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A Nutrition Evaluation System Based on Hierarchical Fuzzy Approach

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Abstract

In this paper, we propose a hierarchical fuzzy based nutrition evaluation system that can analyze the individuals' nutrition status through the inference results generated by each layer. Moreover, a method to minimize the uncertainty of inference in the evaluated nutrition status is discussed. To show the effect of the uncertainty in fuzzy inference, we compared the results of nutrition evaluation with/without the certainty factor of rules on 132 people over the age of 65. From the experimental results, we can see that the evaluation method with the modified certainty factor provides better reliability than that of the general evaluation method without the certainty factor.

Key Words: nutrition status evaluation, hierarchical fuzzy system, uncertainty

1. Introduction

Nutrition assessment is a process used to evaluate nutritional status, identify disorders of nutrition, and determine which individuals need nutritional instruction and/or nutrition support [1]. The assessment is conducted by evaluating and diagnosing the collected data through the anthropometric measurement, biochemical test, dietary survey, and clinical observation. In recent years, each individual's quality of life has been increased in Korea, so that a well-being culture has been extended to enjoy the healthy life. For the healthy life, the adequate exercise and medical supports are important, but the nutrition that is influenced by the long-term eating habit becomes more important factor. Obesity caused by the energy over-intake increases the rate of chronic degenerative diseases such as causes diabetes and hypertension. Under-nutrition caused by excessive weight-loss or unbalanced dietary life brings about a variety of diseases including anemia, osteoporosis, delayed development, and immunity decline. Such the problem of poor nutrition can be improved through the personal eating habits and nutritional management. For it, it is necessary to analyze systematically the nutritional status. In this paper, we propose a nutrition evaluation system based on hierarchical fuzzy approach [2-4] to analyze the individual's nutrition status through the inference result generated by each layer. Moreover, a method to minimize the uncertainties of inference results in the analyzed nutrition status is discussed. To show the effectiveness of the proposed system, we compared the results of nutrition evaluation with/without the certainty factor of rules on 132 people over the age of 65.

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2. Related Works

In this study, the anthropometric measurement, dietary survey data and KDRIs(Dietary Reference Intakes for Koreans) were used for the nutritional assessment..

- Anthropometric measurement

Anthropometric measurement measures the object's height, weight, and waist. For the obesity measurement, BMI calculated by dividing the person's weight in kilograms by the square of their height in meters. When BMI is lower than 18.5 in Asian areas, it is labelified as under-weight. When BMI is 18.6 ~ 22.9, it is labelified as normal. When BMI is 23 ~ 24.9. It is labelified as overweight. When BMI is higher than 25, it is labelified as obesity. In addition, when the waist measurement is 90cm for man and 80cm for woman, it is labelified as the abdominal obesity [5].

- Dietary survey

As the dietary survey, there are 24-hour recall, food diary, and food frequency questionnaire. Nutrition is mainly analyzed after surveying the dietary intakes by using 24-hour recall.

- Energy balance

Energy is mainly composed of fat, protein, and carbohydrates. It is recommended to take 20 ~ 25% of total energies for fat, 15 ~ 20% of total energies for protein, and 60 ~ 65% of total energies for carbohydrates.

- KDRIs

KDRIs is labelified into an age and a gender based on Korean's Standard Physique, and is composed of Estimated Average Requirements (EAR), Recommended Intake(RI), Adequate Intake(AI), Tolerable Upper level(UI) for each nutrient. As the standard of daily energy intake, the EAR is used. EAR of man and woman aged over 65 is 2,000Kcal and 1,600Kcal respectively.

3. Hierarchical Nutrition Evaluation System

3.1 Structure of Hierarchical Nutrition Evaluation System

Fig. 1 shows a structure of hierarchical nutrition evaluation system, which performs fuzzy inference using the data gathered from anthropometric measurement, 1st, and 2nd dietary survey.

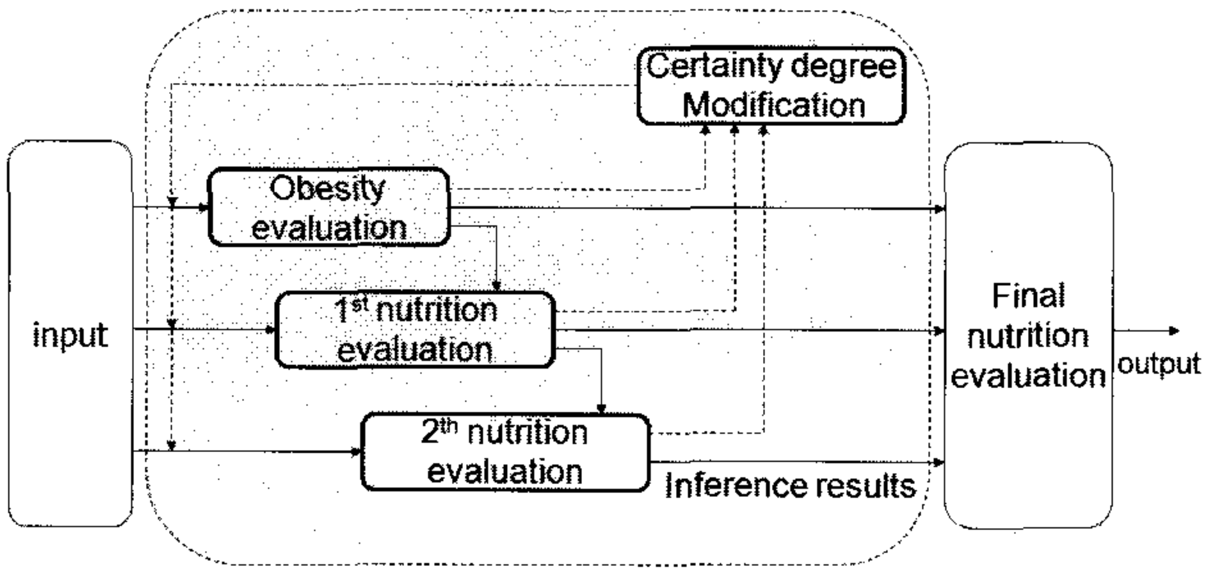

Fig. 1. Structure of hierarchical nutrition evaluation system

where the inputs used in three layer such as obesity evaluation, 1st nutrition evaluation, and 2nd nutrition evaluation, are as follows: 1) Layer1 (BMI, Waist circumstance, and Exercise), 2) Layer2 (inference results of Layer1, Protein_1, Lipid_1, and Carbohydrate_1), and 3) Layer3 (inference results of Layer2, Protein_2, Lipid_2, and Carbohydrate_2).

The layer1, an obesity evaluation, evaluates the degrees of obesity using the data, e.g., BMI, Waist circumstance, and Exercise, which is gathered through the anthropometric measurement of 132 people over the age of 65. The layer2 evaluates the energy balances by using the inference results of layer1, 1st dietary survey, Protein_1, Lipid_1, and Carbohydrate_1. The layer3 evaluates the final energy balances by using the results of layer2, 2nd dietary survey, Protein_2, Lipid_2, and Carbohydrate_2. In Fig. 1, the certainty degree modification adjusts the certainty factors of fuzzy if-then rules on the basis of the view of experts in order to overcome the limitations, that is, the degrees of fulfillment (DOF) of rules between the labels have the same membership values, since it cannot provide the reliability of inference in decision making problems. In addition, the final nutrition evaluation is to provide the nutrition assessment for an individual by combining the inference results of each layer applied to the modified certainty factors.

3.2 Rule Selection for Assessing the Nutrition Status

In this section, we generated the fuzzy if-then rule from the given data, which is labeled by experts, to assess the nutrition status of an individual. Suppose we consider the following fuzzy if-then rules with n input attributes for the nutrition status evaluation.

$$R^i : IF\ x_1\ is\ A_{i1}\ and, \ldots, and\ x_n\ is\ A_{in}$$
$$THEN\ y\ is\ C_l\ with\ CF_i$$

where $x_1, \ldots, x_n$ are the antecedent variables and $A_{ij}(j=1,\ldots,n)$ is the fuzzy membership function such as low, medium, and high. y is the consequent variable, $C_l(l=1,\ldots,k)$ is the output level, e.g., one of the k labels, at i-th rule, and CF_i is the certainty factor for the rule, as described by Ishibuchi and Nakashima [6].

In general, the rule number of possible combinations will be increase in geometric progression, when the number of linguistic variables is added. Therefore, in the proposed system, we extracted the rules with the maximal DOF among the rules generated from the data. For example, if n input patterns are given, the fuzzy if-then rules are then generated from Eq. (1).

$$\begin{aligned} r_i &= \max\left(\mu_i(X)\right), \\ \mu_i(X) &= \min\left(\mu_{i1}(x_1), \mu_{i2}(x_2), \ldots, \mu_{in}(x_n)\right) \end{aligned} \tag{1}$$

where r_i is i-th rule generated by the max-min operation, $\mu_{ij}(\cdot)$ is the membership value.

3.3 Nutrition Evaluation

3.3.1 The Initial Nutrition Evaluation

The steps for the nutrition evaluation on each layer are as follows:

Step 1: Calculate the compatibility grade of the given data corresponded to each rule.

$$\mu_i(X) = \min\left\{\mu_{i1}(x_1), \mu_{i2}(x_2), \ldots, \mu_{in}(x_n)\right\} \tag{2}$$

where $\mu_{ij}(\cdot)$ is the membership value of the fuzzy membership function $A_{ij}(j=1,\ldots,n)$.

Step 2: Calculate the DOF of each rule based on their compatibility grade calculated from Step 1. In the proposed system, the initial certainty factor assigned by all the same values as 1.0.

$$\mu_{oi}(Y) = \mu_i(X) \cdot CF_i,\ CF_i \in [0,1] \tag{3}$$

Step 3: Calculate the results for the final inference from the DOF of rules obtained by Step 2.

$$\mu_{oi}(Y) = \max\left(\mu_{o1}(y_1), \mu_{o2}(y_2), \ldots, \mu_{on}(y_n)\right) \tag{4}$$

Step 4: Calculate the defuzzified values from the results of Step 3. We also used the center of gravity (COG) as the defuzzification method.

$$d_i = \frac{\sum_{i=1}^{n}\left(y_i \times \mu_{oi}(Y)\right)}{\sum_{i=1}^{n}\left(\mu_{oi}(Y)\right)} \tag{5}$$

3.3.2 The Process to Minimize the Uncertainty of Inference Results

We adjusted the certainty factors of rules based on the views of experts to overcome the limitation that the DOF of rules between the labels have the same membership by using Eqs. (6) - (9).

$$E_i = \frac{1}{k}\sum_{i=1}^{k} C_i \qquad (6)$$

$$CF_{i+1} = CF_i \qquad (7)$$

$$CF_{i+1} = CF_i - (1 - E_i) \qquad (8)$$

$$\mu_{oi}(Y) = \mu_i(X) \cdot CF_{i+1},\ CF_{i+1} \in [0,1] \qquad (9)$$

where k is the number of experts, C_i are the view of experts on the output label with the uncertainty of inference result at each layer such as the obesity, 1st, and 2nd nutrition evaluation, and E_i are the relative strength on i-th output label with the uncertainty of result. Moreover, in Eq. (8), CF_{i+1} are the certainty factor of rule for i-th label, which is modified by considering the relative strength of experts, whereas CF_{i+1} in Eq. (7) are the certainty factor of i-th label without the certainty of result. Therefore, Eq. (9) denotes the modified DOF of rule when the modified certainty factors are considered.

4. Experimental Results

In order to show the effectiveness of the proposed system, we evaluated the nutrition status on 132 people over the age of 65 (man: 49, woman: 83).

4.1 Initial Obesity Evaluation

Fig. 2 shows membership intervals of the antecedent fuzzy sets defined to the initial obesity evaluation based on KDRIs. In Fig. 2, the fuzzy sets for the antecedent variables 'BMI' and 'Waist circumference' used 5 and 2 triangle membership functions, respectively, and those for the antecedent variable 'Exercise' used 2 fuzzy singleton.

Fig. 3 shows membership intervals of the consequent fuzzy sets used to the initial obesity evaluation.

The total number of rules used for the initial obesity evaluation is 20. Table 1 shows the defuzzification intervals generated from Eq. (2) - (5), where 'CG' represents the number of patterns with the same fuzzy values in the consequent part of fuzzy if-then rules during defuzzification operation. As shown in Table 1, the patterns have the same output values are yielded in a boundary point between 'normal' and 'over'.

In this case, the obesity evaluation cannot provide an appropriate inference (evaluation) result to assess the degree of obesity. Therefore, the proposed system reevaluated the patterns by modifying the certainty factors of rules associated with those to improve the reliability of inference results.

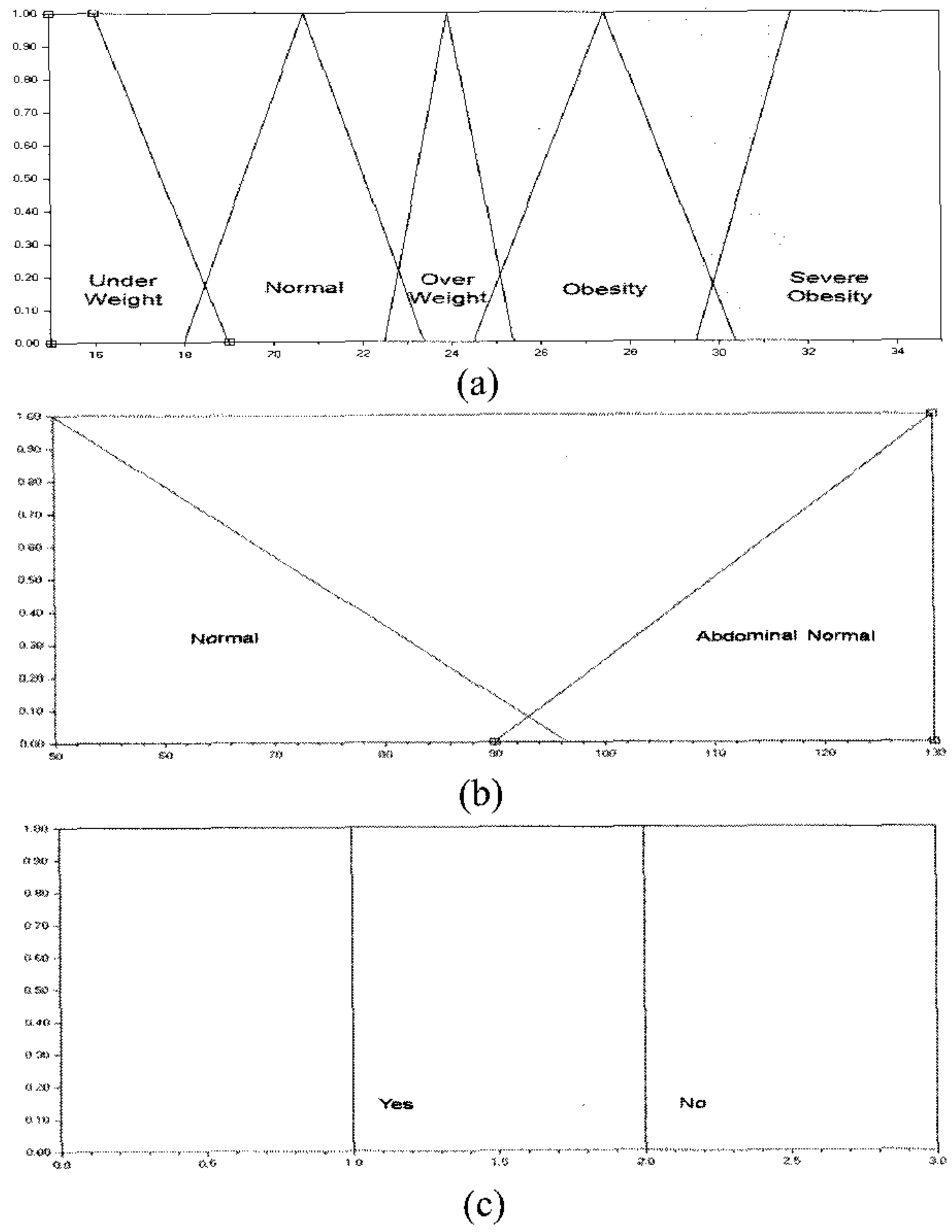

Fig. 2. Antecedent membership intervals for the initial obesity evaluation: (a) BMI; (b) Waist circumstance; (c) Exercise

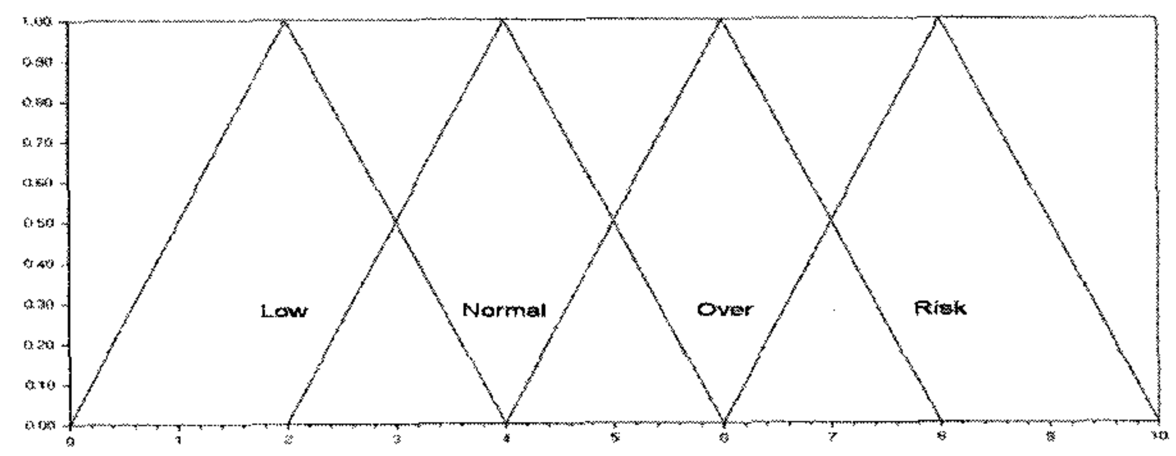

Fig. 3. Consequent membership intervals for the initial obesity evaluation

Table 1. Defuzzified intervals

Label	Low	Normal	Over	Risk
Intervals	2-2.9575	3.0626-5	5-6.9723	6.4247-8
CG	None	2		None

Table 2 shows the fuzzy outputs and their defuzzified values of the two patterns (no. 13 and 25) with the uncertainty of inference results. In addition, from Table 1 and 2, we can see that the maximum and minimum values of the defuzzification intervals between the label 'normal and 'over' is the same each other. In other words, they cannot be utilized as objective information to evaluate the degree of obesity, because their inference results have the same values on a boundary point.

Table 2. Patterns with the same fuzzy values

No.	Sex	BMI	Wt.	Ex.	Fuzzy output				DF
					L	N	O	R	
13	M	22.8	89	2	0	0.1643	0.1643	0	5
25	M	22.8	90	2	0	0.1643	0.1643	0	5

Wt: Waist; Ex: Exercise; L: Low; N: Normal; O: Over; R: Risk;
DF: Defuzzification

In Table 2, `BMI`, `Wt`, and `Ex` represent the antecedent variables which are used to evaluate the degree of obesity. `L`, `N`, `O`, and `R` denote the linguistic terms defined on the consequent variable `Obesity`. Fig. 4 shows the inference results of the obesity evaluation generated from Eq. (5). In Fig. 4, the symbol 'o' indicates the patterns that have the same fuzzy values between 'normal' and 'over' as shown in Table 2.

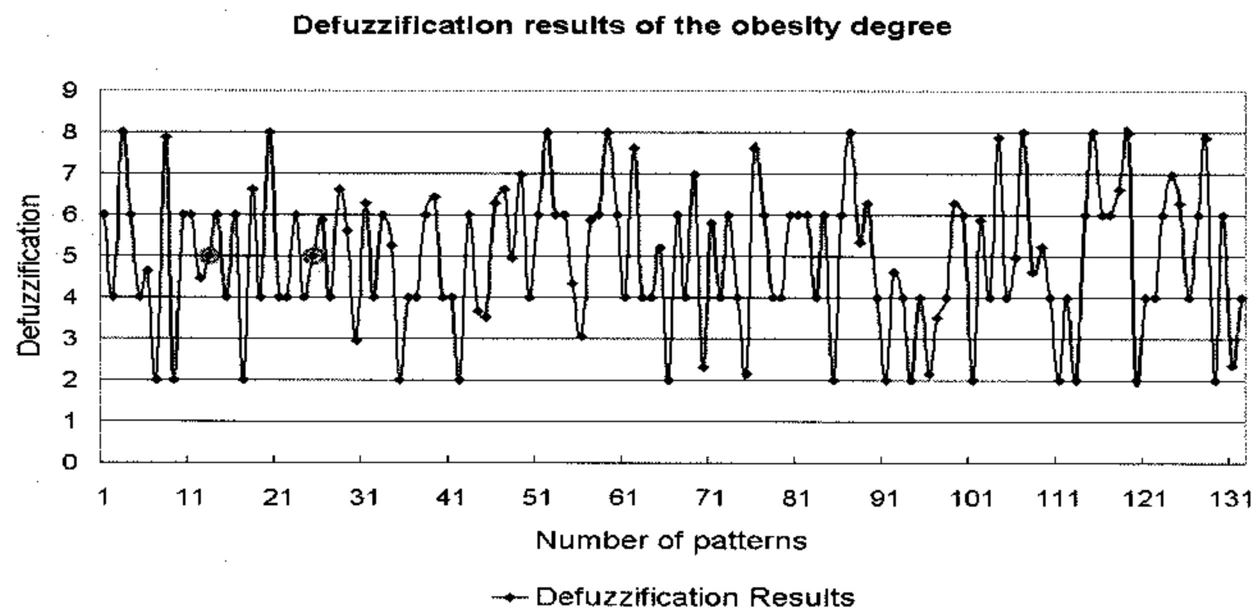

Fig. 4. Inference results of the initial obesity evaluation

4.2 1st Nutrition Status Evaluation

To measure the state of nutrition in the body, we evaluated 1st nutrition status of an individual based on the results of the previous evaluation, i.e., the obesity evaluation, and ingredients, Protein_1, Lipid_1, and Carbohydrate_1, of ingested foods.

Fig. 5 shows membership intervals of the antecedent fuzzy sets to evaluate 1st nutrition status based on the ingredients of ingested foods. In Fig. 5, membership functions used 4, 3, 3, and 3 triangle fuzzy sets, respectively.

For the evaluation of 1st nutrition status, furthermore, we adjusted the width of membership functions into $\pm\alpha(\alpha = 0.5)$ from the inference results of the initial obesity evaluation. The key issue adjusts those is as follows: if the defuzzified intervals of the nutrition status, then compatibility grade of several input patterns corresponding to the boundary intervals is 0. Fig. 6 shows membership intervals of consequent fuzzy sets for evaluating the 1st nutrition status. The total number of rules required for assessing the 1st nutrition status is 108 (4*3*3*3).

Hence, we generated 21 fuzzy if-then rules by extracting rules with only the maximal DOF from Eq. (1), and their inference results are displayed in Table 3.

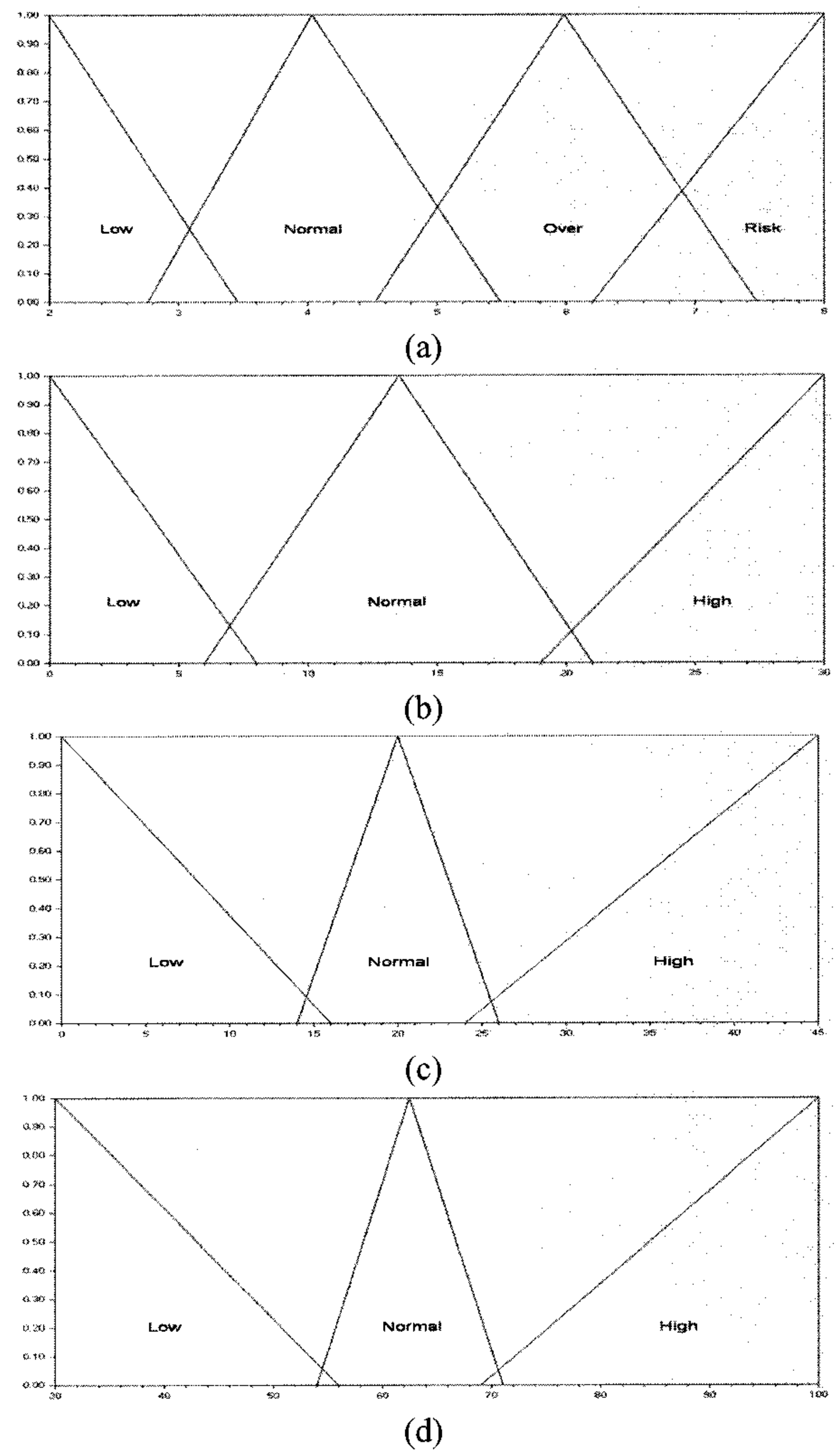

Fig. 5. Antecedent membership intervals for the 1st nutrition status evaluation: (a) The initial obesity evaluation; (b) Protein_1; (c) Lipid_1; (d) Carbohydrate_1

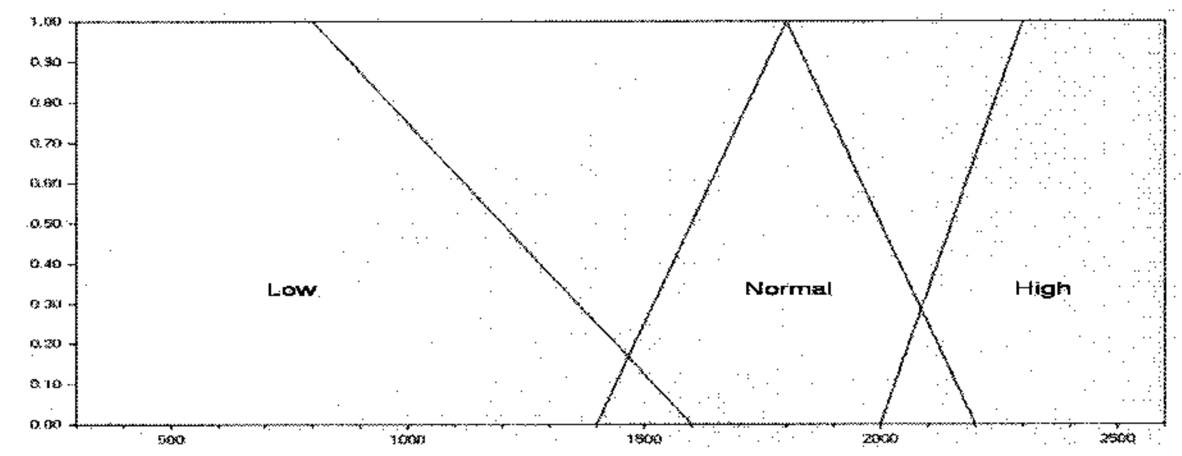

Fig. 6. Consequent membership intervals for the 1st nutrition status evaluation

Table 3. Defuzzification intervals

Label	Low	Normal	High
Intervals	732.9119 ~ 916.8519	1480.5905 ~ **2102.6627**	**2102.6627** ~ 2368.9883
CG	None	3	

From Table 3, we can see that the uncertainty of inference results is yielded in 3 patterns (no. 34, 48, and 106) between the overall patterns, where their fuzzy output values between the label 'normal' and 'high' are equal to a boundary point and their boundary points are determined in the interval [2102.6627, 2102.6661].

Table 4. Patterns with the same fuzzy values

No.	Sex	Obs	Pro _1	Lp _1	Car _1	Fuzzy output			DF
						L	N	H	
34	M	5.3	14.9	12.7	72.4	0	0.11	0.11	2102. 6627
48	M	4.9	13.4	11.3	75.4	0	0.21	0.21	2102. 6661
106	F	4.9	15.9	9.3	74.7	0	0.18	0.18	2102. 6653

Obs: Obesity; Pro_1: Protein_1; Lp_1: Lipid_1; Car_1: Carbohydrate_1; L: Low; N: Normal; H: High; DF: Defuzzification

Fig. 7 shows the inference results for the 1st nutrition obesity evaluation generated from Eq. (5), and the symbol `o` indicates the patterns which have the same fuzzy value between the label `normal` and `high` as shown in Table 4.

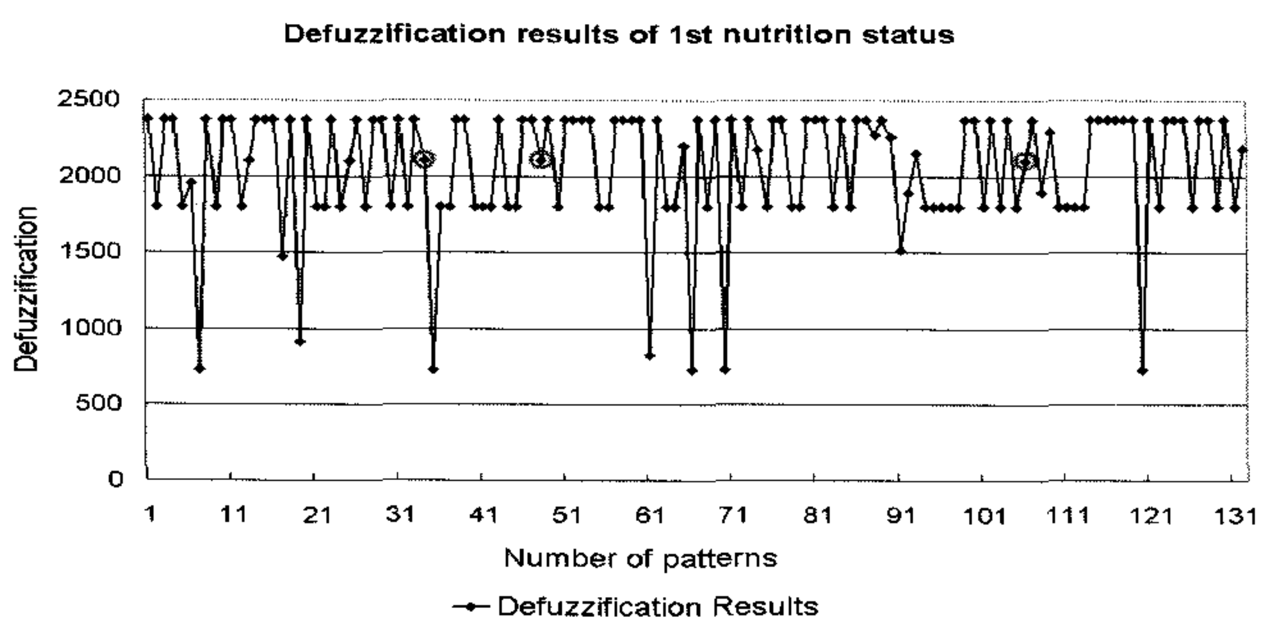

Fig. 7. Inference results of the 1st nutrition status evaluation

4.3 2nd Nutrition Status Evaluation

As the final step for measuring the state of nutrition in the body, we evaluated the 2nd nutrition status of an individual based on results of the previous result and ingredients, i.e., Protein_2, Lipid_2, and Carbohydrate_2, of ingested foods. Fig. 8 shows membership intervals of the antecedent fuzzy sets, which are used to evaluate 2nd nutrition status based on the ingredients of ingested foods.

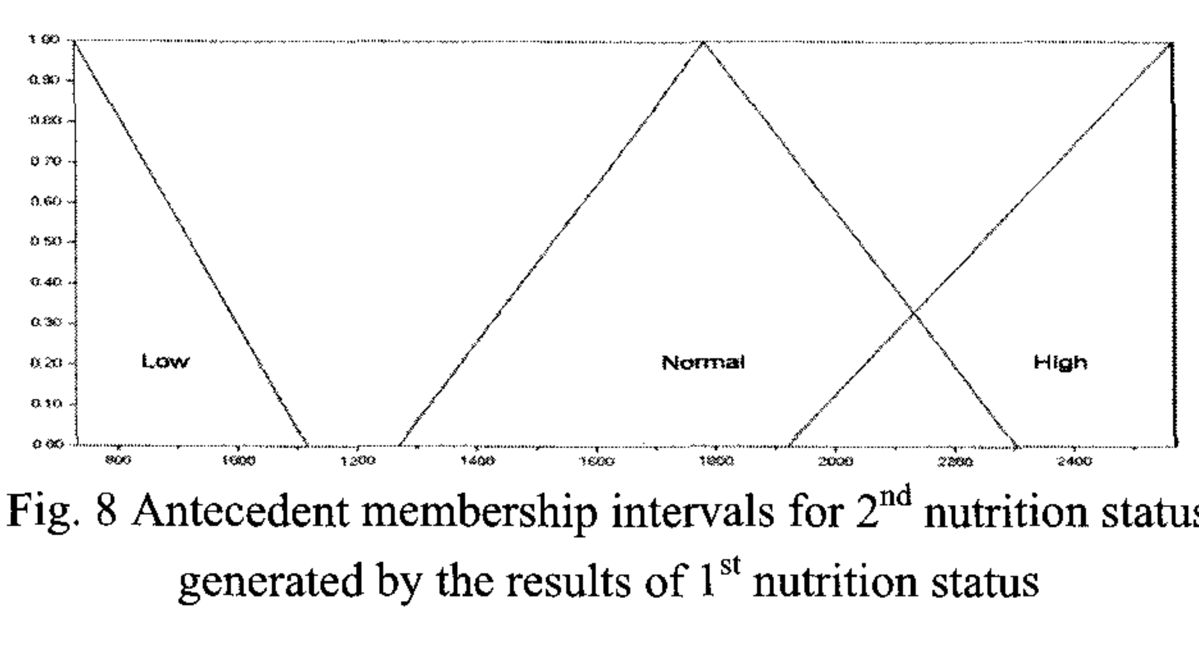

Fig. 8 Antecedent membership intervals for 2nd nutrition status generated by the results of 1st nutrition status

To evaluate 2nd nutrition status, the antecedent fuzzy sets, Protein_2, Lipid_2, and Carbohydrate_2, used the same membership functions as shown in Fig. 5(b) - (d). For the evaluation, we adjusted the widths the membership functions into $\pm\alpha\,(\alpha = 200)$ based on the inference results of the 1st nutrition status. In order to minimize the number of rules, we generated 19 fuzzy rules from Eq. (1). Table 5 shows the final defuzzification intervals generated from the 19 rules.

Table 5.Defuzzification intervals

Label	Low	Normal	High
Intervals	732.9119 ~ 938.2917	1800.0188 ~ **2348.4584**	**2055.5698** ~ 2368.9883
CG	None	4	

The results show the uncertainty of inference results is yielded in 4 patterns between the overall patterns as shown in Table 6.

Table 6. Patterns with the same fuzzy values

No.	Sex	1st	Pro _2	Lp _2	Car _2	Fuzzy output			DF
						L	N	H	
13	M	2100. 9943	12.8	8.7	77.5	0	0.27	0.27	2102. 6685
34	M	2102. 6627	14.9	12.7	72.4	0	0.11	0.11	2102. 6627
74	F	2177. 4458	16.7	10.4	72.9	0	0.13	0.13	2102. 6634
106	F	2102. 6653	15.9	12.9	71.1	0	0.07	0.07	2102. 6613

1st : 1st nutrition status evaluation; Pro_2: Protein_2; Lp_2: Lipid_2; Car_2: Carbohydrate_2; DF: Defuzzification

Furthermore, the uncertainty regions in the 2nd nutrition evaluation are determined in the interval [2102.6613, 2102.6685] within overlapping intervals [2055.5698, 2348.4584] between the label 'normal' and 'high' (see Table 5 and 6). Fig. 9 shows the final inference results for the 2nd nutrition evaluation.

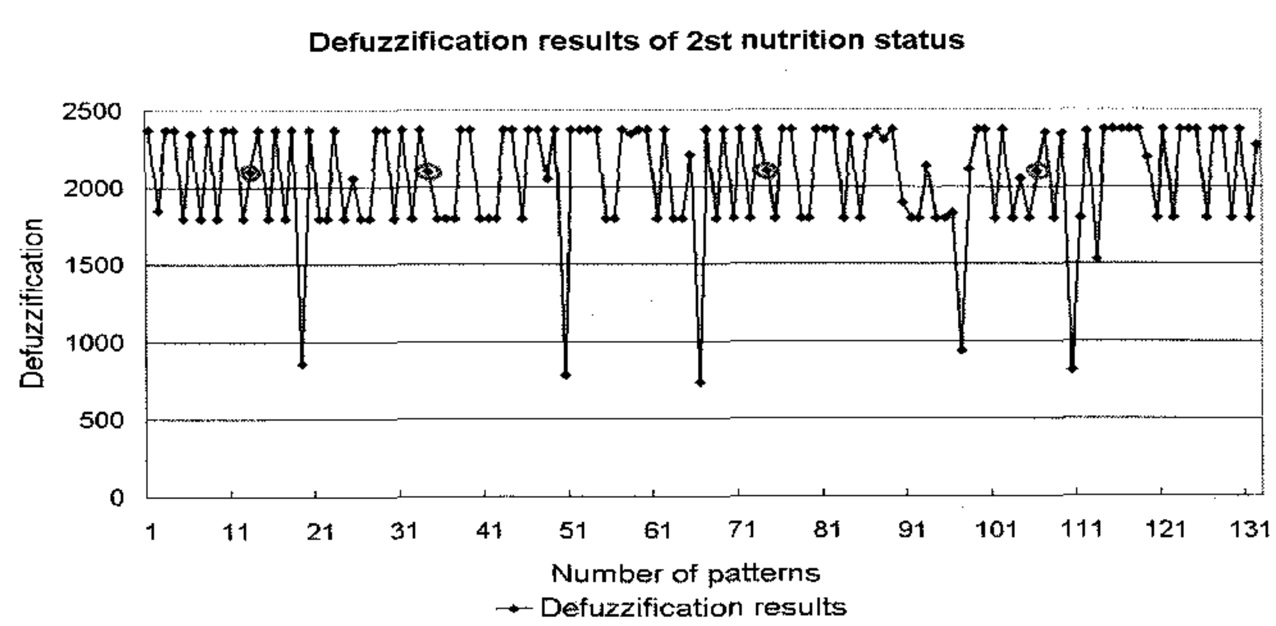

Fig. 9. Inference results of the 2nd nutrition status evaluation

4.4 Final Nutrition Status Evaluation

In this section, we reevaluated several patterns (see Table 2, 4, and 6) by modifying the certainty factors of fuzzy rules using Eqs. (6) - (9), to improve the reliability of the results. Table 7 shows the views of experts for the patterns that have the same fuzzy values in the initial obesity evaluation as shown in Table 2. Based on Table 7, the certainty factors of rules associated with the patterns are modified as 0.6 and 0.4.

Table 7. Experts` views on the initial obesity evaluation

Label	The initial obesity evaluation (No. 13 and 25)			
	Low	Normal	Over	Risk
Expert1		O		
Expert2			O	
Expert3			O	
Expert4		O		
Expert5		O		

Table 8 shows the defuzzification intervals of the final obesity evaluation calculated from the modified certainty factor.

Table 8. Defuzzification intervals

Label	Defuzzification intervals for the final obesity evaluation			
	Low	Normal	Over	Risk
Intervals	2-2.9575	3.2566 ~ 4.9862	5.0168 ~ 6.9723	6.7091~8
CG	None			

In Table 8, the results for the final obesity evaluation are not provide the same values with respect to 2 patterns (no. 13 and 25) used for the initial obesity evaluation. We also reevaluated the previous experimental results as the method used in the final obesity evaluation.

Table 9. Experts` views on the 1st nutrition status evaluation

Label	1st nutrition status evaluation (No. 34, 48, and 106)		
	Low	Normal	High
Expert1		O	
Expert2		O	
Expert3		O	
Expert4		O	
Expert5			O

From Table 9, the certainty factors of rules corresponding to the patterns are modified as 0.8 and 0.2 respectively. Table 10 shows the defuzzification intervals of the final 1st nutrition evaluation calculated from the certainty factors.

Table 10. Defuzzification intervals

Label	Defuzzification intervals for the final 1st nutrition status evaluation		
	Low	Normal	High
Intervals	732.9119 ~ 916.8519	1470.5905 ~ 2105.3875	2119.8721 ~ 2368.9883
CG	None		

Based on Table 11, the certainty factors of rules corresponding to the patterns are modified as 0.4 and 0.6 respectively.

Table 11. Experts` views on 2nd nutrition status evaluation

Label	2nd nutrition status evaluation (No. 13, 34, 74, and 106)		
	Low	Normal	High
Expert1			O
Expert2		O	
Expert3		O	
Expert4			O
Expert5			O

Table 12 shows the defuzzifiction intervals for the final 2nd nutrition evaluation, which is evaluated by using the modified certainty factors.

Table 12. Defuzzification intervals

Label	Defuzzification intervals for the final 2nd nutrition status evaluation		
	Low	Normal	High
Intervals	732.9119 ~ 1447.7663	1800.0186 ~ 2005.6885	1874.7199 ~ 2368.9883
CG	None		

From Table 12, we can reconfirm that the final 2nd nutrition evaluation with the modified certainty factor show reliable results on the overall patterns, while the previous 2nd nutrition evaluation provides the uncertainties of inference results in several patterns. In conclusion, we can see that the final nutrition evaluation with the modified certainty factor provides better results than those of the evaluation without the certainty factor.

5. Conclusions

In this paper, we have been proposed a hierarchical fuzzy based nutrition evaluation system that can analyze the individuals' nutrition status through the inference results generated by each evaluation layer. To show the effectiveness of the proposed system, we compared the inference results, which are generated from each evaluation layer to evaluate the nutrition status, of an individual based on anthropometric measurement and ingredients of ingested foods on 132 people over the age of 65. From the results, we found that the method with the modified certainty factor provides better reliability than that of the method without the certainty factor.

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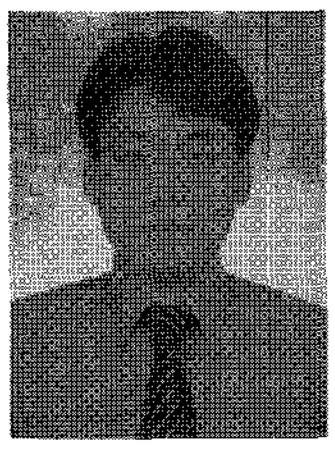

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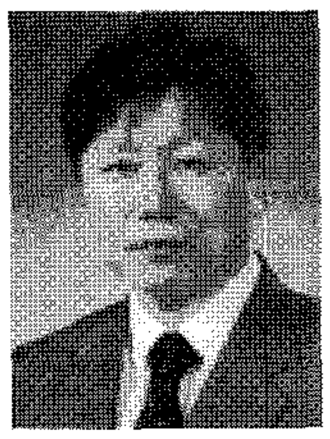

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