ISSN 2229-5518

Ontology-based intelligent multi-agent for diet food recommendation

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Abstract— A healthy diet and lifestyle are the most effective approaches to prevent disease. When a person eats too much or too little on a continual basis, the risk of disease will increase. Therefore, developing healthy and balanced eating habits is essential to disease prevention. This study proposes an intelligent diet food recommendation multi-agent (IDFRMA), including a personal profile agent, a nutrition facts analysis agent, a knowledge analysis agent, a discovery agent, a fuzzy inference agent, and a semantic generation agent for healthy diet planning. The IDFRMA provides a semantic analysis of healthy diet status for people based on the preconstructed ontology by domains experts and results of fuzzy inference. With the generated semantic analysis, people can get healthy information about what they eat and make it easier to eat a balanced and healthy diet. The experimental platform has been constructed to test the performance of the IDFRMA. The results indicate that the IDFRMA can effectively work for healthy diet planning.

Index Terms— Multi-agent system, Ontology, Fuzzy inference System

1 Introduction

During the entire human history populations have experienced changes in ecological relationships that have modified their diet and physical activity and eventually altered their disease pattern.

Population growth was low and stable at the time of their existence. However, there was a dramatic shift to domestication of plants and animals for agricultural food production about 10,000 years ago and subsequent changes in disease profiles [1].

Therefore, an intelligent agent for planning healthy diets is becoming an increasingly important research topic. An intelligent agent that automatically provides tips for how to choose foods that improve health and avoid foods that increase risk of illness would be great assistance for most people, especially those with diabetes or cardiovascular diseases.

The agent technology is a key area in the field of artificial intelligence research [2]. The function of an intelligent agent covers six attributes, including autonomy, continuity, adaptivity, goal orientation, learning ability, and communication [3]. For example, presented the Semantic Web services and Multi-Agent Systems framework (SEMMAS) for seamless integration of technologies by using ontologies that facilitate the interoperation of agents and Web services[5]. The proposed multiagent system called Chronos assists users in organizing meetings. Each person has a unique diet. Therefore, to determine individual dietary status, an ontology is a good idea for building personal dietary patterns and providing nutritional facts for a healthy diet is needed.

Ontology is a very powerful TOOL FOR REPRESENTING

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information and its semantics; ontologies can be thought of as information and its semantics; ontologies can be thought of as knowledge representations as ontologies do more than just control vocabulary [7]. Consequently, ontologies are applied to many such research fields as news summarisation [8] and medical information systems[9]. Furthermore, The proposed ontologybased approach provides a rich environment for expressing different information types, including perceptions[7]. Multi-agent systems combined with ontologies have been utilized to support distributed decisionmaking in such fields as manufacturing, business and engineering[4].

It presented a meeting scheduling system by combing a genetic fuzzy agent with an ontology model[10]. The structured dialogues and process information collected by agents using an agent communication language [11].

Applying agent technology to healthcare is also an important research topic. For example, Lee and Wang presented an ontology-based intelligent agent to recognise the respiratory waveform [12] and an ontological fuzzy agent to apply for electrocardiogram (ECG) [13]. This paper combines ontology and agent technologies in developing an intelligent multi-agent for diet evaluation. In the proposed approach, domain experts first use Protégé software (Noy and McGuinness 2001) to pre-define a food ontology according to nutritional facts obtained from the Internet and convenient stores in India. Additionally ontology domain experts pre-built the personal profile ontology for users.

Then, a Fuzzy Markup Language (FML), proposed by Acampora and Loia [14], is adopted to model the necessary knowledge base and rule base of the fuzzy inference. Next, the proposed intelligent diet food recommendation multi-agent (IDFRMA), including a personal profile agent, a nutrition facts analysis agent, a knowledge analysis agent, a discovery agent, a fuzzy inference agent, and a semantic generation agent, can help people deal with diet food recommendation. Based on the food ontology, knowledge base, and rule base, each agent executes different kinds of functions to detect the semantics of the diet food status. Finally, the results of the healthy diet status are stored into the healthy diet status repository. The remainder of this paper is structured as follows: Section II de-

ISSN 2229-5518

scribes the system structure and the diet ontology for the diet food recommendation. Section III introduces the details of the proposed intelligent multi-agent. The experimental results are shown in Section IV and the conclusions are finally given in Section V.

2 Procedure for Paper Submission

In this section, the system structure of the IDFRMA and the diet ontology are presented. Additionally, the FML is also briefly described in this section.

2.1 System Structure

Fig. 1 shows the architecture of the IDFRMA platform. It is composed of three including a knowledge layer, a communication layer, and an application layer.

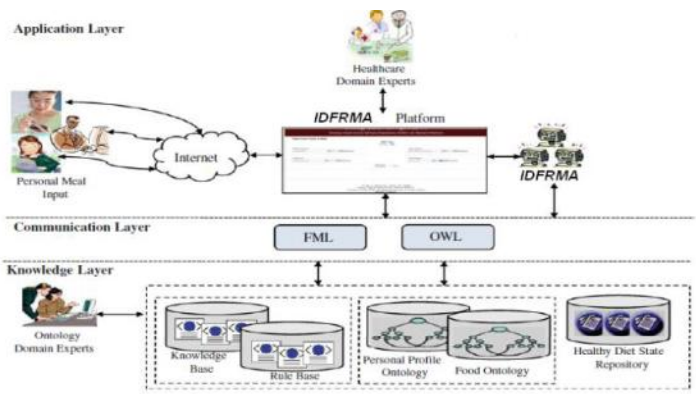

Fig.1. IDFRMA platform architecture

The knowledge layer includes the knowledge base, the rule base, the profile ontology, the food ontology, and the healthy diet status repository. The communication layer is designed to offer some application interfaces, such as FML, web ontology language (OWL), and healthy diet status, to interact between the application layer and the knowledge layer. First, the user with a personal digital assistant (PDA), a personal computer, or a notebook utilizes the IDFRMA platform through the Internet. After successful authentication, the user can deal with the personal meal based on the knowledge stored in the knowledge layer and then perform the analysis of the healthy diet status through the communication layer

2.2 Ontology model

Based on the levels of organization [15] and previous work [8], this paper presents a domain ontology model for healthcare applications. Figure. 2 shows the structure of the domain ontology model, which has a domain name, category set, and concept set.

The domain name represents the name of the ontology model. The category set contains several categories, labeled‘‘category1, category2,category3, …, and categoryk.’’

Each concept in the concept set contains a concept name Cm and an attribute set for an set {Acm1,……..Acmqm} for an application domain. In addition, a relationship exists among concepts that belong to the same category.

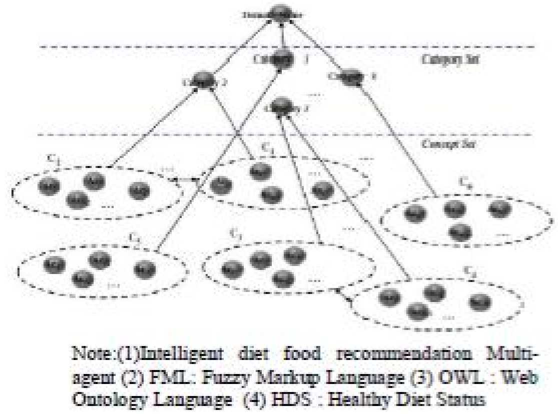

Fig.2. Structure of the domain ontology

For example, there is a bi-directional arrow between concepts C1 and C2 because these two concepts belong to the category 2.

Based on the structure of the domain ontology we apply it to the food ontology, shown in Fig.3. The domain name of this ontology is "six food groups." The categories in the category layer include grains & starches group, vegetables group, fruits group, milk group, meats & proteins group, and fats group" According to the nutrition facts label of each food product [16], the nutrition facts contain product-specific information such as serving size, calories, and nutrient information as well as a footnote with Daily Values (DVs) based on a 2000 calorie diet.

In this study, the calories per portion and the grams of carbohydrate, protein, and fat per portion are considered in the construction of the food ontology. Therefore, in the nutrient facts sub-layer, concept contains product-specific information such as "calories" and "nutrient information (carbohydrate, protein, and fat)." For instance, the nutrition facts for each portion of the

Fig. 3. Structure of the food ontology

"Fruit" are 32kcal and the grams of carbohydrate, protein, and fat are 8.31g, 0.42g, and 0.1g, respectively.

3. FUZZY MARKUP LANGUAGE

Acampora and Loia [14] proposed a Fuzzy Markup Language (FML), which is a fuzzy-oriented markup language that can manage fuzzy concepts, fuzzy rules, and fuzzy inference engine directly. Additionally, the FML is essentially composed of three layers, including eXtensible Markup Language (XML), document type definition, and extensible stylesheet language transformations [14]. Based on the FML, we developed an FML editor to construct the important knowledge base and rule base of the IDFRMA. The knowledge base describes the fuzzy concepts related to the fuzzy inference, including fuzzy variables, fuzzy terms, and membership functions of fuzzy sets.

sOn the other hand, the rule base describes the fuzzy rule set, including the antecedent and consequence rule part. The knowledge base and the rule base of the IDFRMA FML, where there are one output fuzzy variable (Diet Food Recommendation, IDFRMA), 150 fuzzy rules, and six input fuzzy variables, including Age, Body Mass Index (BMI), Percentage of Calories from Carbohydrate (PCC), Percentage of Calories from Protein (PCP), Percentage of Calories from Fat (PCF), and Calories Difference (CD). Each fuzzy variable has several fuzzy terms. For example, fuzzy variable Age has three fuzzy terms, namely "Young," "Middle," and "Old."

4 INTELLIGENT DIET FOOD RECOMMENDATION MULTI-AGENT

The IDFRMA comprises six agents, including a personal profile agent, a nutrition facts analysis agent, a knowledge analysis agent, a discovery agent, a fuzzy inference agent, and a semantic generation agent, which are described below.

4.1 System Structure

Fig.4 shows the structure of the IDFRMA. First, the food data are gathered from the Internet and convenient stores in India. The processing mechanism then deals with the collected food data and transforms them into the information. Next, the extracting mechanism mines the information to the important knowledge and sends them into the acquiring mechanism.

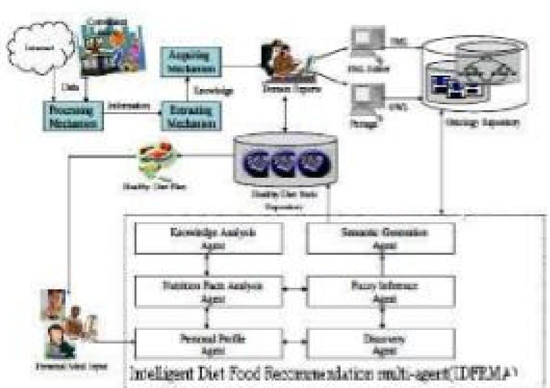

Fig.4 Structure of the IDFRMA

Fourth, the acquiring mechanism obtains the important knowledge and passes them to the domain experts. Fifth, the domain experts construct the FML and OWL using the FML editor and the protege [17], respectively, and store both of them into the ontology repository. Sixth, based on the pre-defined ontology repository, the IDFRMA finds out the user's personal profile, analyzes the nutrition facts of the meal records, calculates the percentage of calories from nutrients, discovers the necessary knowledge from the ontology repository, infers the possibility of healthy diet status, and eventually generates the semantic sentences. At last, the inferred results are stored into the healthy diet status repository and the domain experts then plan the healthy diet for the user on the basis of the inferred results. Fig. 6 shows the communication sequence among the sub-agents of the IDFRMA.

4.2 Structure Personal Profile Agent

The personal profile agent plays a role in retrieving the user's personal profile, such as age, sex, height, weight, and BMI, from the profile ontology. Additionally, the past personal food records also could be found by the personal profile agent.

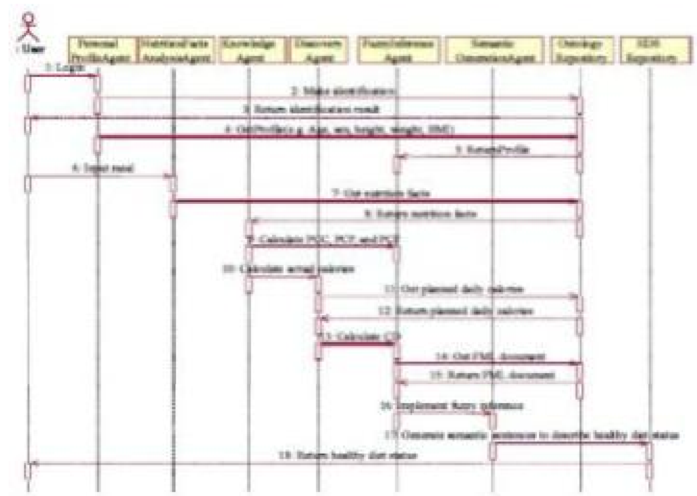

Fig. 6. Communication sequence of the IDFRMA

4.3 Nutrition Facts Analysis Agent

In this study, the nutrition facts analysis agent is responsible of examining the number of carbohydrate, protein, and fat grams contained in one portion of the collected meals according to the pre-constructed food ontology. Meanwhile, how many calories are contained in one portion is also acquired.

4.4 Knowledge Analysis Agent & Discovery Agent

With the nutrition facts of eaten foods, the knowledge analysis agent further transforms them into the actual calories, the percentage of calories from carbohydrate, the percentage of calories from protein, and the percentage of calories from fat. The suggested percentages of calories from the carbohydrate, protein, and fat are 55%~65%, 10%~20%, and 25%~35%, respectively. The discovery agent then gets the planned daily calories to calculate the calories difference between the actual calories and planned calories.

4.5 Fuzzy Inference Agent

The fuzzy inference agent is the core of the proposed multi-agent system. Based on the pre-constructed FML document, it performs the fuzzy inference to infer the possibility of the healthy diet status. Fig. 7 shows parts of the knowledge base and rule base stored in the ontology repository. The FS is specified by four parameters FS(x: param1, param2, param3, param4) and can be expressed as [param1, param2, param3, param4] Eq1.

$$FS(x{:}param1,param2,param3,parm4)=\begin{cases}0 & x<param1\\ (x-param1)/(param2-param1) & param1\leq x<param2\\ 1 & param2\leq x\leq param3\\ (param4-x)/(parm4-param3) & Param3<x\leq param4\\ 0 & x>param4\end{cases} \quad (1)$$

Another reason for adopting the trapezoidal membership function in this paper is that when param2 equals param3, then the trapezoidal membership function will be reduced to the triangular membership function. Fuzzy variable Age has three linguistic terms, AgeYoung, AgeMiddle, and AgeOld, that express user's age, whose trapezoidal membership functions are [20, 20, 25, 30], [25, 33, 38, 50], and [45, 50, 60, 60], respectively.

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</Clause>
</Consequent>
...
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    </FuzzyController>
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</Antecedent>

According to the BMI definitions (1) Underweight, BMI < 18.5; (2) Normal, 18.5 ≤ BMI<24; (3) Overweight, 24≤ BMI<30; (4) Obese, BMI ≥ 30, the BMI fuzzy variable defines three linguistic terms, namely, BMIUnderWeight, BMINormal, and BMIOverWeight, whose trapezoidal membership functions are [15, 15, 18.5,20], [18.5, 20, 22, 24], and [22, 24, 40, 40], respectively. The suggested percentages of calories from carbohydrate, protein, and fat are 55–65, 10–20, and 25–35%, respectively. Hence, the linguistic terms of fuzzy variable PCC are PCCLow, PCCBalanced, and PCCHigh, whose trapezoidal

membership functions are [0, 0, 50, 55], [50, 55,65, 70], and [65, 70, 100, 100], respectively. The linguistic terms of fuzzy variable PCP are PCPLow, PCPBalanced, and PCPHigh, whose trapezoidal membership functions are [0,0, 5, 10], [5, 10, 20, 25], and [20, 25, 100, 100], respectively.

The linguistic terms of fuzzy variable PCF arePCFLow, PCFBalanced, and PCFHigh, whose trapezoidal membership functions are [0, 0, 20, 25], [20, 25, 35, 40], and [35, 40, 100, 100], respectively. The membership functions of fuzzy variable CD are CDAcceptable, CDMore-or LessUnacceptable, and CDUnacceptable, whose trapezoidal membership functions are [0, 0, 50, 100], [70, 100, 150, 200], and [150, 200, 5000, 5000], respectively. Second, the fuzzy inference mechanism performs membership functions to compute the membership degrees for each meal recorded in the ontology repository. The MIN operator is then used to combine the degree of match between

ISSN 2229-5518

each fuzzy rule's conditions.

Third, the area center of each rule is calculated. The HDS fuzzy variable is utilized with five linguistic terms to represent the level of healthy dietary state for the meal eaten. The lin uistic terms are HDSVeryUnHealthy, HDSUnHealthy, HDSMediumHealthy, HDSHealthy, and HDSVeryHealthy, whose trapezoidal membership functions are [0, 0, 0.1, 0.25], [0.1, 0.25, 0.25, 0.5], [0.25, 0.5, 0.5, 0.75], [0.5, 0.75, 0.75, 0.9], and [0.75, 0.9, 1.0, 1.0], respectively. Fourth, the fuzzy inference mechanism performs the MAX operation to integrate triggered rules with the same consequences and outputs the maximum area center. The parameters of all membership functions are determined by domain experts. The trapezoidal membership functions for fuzzy variables Age, BMI, PCC, PCP, PCF, CD, and HDS, respectively. Finally, the level of a healthy dietary status of a meal eaten is inferred.

5 SEMANTIC GENERATION AGENT

The results of the fuzzy inference agent are transformed into the knowledge by the semantic generation agent to present the healthy diet status through the semantic descriptions according to the sentence patterns.

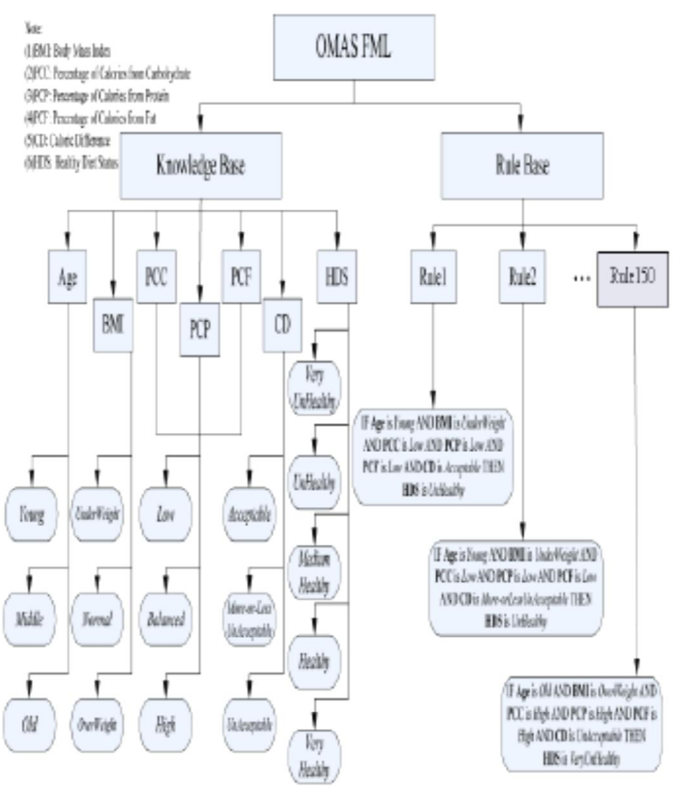

Fig. 3. Knowledge base and rule base of the intelligent diet food recommendation

Intelligent Diet Food Recommendation Multiagent (IDFRMA) Algorithm

Input:

1. Input the ontology repository

2. Input the eaten six food groups set $\overline{M} \leftarrow$

{[Food$_1$,…., Food$_N$]

[Grains & Starche$_1$,….. Grains & Starches$_Q$]

[Vegetables$_1$,………………, Vegetables$_R$]

[Fruits$_I$,…………………… Fruits$_L$]

[Milk$_I$,…………………… Milk$_M$]}

/*where N,Q,R,L,M,G and F denote the number of food items grouped into Grains & Starches, Vegetables, Fruits and Milk respectively.*/

3. Input the portions of the eaten meal set

$\overline{P} \leftarrow$ {[Portion_Food$_1$,…., Portion_Food$_N$],

[Portion_Grains & Starches$_1$,……….

Portion_Grains & Starches$_Q$]

[Portion_Vegetables$_1$,…………Portion_Vegetables$_R$]

[Portion_Fruits$_1$,……Portion_Fruits$_L$]

[Portion_Milk$_1$,……Portion_Milk$_M$]

Output:

1. Healthy diet status set Set$_{HDS}$

2. Semantic analysis for the eaten food

Method :

Step1: If user's identification is passd then

Step1.1 : Retrieve the user's Age (Value$_{Age}$), Height(Value$_{Height}$), and Weight(Value$_{Weight}$) from the ontology repository to calculate the user's BMI by Value $\leftarrow$ Value$_{weight}$ / Value$_{Height^2}$

Step 2: Retrieve nutrition facts (calories per portion, the number of carbohydrate, protein, and fat grams contained in one portion) of eaten Grains & Starches, Vegetables,Fruits,Milk,Meats & Proteins, and Fats from the ontology repository.

$\overline{C} \leftarrow$ {[C_ Grains & Starches$_1$,................ C_ Grains & Starches$_Q$]
[C_Vegetables$_1$,...........................C_Vegetables$_R$]
[C_Fruits$_1$,…………………… C_Fruits$_L$]
[C_Milk$_1$,……………………. C_Milk$_M$]}

$\overline{G}$ Carbohydrate $\leftarrow$ {[G Carbohydrate_Grains & Starches$_1$,...... GCarbohydrate_Grains & Starches$_Q$]
[GCarbohydrate_Vegetables$_1$,............GCarbohydrate_ Vegetables$_R$]
[G Carbohydrate _Fruits$_1$,………G Carbohydrate_ Fruits$_L$]
[GCarbohydrate_Milk1,………GCarbohydrate_Milk$_M$]}

$\overline{G}$ protien $\leftarrow$ {[Gprotien_Grains&Starches$_1$,.............Gprotien_ Grains & Starches$_Q$]
[Gprotien_Vegetables$_1$,...............Gprotien_Vegetables$_R$]
[Gprotien _Fruits$_1$,……………G C protien _Fruits$_L$]
[Gprotien_Milk1,…………………Gprotien_ Milk$_M$]}

G Fat $\leftarrow$
{[GFat_Grains&Starches$_1$,............G Fat_Grains & Starches$_Q$]
[GFat_Vegetables1,.....................GFat_Vegetables$_R$]
[GFat_Fruits$_1$,……………………GFat_ Fruits$_L$]
[GFat_Milk$_1$,…………………… Fat _Milk$_M$]}

Step3: Calculate the total calories intake, the total calories from carbohydrate, protein, and fat, respectively, by

Step 3.1 $\overline{C}_{Actual} \leftarrow \Sigma \overline{C} \times \overline{P}$

Step 3.2 : $\overline{C}_{carbohydrate} \leftarrow (\Sigma \overline{G}_{carbohydrate} \times \overline{P}) \times 4$

Step 3.3 : $\overline{C}_{Protein} \leftarrow (\Sigma \overline{G}_{Protein} \times \overline{P}) \times 4$

Step 3.4 : $\overline{C}$ Fat $\leftarrow$ (Σ Fat x $\overline{P}$) x 9

Step4: Calculate values of PCC,PCP and PCF by

Step4.1: Value$_{PCC}$ $\leftarrow$(carbohydrate / $\overline{C}$ Actual) x 100%

Step4.2 Value$_{PCP}$$\leftarrow$($\overline{C}$ Protien / $\overline{C}$ Actual) x 100%

Step4.3 Value$_{PCF}$$\leftarrow$($\overline{C}$ Fat / $\overline{C}$ Actual) x 100%

Step5: Retrieve the planned calories needs ($\overline{C}$ Planned) from the ontology repository

Step 6: Calculate the value of CD by

$$\text{Value}_{CD} \leftarrow \left| \overline{C}_{Planned} - \overline{C}_{Actual} \right|$$

Step7:Retrieve the FML document (IDFRMA.xml) from the ontology repository

Step8: Based on the IDFRMA.xml, implement the fuzzy inference.

Let X $\leftarrow$ [Value$_{Age}$,Value$_{BMI}$, Value$_{PCC}$, Value$_{PCP}$, Value$_{PCF}$, Value$_{CD}$]

Step 8.1.1 : Calculate the matching degree of the Rule k by $\mu_k \leftarrow MIN(\mu_{Ain}(X))$

Step 8.1.2 : Calculate the center of area of theRule k by YAout_k $\leftarrow$COA(μ_k)

Step 8.2.1: Calculate the membership values of X to the fuzzy classes Y_t

By $y_t \leftarrow MAX(yA_{out}k)$ where Ft means the fuzzy class for all of fuzzy rules. Each fuzzy class is an aggregation of the fired rules that have the same consequences

Step 8.2.2 : Defuzzify into a crisp value by

$$HDS \leftarrow \sum_{t=1}^{T} w_t y_t \Big/ \sum_{t=1}^{T} w_t$$

Where wt means the weight for yt and T means the number of Fuzzy numbers of the output fuzzy variables, HDS

Step8.2.3 : Add HDS to Set$_{HDS}$

Step9 : Generate the semantic description based on the inferred results and sentence patterns.

Sentence Patterns:

Semantic Analysis Sentence:

The eaten items at food by this use exhibit that the person is at [FN$_{Age}$: Young,Middle,Old] age and the body mass index is [FN$_{BMI}$: UnderWeight, Normal, OverWeight], meanwhile Percentage of calories from carbohydrate is [FN$_{PCC}$:Low,Balanced,High], Percentage calories from protein is[FN$_{PCP}$: Low,Balanced,High], Percentage of calories from fat is [FN$_{PCF}$: Low,Balanced,High] and calories difference is [FN$_{PCF}$: Low,Balanced, High], and calories difference is [FN$_{CD}$: Acceptable, More or LessUnacceptable, UnAcceptable].

Semantic Decision Sentence:

The IDFRMA justifies that the possibility of healthy diet status for food is [FN$_{HDS}$: VeryUnHealthy,UnHealthy, MediumHealthy, Healthy, Very Healthy]. (Possibility:[0,1]).

ISSN 2229-5518

The IDFRMA platform was a built Active Server Pages (ASP).Net website using Microsoft C# programming language. This study focuses on people who are aged from 20 to 60 years old and with the average levels of physical activity Twenty students of A.V.V.M Sri Pushpam College (Autonomous) Poondi Thanjavur (AVVMSPC), Thanjavur were in volved in this experiment. They recorded their dinner meals from Monday to Friday for about one month. Therefore, 20 records were collected for each volunteer. Herein, we take one of volunteers, a 25-year-young man with 55 kilograms, and 170centimeters, as an example to describe the experiments. In

the first experiment, we test the performance of the IDFRMA according to the collected records of 20 dinner food. The No. 2 food, which displays that if the involved volunteer eats one portion of " rice with Sambar," one portion of "Banana with Milk," one portion of "Chocolate balls with peanut," and one portion of "Apple juice," then both the domain experts and the IDFRMA justify that the eaten meal is "VeryUnHealthy."

Table IV. Results of food Nos.2 and 19.

No	Semantic Descriptions of Healthy Diet Status for eaten items at Six group food					
	Age 25	BMI 18.16	PCC 42.31	PCP 6.41	PCF 28.12	CD 612.82
2	The eaten items at meal by this user exhibit that the person is at Middle age and the body mass index is Normal, meanwhile percentage of calories from carbohydrate is Balanced, percentage of calories from protein is Low, percentage of calories from fat is Balanced, and calories difference is UnAcceptable. The IDFRMA justifies that the possibility of healthy diet state for meal is VeryUnHealthy. (Possibility: 0.1)					
	The domain experts justifies that the meal is VeryUnHealthy					
	Age 25	BMI 18.16	PCC 55.69	PCP 8.00	PCF 17.13	CD 86.22
18	The eaten items at meal by this user exhibit that the person is at Middle age and the body mass index is Normal, meanwhile percentage of calories from carbohydrate is Balanced, percentage of calories from protein is Low, percentage of calories from fat is Balanced, and calories difference is Acceptable. The IDFRMA justifies that the possibility of healthy diet status for meal is VeryHealthy. (Possibility: 0.81)					
	The domain experts justifies that the meal is VeryHealthy.					

indicates that the involved volunteer had better try not to eat this kind of food as often as possible in order to keep healthy. On the other hand, the experimental result of meal No. 19 is that both the domain experts and the IDFRMA justify that this meal is "VeryHealthy." Therefore, it is helpful for the involved volunteer to eat meal No. 19. The detailed experimental results of meals Nos. 2 and 19 are listed in Table IV. The second experiment is to observe the variance in the possibility of healthy diet status evaluated by the domain experts and the IDFRMA. Fig. 8 shows the curves of possibility of healthy diet status expected by the domain experts and the IDFRMA, respectively. Additionally, Fig. 8 also shows the curves of difference between the domain experts and the IDFRMA. It reveals that the difference between the domain experts and the IDFRMA of meals No. 1-20 is below 0.25. The final experiment is to evaluate the accuracy, precision, and recall for the IDFRMA. Table V shows four different possible outcomes of a single prediction [8]. The accuracy, precision, and recall are calculated by (2), (3) and (4), respectively. Based on various threshold bounded in the interval of [0.05, 0.90], Fig. 9 shows the curves of accuracy

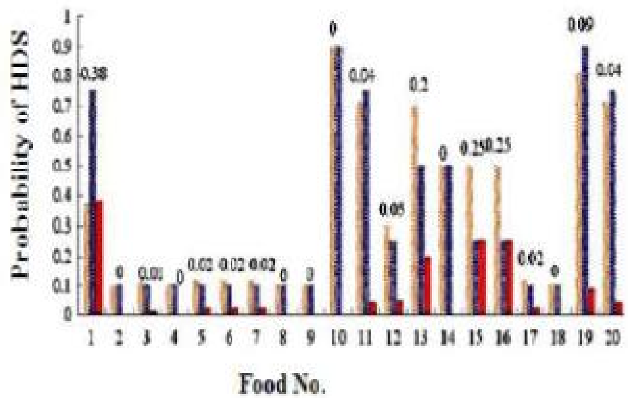

Fig. 8. Curves of the possibility of healthy diet status.

precision, and recall. Herein, the threshold denotes the membership degree threshold for HDS. It reveals that the accuracy is 90% when the threshold is from 0.55 to 0.70. It also indicates that the recall and precision are inversely related. As the recall increases, the precision decreases, and vice versa.

Table V. Classification of Results

Actual Class	Predicted Class	
	Yes	No
Yes	True Positive(TP)	False Negative(FN)
No	False Positive (FP)	True Negative(TN)

Accuracy = (TN+TP) / (TN+FN+FP+TP) x 100% (2)

Precision = TP / (TP+FP) x 100% (3)

Recall = TP / (TP+FN) x 100% (4)

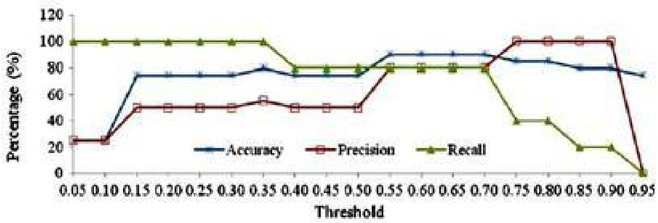

Fig. 9. Curves of the accuracy, precision, and recall

6 Conclusion

An intelligent multi-agent system, including a personal profile agent, a nutrition facts analysis agent, a knowledge analysis agent, a discovery agent, a fuzzy inference agent, and a semantic generation agent, is proposed in this study, which describes how fuzzy rules and fuzzy sets can be used to represent conceptual data based on physical characteristics of an individual and an opinion on the diet. Experimental results show that the proposed system enables an intelligent behavior able to generate the more suitable healthy diet for a given human being. Additionally, combined with the ontology, the proposed multi-agent system becomes much intelligent. With the support of the proposed agent, it not only can help a human eat healthily and keep his body in top shape but also cut down the workload of a medical domain expert. In the future, introducing the concept of type-2 fuzzy set to the follow-up researches, comparing the IDFRMA to other existing prior art are considered. In addition, the eating habit of the person, the time of day the person eats, whether the person eats in-between meals, life style of the person, and when the person consumes a high calorie meal will also be taken into considerations in the future. It is hoped that the performance will be get better than now.

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