrm{plan}(\mathrm{M}, \mathrm{P}, \mathrm{K}) \rightarrow \mathrm{recommend}(\mathrm{P}, \mathrm{M}, \mathrm{K})]$$

Prototype implementation:

output = [(x,y,z) for x,y,z in run(10,(P,M,K), gusto(I,GustoDesayuno[recurrido]),ingrediente(I, M), plan(M,P,K)) if x=="Desayuno"]

outputC = [(x,y,z) for x,y,z in run(10, (P,M,K),

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Table 5. Final result of the healthy diet recommendation prototype

N°	Edad	Peso	Talla	Nivel A	K.cal. LD	GustoD	GustoMM	GustoA	GustoMT	GustoC	Rec-D	Rec-MM	Rec-Al	Rec-MT	Rec-C	Kcal Consumir
1	52	69	170	1.3	1546	3	3	2	5	6	D4	MM1	A7	MT2	C2	1808
2	54	76	152	1.6	2168	3	5	8	5	4	D7	MM4	A3	MT7	C5	2056
3	57	53	157	1.76	2093	5	5	2	3	6	D1	MM8	A2	MT5	C1	2093
4	59	87	179	1.5	1898	5	5	2	3	4	D9	MM8	A7	MT5	C8	1898
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
199	44	85	180	1.4	2001	3	1	3	1	3	D7	MM7	A3	MT1	C7	2000
200	56	75	158	1.3	1858	3	5	2	5	4	D4	MM2	A4	MT2	C9	1858

gusto(I,GustoCena[recurrido]),ingrediente(I,M), plan(M,P,K)) if x=="Cena"]

Rule design to recommend mid-morning snack:

Quantifiers**:**

$$\forall I, \exists GMM, \forall M, \forall P, \exists M, \exists K$$

$$\textbf{Rule2}: [\text{taste}(\text{I}, \text{GMM} \land \text{ingredient}(\text{I}, \text{M}), \text{plan}(\text{M}, \text{P}, \text{K}) \rightarrow \text{recommend}(\text{P}, \text{M}, \text{K})]$$

Prototype implementation:

outputMM = [(x,y,z) for x,y,z in run(10, (P,M,K), gusto(I,GustoMediaM[recurrido]),ingrediente(I,M), plan(M,P,K)) if x=="Media Mañana"]

Rule design to recommend lunch

Quantifiers:

$$\forall I, \exists GA, \forall M, \forall P, \exists M, \exists K$$

$$\textbf{Rule3}: [\text{taste}(\text{I}, \text{GA} \land \text{ingredient}(\text{I}, \text{M}), \text{plan } (\text{M}, \text{P}, \text{K}) \rightarrow \text{recommend}(\text{P}, \text{M}, \text{K})]$$

Prototype implementation:

outputA = [(x,y,z) for x,y,z in run(10, (P,M,K), gusto(I,GustoAlmuerzo[recurrido]),ingrediente (I,M), plan(M,P,K)) if x=="Almuerzo"]

Rule design to recommend mid-afternoon snack

Quantifiers:

$$\forall I, \exists GA, \forall M, \forall P, \exists M, \exists K$$

$$\textbf{Rule 4}: [\text{taste}(\text{I}, \text{GA} \land \text{ingredient } (\text{I}, \text{M}), \text{plan}(\text{M}, \text{P}, \text{K} \rightarrow \text{recommend}(\text{P}, \text{M}, \text{K})]$$

Prototype implementation:

outputA = [(x,y,z) for x,y,z in run(10, (P,M,K), gusto(I,GustoAlmuerzo[recurrido]), ingrediente(I,M),plan(M,P,K)) if x=="Almuerzo"]

Rule design to recommend dinner

Quantifiers:

$$\forall I, \exists GC, \forall M, \forall P, \exists M, \exists K$$

$$\textbf{Rule 5}: [\text{taste}(\text{I}, \text{GC} \land \text{ingredient}(\text{I}, \text{M}), \text{plan}(\text{M}, \text{P}, \text{K}) \rightarrow \text{recommend}(\text{P}, \text{M}, \text{K})]$$

Prototype implementation:

outputC = [(x,y,z) for x,y,z in run(10, (P,M,K), gusto(I,GustoCena[recurrido]),ingrediente(I,M), plan(M,P,K)) if x=="Cena"]

The final result of the healthy diet recommendation architecture has the following structure:

- Recommendation for breakfast (Rec-Des.).
- Recommendation for mid-morning snack (Rec-MM).
- Recommendation for lunch (Rec-Al).
- Recommendation for mid-afternoon snack (Rec-MT).
- Recommendation for dinner (Rec-C).

– Total Kilocalories of the plan (KCalConsumir).

Considering that a person's taste fits as a component of several menus, therefore, first-order logic inference selects a set of menus as a recommendation for each type of meal of the day with its respective kilocalories.

3.3.3 Selection of the Recommended Menu

Taking as a result of fuzzy logic that provides the required kilocalories of the person and, on the other side, we have the list of menus recommended by the first-order logic, then by means of an algorithm it has been necessary to select the best candidate menu that most closely approximates the required kilocalories of the person.

4 Results and Discussion

Considering the Cardiovascular Disease dataset of the Kaggle data scientific community, we used data from 500 people for validation, for each person we have the data (age, weight, height and activity level), also for each person we have added the taste or preference of the type of food for each person.

These data have been submitted to the prototype that we built using the proposed architecture, obtaining as a final result the menu recommendation (breakfast, mid-morning snack, lunch, mid-afternoon snack and dinner) for each person.

4.1 Fuzzy Logic Results

Applying the fuzzy logic inference rules to the fuzzy sets age, weight and height, the GER was obtained, then multiplied by the activity level to obtain the kilocalories for each person, as shown in Table 3.

The respective kilocalories calculated for each person is shown. In row 1, the person's data are: age 52, weight 69 kilos, height 1.70 cm and the activity level 1.3, applying the inference rules to these data we obtain 1546 kilocalories per day required.

The kilocalories found in this research have been contrasted with the MIFFLIN-ST. JEOR equation, obtaining a variability of 1.4%.

The results shown in Table 3 determine the caloric requirement for each person using fuzzy logic, while in the research (Marji & Ratnawati 2016), proposed an expert system that recommends the amount of each food ingredient for each person using the optimal nearest neighbor algorithm without using the required kilocalories.

On the other hand [27], proposed a system based on fuzzy optimization for the composition of daily diet made up of individual meals, while this research has considered the person's data: age, weight, height and level of physical activity applying fuzzy logic to find the required energy expenditure.

4.2 Results of the First-Order Logic

As input to the first-order logic we have taken people's taste in food: (1) Milk and dairy products, (2) Meat, eggs, (3) Tubers, legumes and dried fruit, (4) Vegetables, (5) Fruit, (6) Bread, pasta, cereals and sugar, (7) Fats, oils and butter and (8) Fish. In addition, the same experiment has been applied for each menu plan (breakfast, mid-morning snack, lunch, mid-afternoon snack, dinner according to the food distribution).

To these input data the first-order logic inference rules designed to obtain a list of recommended menus for each person according to their tastes are applied as shown in Table 4:

Through the application of the designed architecture a list of recommended menus of the menu plan: breakfast, mid-morning snack, lunch, mid-afternoon snack and dinner, each one according to the taste on the food, is shown for each of the 500 people, also the kilocalories for the whole day, for example in row 3 it can be observed that the system recommended breakfast D1 with 506 kilocalories, mid-morning snack MM8 with 212 calories, for lunch it recommends A2 with 768 kilocalories, for mid-afternoon snack MT5 with 199 kilocalories and for dinner C1 with 408 kilocalories, in total 2093 kilocalories would be consumed, in this case there are 80 recommended menus according to the taste of the person.

The researchers [10], proposed an expert system for the recommendation of healthy diets,

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where they request the information of the person (age, weight, height, gender, chronic diseases and medical history), once this information is obtained they calculate the BMI to be transferred to the next module of menu generation, where they analyzed the nutritional requirements and generated a table of exchange of ingredients and dishes suggesting a menu.

In this research we managed to recommend the menu based on tastes or preferences regarding the type of food.

4.3 Results of the Application of the Diet Recommendation Architecture

Table 5 shows the final result of the healthy diet recommendation architecture applying the fuzzy logic inference rules and the first-order logic; in this case from the list of recommended menus was selected the one that is closest to the required kilocalories of the person therefore only the best one is recommended.

The final result of the architecture recommends a healthy diet for the 500 people, the following columns were the inputs for the model for the first row:

- Age: 44,
- Weight: 85,
- Height: 180 cm,
- Activity level (NivelA): 1.4,
- Gender: F,
- Kilocalories (K.cal.LD): 2001,
- Taste for breakfast (GustoD): 3,
- Taste for mid-morning snack (GustoMM): 1,
- Taste for lunch (GustoA): 3,
- Taste for mid-afternoon snack (GustoMT): 1,
- Taste for dinner (GustoC): 3.

The following columns are the outputs as healthy diet recommendation, each field is explained:

- Recommendation for breakfast (Rec-Des.).- D3 ("Soy beverage with strawberry and oatmeal + whole wheat bread with olives").
- Recommendation for mid-morning (Rec-MM).- MM1("Grapes + almonds").
- Recommendation for lunch (Rec-Al).- A3("Tallarines rojos with chicken + papa la huancaína + lemonade").
- Recommendation for mid-afternoon (Rec-MT).- MT1 ("Yogurt with chopped prickly pear and granola").
- Recommendation for dinner (Rec-C).- C3 ("Orange juice + whole wheat toast with strawberry jam and toasted sesame seeds + egg").
- Total kilocalories of the plan (KCalConsumir). 2000.

In Table 5, for person 1, the prototype recommends a soy drink with strawberry and oatmeal and a whole meat bread with olives for breakfast, for mid-morning it recommends grapes and almonds, for lunch red noodles with chicken and papa a la huancaína and lemonade, for mid-afternoon yogurt with chopped prickly pear and granola, and for dinner orange juice, whole wheat toast with strawberry jam, sesame seeds and an egg.

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