Development of a Fuzzy Expert System for a Nutritional Guidance Application

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Abstract*— The importance of nutritional guidance grows as nutritional problems, such as obesity and type-2 diabetes, are becoming more common. Nutritional guidance is carried out by mapping the nutritional state of an individual using a food diary and by comparing the nutrition intake levels to the recommended reference values. Typically, the expert knowledge of a nutritionist is required to balance the diet.*

This paper presents a fuzzy expert system for a nutritional guidance application. Expert knowledge acquisition is carried out using variable tabulation creating the basis for the rulebase of the fuzzy system. The recommended nutrition intake values are used to generate membership functions for fuzzification. The development of a Mamdani-type fuzzy system is illustrated using a hierarchical structure. The first level system refers to groups of similar foods and the second level model defines the added and reduced foodstuffs.

The validation of the fuzzy model was carried out in three phases: first two types of sensitivity analysis were performed, and then the output was analysed with expert knowledge.. The results from the validation schemes are promising.

Keywords*—* expert system, fuzzy logic, nutritional guidance

1 Introduction

Unhealthy diets and physical inactivity are the main causes of non-communicable diseases such as Cardiovascular disease, type 2 diabetes, and osteoporosis. Obesity is a large and growing problem in developed countries. [1] There have been regular surveys of Finnish health behaviour since 1978. According to the latest survey, over 50 percent of Finnish men and women are overweight [2]. The best way to avoid nutritional problems is to have a well-balanced diet and to ensure the sufficient intake of essential nutrients [3].

Individual nutrition guidance is becoming more and more important as problems with obesity and type-2 diabetes are increasing rapidly. The nutrition guidance is based on information from food diaries kept by the users where they record all the foods they consume. This information is converted into nutrient intake levels with the help of a food composition database. The intake levels are compared to the recommended intake levels and the expert knowledge of a nutritionist is used to balance the diet to meet the recommendations. There are restrictions, for example allergies, diseases, and special diets which must also be taken in to account when balancing diets.

Some software has been developed for the purpose of nutritional guidance. For example, a French research group developed a nutrition software application for hospital use [4]. They use fuzzy arithmetic to handle imprecise and uncertain information in the computations. Fuzzy logic is first used by the application to determine how well the current meal is balanced, after which a heuristic search is performed to provide nutritional guidance. Fuzzy logic is also used in a nutritional guidance application in [5]. They define the optimality of a nutrient intake level as a fuzzy set (Fig. 1). The values of the points from "a" to "e" in Fig. 1 are based on the recommended intake levels. In [5], the Prerow value (PV) is used to measure how well the diet is balanced. In the calculation of PV, the nutrient with the lowest value has the strongest influence on the result. The gradient optimization method is used to find the shortest route to maximize PV in the discrete multidimensional search space.

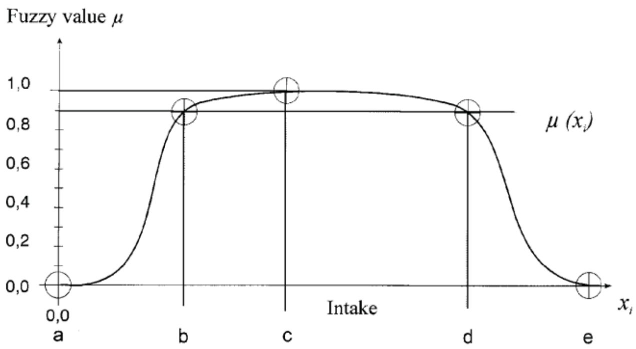

Figure 1: Membership function of optimal nutrient intake level [5].

In [6], the optimization results of two approaches to the nutrition calculation are compared. The first approach considers the use of non-fuzzy numbers and the second approach the use of fuzzy numbers in calculations and optimization. They concluded that optimization with plain numbers always yields results which meet the selected recommendations. The downside of this method is that it recommends drastic changes to eating habits. According to [6], the optimization with fuzzy numbers is not Pareto optimal. The results from fuzzy optimization are sometimes unbalanced. While the most of the nutrient intake levels are on an optimal level, some intake levels are either insufficient or excessive, and some are even less in balance

ISBN: 978-989-95079-6-8

than initially. However, the instructions given are closer to the original eating habits and are therefore easier to follow.

Dietary guidance applications usually present their results in the form of large tables where the suitable amounts of each nutrient are listed. However, this information is not very informative if you want to know what foods you should cut back on and what should you eat more. Therefore, there is a need for software which interprets the nutrient level results into the foodstuff level guidance.

The aim of this study is to develop a fuzzy model for the Nutri-Flow dietary analysis application. The Nutri-Flow application provides nutrition guidance in a user-friendly way: the balanced diet does not alter the original diet too much and the recommended adjustments to the diet are given on a foodstuff level in text format. This paper presents the fuzzy model developed for the Nutri-Flow application.

2 Nutrition recommendations and guidance

The prerequisite for good health is a well balanced diet. In a well balanced diet energy intake is in proportion to energy consumption and the nutrition intake is balanced. This often implies increasing the amount of dietary fibre in the carbohydrate intake and reducing the intake of purified sugars. Dietary guidance is based on the calculation of the user's nutrient intake levels and the nutrition recommendations.

2.1 Nutrition recommendations

The first nutrition recommendations were given to prevent deficiency disorders. The basis of traditional nutrition recommendations is physiological data on nutrient intake requirements. The Finnish Nutrition Recommendations are based on the Nordic recommendations which in turn are based on scientific data. The main objective of the national recommendations is to get Finnish people to balance their diets and to improve their health. The recommendations are defined for healthy and moderately physically active people. Therefore, they should only be used as guidelines for individuals and with great precaution. Nutrition recommendations represent the average daily values of long term intake. [3] Public dietary guidelines are criticized in [7]. They conclude that an adequate scientific background must first be established before public dietary guidelines are declared.

The nutrition recommendations are given as reference values which are defined separately for each nutrient. If there is evidence that the nutrient has an effect on health, a reference value is defined for it. The reference values are determined using estimates and evaluations based on current knowledge of nutritional needs and health. Thus, there will always be a degree of uncertainty and imprecision in the values. The reference values should not be considered as fixed points. Reference values distinguish between the lower intake level (LI), the average requirement (AR), the recommended intake (RI), and the upper intake level (UL). [3] The definitions of the reference values are:

- LI – the minimum requirement of a nutrient without the deficiency symptoms,
- AR – the nutrient intake level that is adequate for maintaining good health for healthy individuals,
- RI – the nutrient intake level that is adequate for maintaining the good nutritional status among 98 % of healthy individuals. RI is calculated based on AR and
- UL – an estimate of the highest level of intake that carries no appreciable risk of adverse health effects [8].

Depending on the nutrient, some reference values may be missing. For example, only RI is defined for magnesium, because the effects of magnesium are not that well known. Whereas, all the reference values have been set for vitamin B_6, because there is reliable scientific data available on how vitamin B_6 affects health with different intake levels. The reference values for vitamin B_6 are presented in Table 1. [3]

Table 1: Reference values for vitamin B_6 [3].

Vitamin B_6 level	Women [mg/d]	Men [mg/d]
LI	0.8	1
AR	1.0	1.3
RI	1.2	1.6
UL	25	25

2.2 Dietary guidance

Nutrient intake is usually assessed using a food composition databases. Food composition information is needed when calculating the composition of menus and recipes. Primary sources of food composition data are government databases, databases provided by academic and other institutions, the food industry, and scientific literature [9]. Finnish food composition information is collected into the Fineli® Nutrition Database which is provided by the National Public Health Institute. The commercial version of the database provides information on 2000 foods and 68 nutrients. The composition data consists of averaged information on Finnish food, and thus the composition of individual foods can vary depending on the given data.

Food composition data and the expert knowledge of a nutritionist are used to balance the user's diet on the basis of a food diary and personal nutrition intake recommendations (reference values). The national recommendations are adjusted individually according to the user's health data to form personal recommendations for evaluation. Typically, a nutritionist is needed to compare the data and to balance a suitable diet. The task is very complex because the information on a nutrient level is not useful in its self and must be converted onto a foodstuff level. In other words, people should know what foods they should eat more and what less. A balanced diet should also be reasonable in comparison to the original diet. Furthermore, some restrictions, for example allergies, diseases, and special diets, must be taken in to account when balancing diets.

3 Fuzzy logic

A rule based fuzzy logic system (FLS) consists of three interconnected main blocks for mapping crisp inputs to crisp outputs. The main blocks are the fuzzifier, the inference machine with the rulebase, and the defuzzifier [10]. The

ISBN: 978-989-95079-6-8

design parameters for a FLS are scaling factors, fuzzification and defuzzification methods, rulebase, and membership function construction, and representation.

Fuzzification is needed to convert the crisp input data into fuzzy sets for the inference machine. The fuzzification is carried out by using membership functions with defined shapes and parameters. In some cases, the input value needs to be normalised before fuzzification.

The mapping from inputs to outputs is done in the fuzzy inference module. The module contains all the necessary information for forming the output of the system. The heart of the inference module is the rulebase. The definition data used to generate and collect the output of the system is stored in the inference machine. The selected implication method and the aggregation method are a part of the definition data. The rulebase is a collection of IF-THEN rules which represent the expert information used to define the behaviour of the system. The antecedent of the rule defines the state of the system and also determines if the rule is triggered. The consequent of the rule is the output of each rule guiding the system output towards the solution. The membership grade of the rule antecedent is utilized through implication to produce the output of each rule. The minimum and the product are typically used as implication methods in Mamdani-type fuzzy systems. In Mamdani-type fuzzy systems, the output of each rule is fuzzy and aggregation is required to obtain the fuzzy output of the system. The fuzzy output needs to be defuzzified to obtain the crisp output of the system. In Takagi-Sugeno and Singleton -type fuzzy systems, the rule outputs are linear functions or constants, respectively. The crisp output of the system in these cases is typically obtained by taking the weighted average of the rule outputs. [11]

The defuzzifier module is needed if the output of the inference machine is fuzzy. There are several defuzzification methods. The most commonly used method is the centre of gravity method (COG). Other typical methods are the first (FOM), the last (LOM), and the middle (MOM) of maxima, and the first (FOS), the last (FOL), and the middle (FOM) of support. The defuzzification method should be chosen carefully because it affects the crisp result considerably. [12]

4 Data acquisition

The Nutri-Flow application uses a commercial version of the Fineli® Nutrition Database. The database is used to convert the information in the food diaries to averaged daily nutrient intake levels. The Finnish recommended nutrient levels (the reference values) are used to define the membership functions for the system inputs. The reference values are updated by nutritionist, and the personal recommendations are revised according to the user's health data.

Expert data acquisition was one of the most challenging parts of this study. The first task was to find an efficient way to convert expert knowledge into the fuzzy rule IF-THEN language. Variable tabulation proved to be a very good tool for this. With tabulation, all the input set conditions with appropriate consequents can be examined separately. Variable tabulation is possible because the number of variables in most of the rules is two or three. If the number of variables connected to a single rule is greater than three, tabulation becomes difficult. Table 2 shows an example of tabulation for carbohydrate and vitamin-C. The "fruits and berries" group is the consequent variable. The notations -, 0, and + represent the fuzzy values "too little", "ideal", and "too much", respectively. In this case, the consequents are limited to "add" and "no action". Naturally, the action "reduce" is also used, however, it is not feasible for the output variable "fruits and berries" group.

Table 2: Variable tabulation for "fruits and berries" group.

	Carbohydrate		
Vitamin-C	-	0	+
-	add	no action	no action
0	no action	no action	no action
+	no action	no action	no action

5 Developed model

The developed fuzzy model is used in the Nutri-Flow application. The schematic diagram of the overall system is provided in Fig. 2. The calculations start by analysing the user's nutrient intake levels based on the food diary and the Fineli® database. The intake levels are then fed into the developed fuzzy system. The fuzzy system is divided into two hierarchical levels. The first level model uses the nutrient intake levels as inputs and produces output on the level of main food groups such as "fruits and berries", "vegetables" and "dairy products". These outputs are then fed into the 2nd level model together with the nutrient intake levels. The 2nd level model produces outputs on a food subgroup level. Fig. 3 illustrates the division of foods into main groups and subgroups.

The fuzzy system requires user information (personal recommendations) to define the membership functions for the input variables. The output variables of the complete fuzzy system are continuous. The behaviour of the fuzzy system is not regulated by user specific information, such as the original diet, allergies, and diseases. The user related specific information is used in the optimization process. As depicted in Fig. 2, the focus of the future development of the Nutri-Flow application is to find an optimization algorithm which takes the outputs of the complete fuzzy system and the user specific information into account. Also, the nutrient density of the recommended foods should be considered when evaluating the final results of the system. Furthermore, the optimization algorithm would be used to search for solutions within a discrete space. The Nutri-Flow application uses the jFuzzyLogic java package for fuzzy inference. This Chapter presents the properties of the fuzzy system in more detail.

5.1 Membership functions

The values of the system inputs are the average daily intake levels of nutrients. The values are crisp numbers and they need to be fuzzified for the fuzzy inference machine. To map the crisp input values into the fuzzy domain, three linguistic variables are used: "too little", "ideal", and "too much" (Fig. 4). The fuzzy output variables are "reduce", "no action", and "add". The selected forms of the MFs are trapezoidal or triangular. The points "A", "B", and "C"

ISBN: 978-989-95079-6-8

correspond to LI, RI, and UL, respectively. If the points "A", "B", and "C" depicted in Fig. 4 are defined, three MFs are used to fuzzify the selected input variables. For example, in case of alcohol, there is no LI value and point “A” is not defined, thus the "too little" MF is not used. It should be noticed that the values "A", "B", and "C" are influenced by the user’s gender, age, mass, height, body mass index, and the level of physical activity. Some other factors, such as diseases and pregnancy, also affect the reference values. The output membership functions are produced similarly but the points from "A" to "C" are kept fixed.

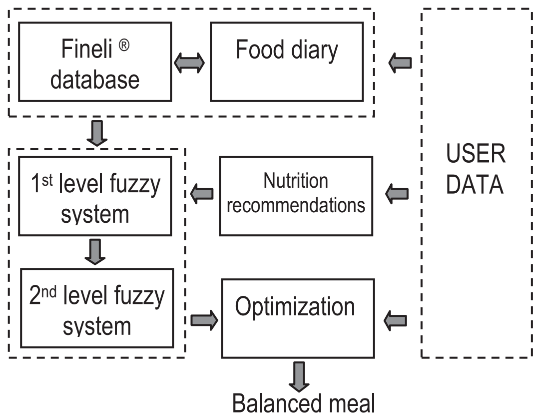

Figure 2: Schematic diagram of overall system.

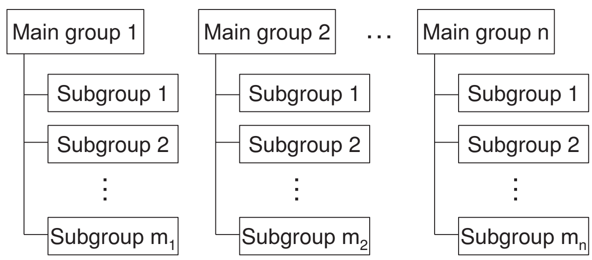

Figure 3: Division of foods to main groups and subgroups.

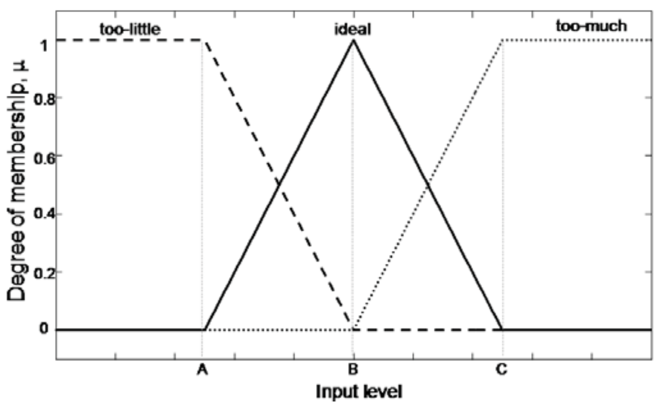

Figure 4: Input membership functions.

5.2 Rulebase and fuzzy inference

The most important and most time consuming phase of this study was building the rulebase. It is the heart of the fuzzy system, and therefore it must work correctly. Every input set condition must trigger at least one rule for each of the output variables. In this study, the rulebase was built on two levels. The first level of the fuzzy system operates on the main food group level and the second one on the subgroup level. The hierarchical structure is used because of the complexity of the system. The purpose of the first level is to roughly evaluate the nutritional status of the user and to produce additional, informative variables for the second level model, which in turn contains more detailed information but uses the additional variables to handle the complexity of the overall system.

As mentioned earlier, expert knowledge is obtained through variable tabulation. As an example, the tabulation of carbohydrate and vitamin-C was presented in Table 2. The consequent variable in this example was the "fruits and berries" -group. The first level rules corresponding to Table 2 are

Rule 1: IF Vitamin-C is "too little" AND Carbohydrate is "too little" THEN fruits and berries group is "add"
Rule 2: IF Vitamin-C is NOT "too little" OR Carbohydrate is NOT "too little" THEN fruits and berries group is "no action"

The output of the first level model directly influences the structure of the second level rules. The second level rules corresponding to the "fruits and berries" group have a general structure which can be written as

IF fruits and berries group is "Add" AND additional propositions THEN …

If the consequent of the first level model is "no action", then the consequent of the corresponding food subgroups determined on the second level is also "no action".

5.3 Design parameters

In this study, the variables are not scaled and thus no scaling factors are needed. The fuzzy inference uses the minimum as an implication method and the maximum as an aggregation method. The used T-norm is a minimum. The consequents cannot be put in the form of an equation or defined by a single number. Therefore, a Mamdani-type inference is used with COG as the defuzzification method.

6 Results and discussion

All the calculations in this study were carried out in Matlab®. The data for membership function generation was extracted from the Nutri-Flow application. The data contains personal nutrient intake recommendations and the nutrient intake levels of the selected test cases. Also, a set of test cases with varying dietary habits were selected from the software for testing purposes.

6.1 Model validation with expert knowledge

The validation of the developed model was challenging because no "right answers" exist, and thus no meaningful error describing values (such as the sum of squared error) could be calculated. Therefore, only qualitative validation was carried out.

The model outputs are calculated using the developed model with the Nutri-Flow application. The output of the application is in text form and contains information on the

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diet and instructions on how the diet should be improved. The output is obtained in text form even though the optimization algorithm mentioned earlier has not yet been implemented. The validity of the output of each test case was evaluated by a nutritionist with promising results.

6.2 Uniformly distributed sensitivity test

The input-output behaviour of the model was tested with an uniformly distributed sensitivity test. The system sensitivity of each input variable was examined as follows: the supplies of all nutrients except the one under examination are fixed on the ideal intake level and the test variable gets random values in the range of [0, UL]. The number of test rounds conducted on one variable was 500. The test range is set so that the variable gets values from all the fuzzy sets. The quadratic error of the output is recorded as a sum of the output variables. The test results show how large the independent impact of an input variable is on the output of the whole system.

The value resulting from the test is the sum of the quadratic error which is the Euclidean distance from the system's ideal state. The test result value is zero for a variable with no individual impact on the output variable. The larger the value of a variable the greater its individual impact on the output variable.

A variable affects the output if it is the only variable in the antecedent part or the OR-connective is used. Also, if the tested variable is connected with an AND-connective to other variables and the other variables have a NOT-term in the proposition, the tested variable affects the output.

After the test, the results were given to a nutritionist for analysis. The analysis showed that the input variables only affected the desired output variables with the desired magnitude. An example of the results from the sensitivity analysis is shown in Table 4.

Table 4: Example results from sensitivity analysis.

	output 1	output 2	output 3	output 4
hard fat	0	0	1	0
soft fat	0	0	1	1
fibre	0.51	0	0.51	0

6.3 Normally distributed sensitivity test

Another type of sensitivity analysis was carried out by changing a group of input variables randomly at the same time. In this approach, the values of the input variables vary around the ideal value and they are taken from a normal distribution. The distributions of the output variables are obtained as a result and they are visually inspected. Fig. 5 illustrates a random test set of a variable. The mean and the standard deviation of the random changes are defined individually for all the input variables. The outputs of the random tests are analyzed by visually inspecting the distributions of the output variables. An example of the distribution of an output variable is given in Fig. 6. From the figure, it can be seen that the histogram does not quite follow a normal distribution. That is anticipated because no adding rules are associated with alcoholic beverages. Thus the histogram of the output variable is slightly skewed, and only values equal to or smaller than zero are obtained. Negative values of the output variables indicate that the consumption of a corresponding foodstuff should be reduced.

Some statistical values can also be calculated to evaluate the shape of the histograms. Mean, standard deviation, skewness, and kurtosis are used in this study. The mean and standard deviation values give an overview of the output data behaviour. The skewness is a measure of the asymmetry of the data around the mean value. If the data is spread out more to the left, the skewness value is negative and if the data is spread out more to the right, the skewness value is positive. For normal distribution the skewness value is zero. The distribution can also be evaluated with the kurtosis value which is a measure of how outlier-prone the distribution is. Table 5 presents the statistical values for some output variables. The evaluation of the histograms, both visually and on the basis of statistical values, shows that the developed model behaves correctly.

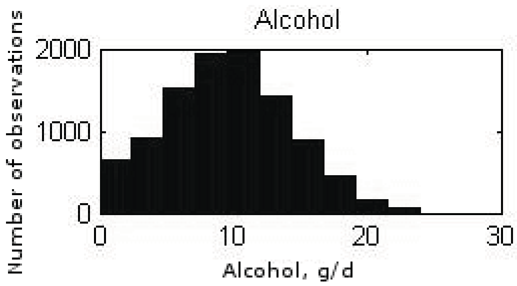

Figure 5: Test set for intake levels of alcohol.

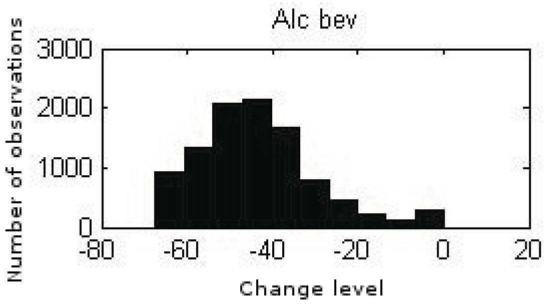

Figure 6: Histogram of output variable.

Table 5: Example statistical values of output variables.

	Mean	Std	Skewness	Kurtosis
Fruits and berries	11.9	19.1	1.1	2.5
Vegetables	-5.0	26.0	-0.2	2.3
Cereals and bakeries	-39.2	17.5	1.4	3.4
Alcoholic beverages	-43.5	14.1	0.9	4.1

6.4 Evaluation of the results

The results obtained from the performed validation are promising but more validation with more efficient methods is required. All of the validation procedures showed that the model performs in correctly, but no solid proof for this was obtained. The addition of the optimization algorithm will

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make validation easier because the numerical values (distance from the original and the recommended diet) can be calculated.

7 Conclusions

The importance of nutritional guidance is growing as nutritional problems, such as obesity and type-2 diabetes, are becoming more common. Nutrition guidance is carried out by mapping the nutrition intake levels from the user's food diary and comparing them to the recommended levels. Typically, balancing the diet requires expert knowledge on nutrition.

This paper presented the development of a fuzzy expert system for a nutrition guidance application. The expert knowledge acquisition was carried out using variable tabulation, thus creating a basis for the development of the rulebase for the fuzzy system. The recommended nutrition intake values were used to generate the membership functions for fuzzification. A Mamdani-type fuzzy system was developed with a hierarchical structure. The first level system only referred to the groups of similar foods while the second level model referred to food subgroups.

The validation of the fuzzy model was carried out in three phases: first two types of sensitivity analysis were performed, and then the output was analysed with expert knowledge. The results from all the validation schemes are promising.

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ISBN: 978-989-95079-6-8