International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Ontology-based Multi-Agent System on Fuzzy Markup Language in Healthy Lifestyle

Jayaprakash Sunkavalli[1], R. Hannah Lalitha[2], R. Reenadevi[3], M. Dhivya[4], K. Sreeramamurthy[5]

Submitted: 07/02/2024 **Revised**: 15/03/2024 **Accepted**: 21/03/2024

Abstract: The best ways to avoid illness are to lead a healthy lifestyle and eat a balanced diet. A healthy lifestyle is centered on good eating practices. A person's risk of illness will rise if they consistently consume too little or too much. Thus, the development of balanced and healthful eating habits is crucial to the prevention of disease. To record and depict the agents as well as their actions, which give them the capacity for reasoning, we also propose an ontology-based category knowledge and context framework. The procedure has been helped to accomplish that goal by the introduction of numerous strategies and technology. One technique that is gaining popularity to support knowledge exchange within organizations is ontology, which is a method of representing knowledge. This work offers an ontology-based multi-agent system (OMAS) for diet health evaluation that consists of a fuzzy inference agent, a semantic generation agent, and an individual information agent. The users are then asked to enter the foods they have consumed. Lastly, subject matter experts construct the ontologies for food and personal profiles. The OMAS's knowledge base and rule base are described using fuzzy markup language (FML). The primary output of basic research in healthcare informatics is the development of domain ontologies and problem-solving techniques. Consequently, our scientific community has to give these ideas more consideration.

Keywords: *Knowledge Management; Ontology; fuzzy markup language; eating habits*

1. Introduction

Reasoning activities requiring a great deal of domain knowledge are usually handled by knowledge-based systems. Large amounts of domain ideas arranged into a knowledge base must be processed for such systems to behave intelligently [1]. Within the knowledge-based systems field, there has been a focus on designing electronic databases and developing reasoning for them for the past thirty years. Employees have had to come up with innovative strategies for handling complexity and guaranteeing maintainability across lengthy system lifetimes. Significant advancements in computer science and software design are required due to the necessity for systems to store a large number of domain facts and reason about them to handle complex domain activities.

[1]Assistant Professor,
Department of Information Technology,
Velagapudi Ramakrishna Siddhartha Engineering College,
Vijayawada, Andhra Pradesh.
Email: prakashsunkavalli@gmail.com
[2]Assistant Professor, Department of EEE,
B.S Abdur Rahman Crescent Institute of Science and Technology, Chennai, Tamil Nadu.
Email: hannahlalitha@gmail.com
ORCID: 0000-0001-6969-1557
[3]Assistant Professor, Department of CSE,
Sona College of Technology, Salem.
Email: reenadevi@sonatech.ac.in
ORCID: 0000-0002-3827-5902
[4]Assistant Professor, Department of CSE,
Panimalar Engineering College, Chennai.
Email: dhivyachweetu@gmail.com
ORCID: 0000-0003-4200-2269
[5]Professor, Department of Computer Science Engineering, Koneru Lakshmaiah Education Foundation, Bowrampet, Hyderabad-500043, Telangana, India.
Email: sreeram1203@gmail.com

People today have access to a wide variety of foods, which increases their chance of illness if they don't practice proper eating habits. Thus, the development of an intelligent agent for designing a balanced diet is a topic of increasing importance for research. One important area of artificial intelligence research is agent technology [2]. Six characteristics comprise the performance of an intelligent agent: independence, consistency,

flexibility, goal orientation, learning capacity, and communication. Furthermore, the intelligent agent system finds application in other study fields. An intelligent multi-agent system for designing a healthy diet is shown in this work. Initially, the domain experts pre-define the food ontology using the model created by the Stanford Centre for Biomedical Informatics Research based on the nutrition information of the food that they have gathered from Taiwanese convenience stores and the Internet. Following that, an FML is used to simulate the required rule and knowledge bases for the fuzzy inference.

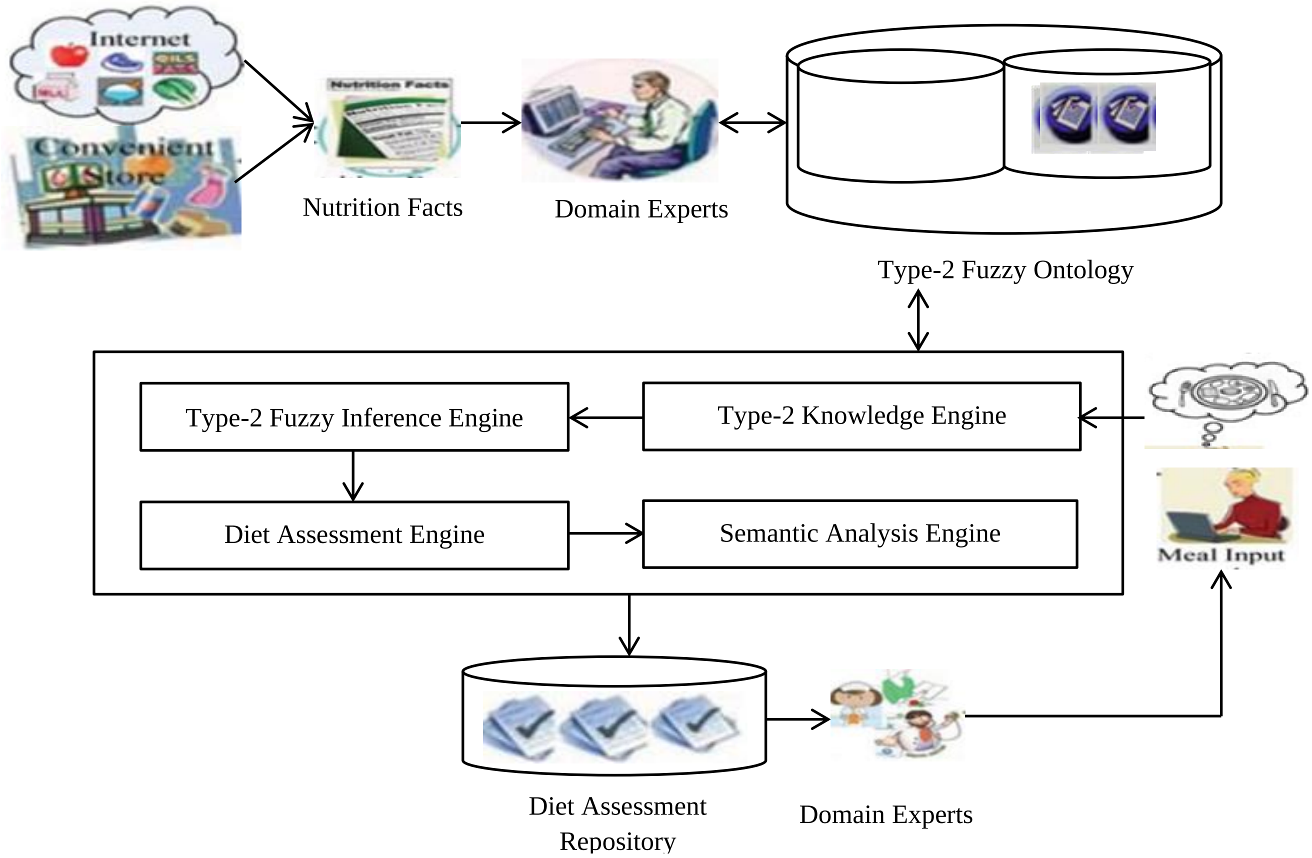

Fig. 1.1. The FML2-based diet assessment's structure

The framework of the FML2-base diet assessment is depicted in Figure 1.1, and the following describes how it works: (1) the nutrition facts of the food consumed by the general public are gathered from Taiwan's convenience stores and the Internet; (2) the domain experts construct a type-2 fuzzy food ontology based on the nutrition facts of the food gathered and the individual histories of the involved subjects; (3) the subjects record and input the daily meals consumed through the constructed platform; (4) the type-2 understanding engine analyses the daily food centred on the constructed type-2 fuzzy food ontology; Using the FML2-based ontology [3], which houses the information base and rule base of the FML2-based diet assessment agent, the type-2 fuzzy inference engine (5) infers the nutrition facts of the consumed meals to determine the level of diet assessment; (6) the diet assessment displays the diet evaluation findings based on the concluded results; (7) the semantic evaluation engine displays the conceptual sentences, stores them into the diet assessment repository, and forwards the results to the domain experts for confirmation.

Each agent performs various types of functions to identify the interpretation of the healthy diet status based on the food ontology, information base, and rule base. Ultimately, the findings of the nutritious food status are kept in the repository for the healthy diet condition.

The rest of this essay is organized as follows: The system architecture and diet ontology for the design of a healthy diet are covered in Section 2. The features of the proposed intelligent multi-agent system are introduced in Section 3. Section 5 provides the conclusions after Section 4 displays the experimental data.

2. Literature Review

Lee, C. S., et.al [4] People's lifestyle, religion, and culture all have a big impact on their nutrition. Every individual has unique eating habits, making diet behavior extremely individualized. Nowadays, owing to the prevalence of the web, it is easy to recover food-related information from the Website to expand the knowledge of the diet. In general, most people are aware of how crucial it is to eat healthily to have a high-quality life, but they may not always be certain that the foods they have consumed are nutritious. This is due to the diet's extreme complexity, high degree of uncertainty, and profound reliance on numerous outside variables. Furthermore, the dieticians claim that they are only able to provide an approximation of the nutrition data for each food, not a specific value. As a result, this research suggests a type-2 fuzzy ontology by combining the T2FSs with the ontology framework.

Chakraborty, S., et.al [5] The author of this paper discusses some key ideas in multi-agent systems and the associated research in this piece. In this instance, the author made the case that loosely linked networks of issue solvers can be described as a multi-agent system if the problem solvers cooperate to find solutions that go beyond their particular expertise or abilities. Here, the author aims to demonstrate the multi-agent systems architecture's effective general approach to problem-solving. One global feature of multi-agent systems was rationality, which was quantified by how well a global solution worked overall. However, a multi-agent system is deficient in global information, worldwide control, and global awareness.

Bukhari, A. C., et.al [6] Information engineering research is currently focused on two hot topics: intelligent decision-making based on retrieved information and personalized information extraction. These problems are made more difficult by the internet's growing heterogeneity. People currently use the search engines that are available to them to find information about particular topics. The majority of search engines still use keyword-matching algorithms as the foundation for their back-end searching systems. Because the search engines currently in use are unable to decipher the deeper significance of the data stored on their servers, users will have to undertake human labor to find the information they need. Over the past 20 years, scientists have been tackling this problem and have put out several strategies for precise information retrieval.

De Nicola, A., et.al [7] A formal, clear specification of a common understanding is called ontology. It is an abstract representation of a portion of reality made up of related ideas related to a certain application domain. This is a useful tool for managing the complexity of smart cities and the corresponding demand for interdisciplinary expertise. There are some pertinent steps towards achieving this goal in the form of ontology catalogs and initiatives to develop ontologies that target the smart city holistically, such as the Km4City ontology. Nonetheless, the notion of the smart city as a system of systems makes it difficult to develop a comprehensive and distinct ontology that can meet all of the demands of different applications and technologies.

Borri, D., et.al [8] Our research focuses on the creation and application of ontologies to foster a common understanding of the different facets of smart cities and lay the foundation for the creation of smart services, including technology for urban sustainability, as demonstrated by our findings. To do this, we used a bottom-up strategy to locate ontology and the smart city industries they cover. It is an abstract representation of a portion of reality made up of related ideas related to a certain application domain. This is a useful tool for managing the complexity of smart cities and the corresponding demand for interdisciplinary knowledge efforts to create ontologies that address the entire smart city, such as the Km4City ontology.

Pazienza, M. T., et.al [9] Many ontology-based and fuzzy ontology-based approaches have been put out recently to capture the semantic structure of the expertise held by experts. Ontology is described by Noy and McGuinness as a formal, explicit description of concepts in a discourse domain. It has also been demonstrated that ontology is a useful tool for finding and exchanging pertinent knowledge and information. For instance, Bukhari and Kim suggested a combined secure type-2 fuzzy ontology multivalent system to fully automate the tiresome procedure of purchasing airline tickets by hand.

Lee, C. S., et.al [10] When you have diabetes, your body is unable to properly use the food you eat as fuel. Diabetes treatment aims to maintain a glucose level as close to normal as feasible. Diabetes is primarily divided into two types: (1) Pancreas absenteeism: the absence of insulin production. (2) Type 2 type 2 diabetes: a biochemical condition in which the body either produces insufficient insulin or the cells refuse to use it. As the number of people with diabetes rises worldwide, more and more researchers from a variety of fields are working on this subject these days.

3. Methods and Materials

3.1 The Ontology Model

This paper proposes a domain ontology model for healthcare applications based on prior work and the levels of organization. The domain ontology approach consists of a concept set, a subcategory set, and a URL [10]. The ontology model's name is represented by the domain name. There are multiple categories in the category set, designated as "group1, group2, group3, and group4."

A concept name of cm and an attribute set for a set for the application domain are contained in each concept in the idea set. Furthermore, there is a connection between ideas that fall into the same category.

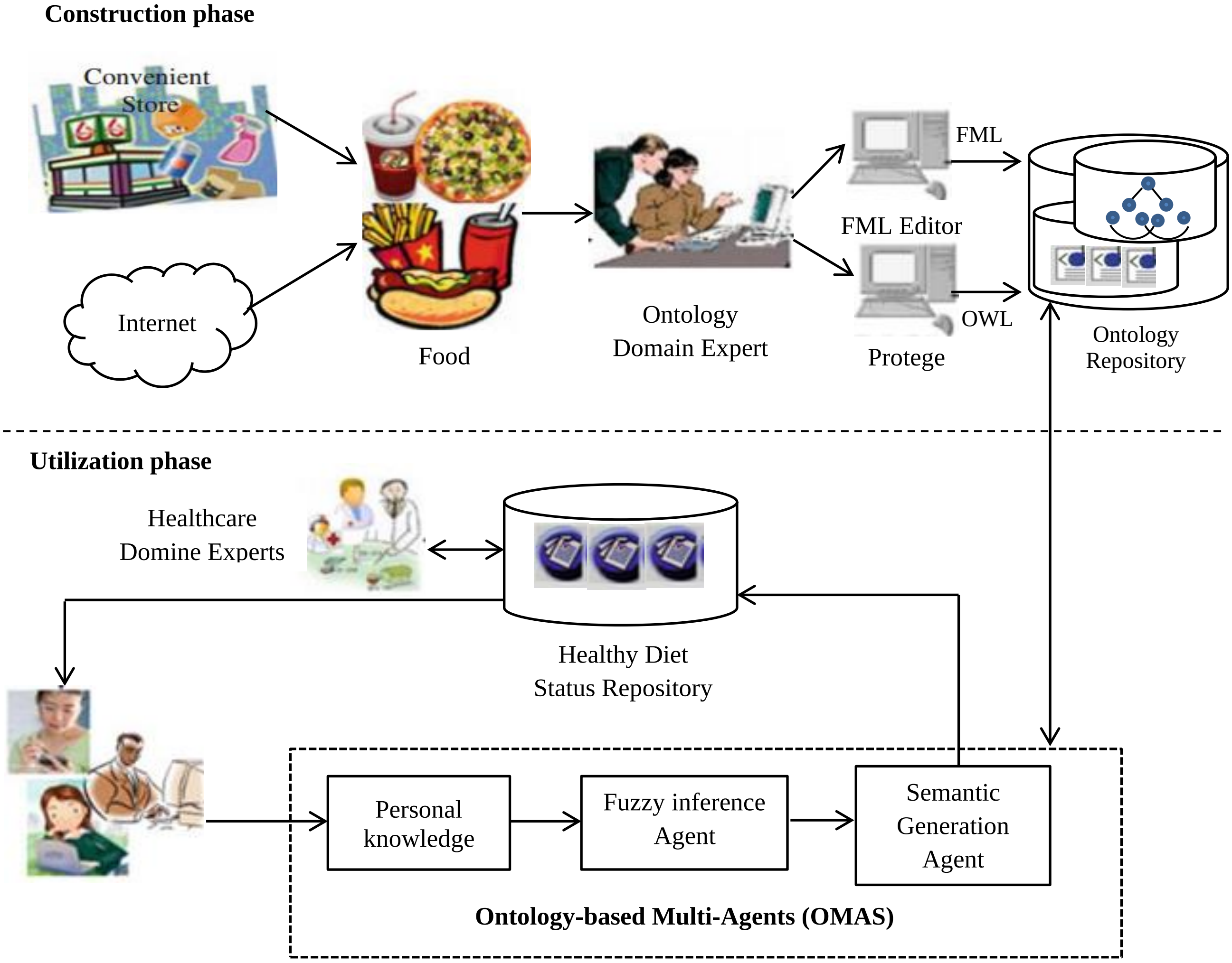

Fig. 3.1. Ontology-based Multi-Agents

For instance, because ideas C1 and C2 are related to group 2, there is a bidirectional arrow between them. We apply it to the food ontology, depicted in Figure 3.1, based on the domain ontology's architecture. This ontology is known by its domain name, "six food groups." The groups for grains and starches, vegetables, fruits, milk, meats and proteins, and fats are among the groups found in the classification layer.

Every food product has a nutrition facts label that lists product-specific details including serving dimensions, energy, and nutritional information. It also includes a footnote that lists the Daily Values (DVs) based on a diet of 2000 calories per day. The building of the food ontology in this study takes into account the gram of fat, protein, and carbohydrates per portion in addition to the number of calories per meal. As a result, product-specific information like "calories" and "nutrient information (carbohydrate, protein, and fat)" are contained in the nutrient facts sub-layer of the idea. For example, the dietary information for each portion of the "Fruit" is 32 kcal, with 8.31 g of carbohydrates, 0.42 g of protein, and 0.1 g of fat, correspondingly.

3.2 Individual Profile Ontology

People's eating habits and profiles differ. A person's gender, height, weight, and age are just a few examples of the variables that could be used in a personal profile. As a result, body mass index (BMI) must be the basis for an individual's daily calorie planning.

The main, side dishes, desserts, and drinks can all be included in a meal; interestingly, most people just know what they eat, not whether it's a healthy diet. Furthermore, nutritional data indicates the grams of protein, fat, and carbs per part of each meal, making it possible to determine the actual calories per serving [11]. The percentage of calories from fat (PCF), proportion of calories from carbohydrates (PCC), proportion of calories from protein (PCP), and proportion of calories from fat (PCF)—the difference between the number of calories people eat and the recommended daily intake of calories determined by nutritionists—are all obtained with the aid of nutritional data. The individual profile ontology is built using the information already mentioned.

3.3 Overview of Type-2 FML

The primary goal of FML, a new computer language built on XML technologies, is to create and execute FLC.35 In particular; it is used to simulate two well-known varieties of fuzzy controls: Mamdani and Takagi–Sugano–Kang (TSK). The main benefit supplied by FML processors is their understandability and openness. The fact that FML is built on XML, the primary technology for abstracting data, enables system designers to represent fuzzy controls in a hardware-independent and legible manner. As a result, by skipping extra development and design stages, the same fuzzy controller can be implemented on several hardware platforms because of FML. Transparent fuzzy controllers are a novel fuzzy control design concept that was created as a result of the use of FML.

The current release of FML only allows for the modeling of "type-1 fuzzy logic devices," or computers built using Zadeh's fuzzy sets as their fundamental concept.38 this is a notable limitation. Even while type-1 FLCs have been used extremely successfully in a wide range of uses, there are a lot of causes of uncertainty that they cannot directly address.22 these unknowns all correspond to uncertainties concerning fuzzy set MFs.32 Type-1 fuzzy sets are unable to capture such uncertainty since they rely on crisp, accurate MFs. Because of this, type-2 fuzzy systems—which make use of type-2 fuzzy sets—have been developed. Type-2 fuzzy logic controllers [12] are a new breed of fuzzy controllers that can handle high degrees of uncertainty, surpassing the constraints of type-1 FLCs and boosting efficiency for a wide range of purposes. Therefore, type-2 FML, a modification of FML that deals with type-2 fuzzy sets, was established to enable FML to transparently model also type-2 FLCs. Interval T2FSs are more common since the statistical analysis required for them is less complex than that required for broad type-2 fuzzy sets. Consequently, type-2 fuzzy structures based on interval type-2 fuzzy sets are described by FML2.

3.1.1. Applications of Fuzzy Markup Language in Healthcare

In contrast to other comparable techniques like the MathWorks' Fuzzy Control Language and MATLAB Fuzzy Inference System, FML offers further advantages in FLC programming because of its XML origination.

FML programmed are indeed programmed using a collection of connected semantic tags that can model various controller components by utilizing the abstraction benefits provided by XML instruments, in contrast to FCL or FIS code, which is entirely dependent on a textual depiction. From a development perspective, these advantages enable fuzzy designers to (1) write code on diverse hardware directly without knowing the specifics of platform programming; and (2) write code for fuzzy controllers without using general-purpose computer languages. In our case, FML enables us to quickly program diet agents and simultaneously test the inferred outcomes on several hardware platforms without requiring extra programming labor.

This subsection begins with a high-level overview of fuzzy systems, which are the most common use cases for fuzzy logic, before going into detail on FML. Fuzzy logic controllers, or FLCs, are used in both industrial and consumer products, including cement kilns and transport, as well as in appliances like dishwashers and CCTV cameras. Since Mamdani's initial FLC presentation and Zadeh's [13] invention of the term fuzzy reasoning, the scientific community has achieved significant strides in both the theoretical and practical realms of FLC. Essentially, a fuzzy control replaces a traditional controller, a proportional-integral-derivative (PID) administrator, with linguistic IF–THEN rules, allowing the designer to express the control in terms of phrases rather than equations. The introduction of linguistic variables marks a major paradigm shift in systems analysis: fuzzy IF-THEN rules in the form of if X is A then Y is B replace differential equations as the center of attention in dependency representations when employing the linguistic method.

3.4 Building a Profile for Nutrition and Health-Conscious Users and Recording Their Opinions

Our goal is to modify the user query linguistically and then personalize the answers in the area of food, dietary habits, and health. The user can express their choices through their profile. We examine and record the user's preferences below, and we then suggest a profile for the user that reflects these interests.

3.4.1. Keeping track of consumer preferences

Studying the factors that affect our food choices is necessary to understand why we prefer one food over another. We gather and examine responses to questions about diet and health to derive these characteristics. These qualities are divided into four groups, as indicated below.

The personal preferences section is the first one. Many people have specific culinary preferences but dislike other foods, often for unknown reasons. There are numerous instances of potential explanations for why some people love or avoid particular foods, including the food's flavor, appearance, color, and aroma, which might influence a person's decision to eat or not. But occasionally, our preferences for or dislikes of particular foods are the result of our habits; for example, we may have grown up without eating a particular meal and have since developed a disdain for it.

The health restrictions make up the second category. Certain foods are prohibited or limited in quantity due to the health condition, yet other foods are encouraged. Another scenario is asthma, where some people have sensitivity to or allergies to particular types of food that can have a major effect on their well-being. For instance, there are known relationships between certain diseases and certain foods and nutrition, whereby some foods can help prevent certain conditions while others can help treat people from specific illnesses.

Cultural preferences make up the third group. Each of our cultures is unique, and none of us share an identical culture [14]. When discussing culture, geography, language, and culture are all related. Our attention is drawn to particular facets of culture that are connected to dietary choices. Several cultural aspects include, for instance: (1) food acceptance and rejection in a given tradition; (2) food preference and rejection in a given tradition; (3) popular nutrition practices used by a given tradition; and (4) prevalent recipes used by a given society.

Religion-related restrictions make up the fourth group. It's critical to recognize the dietary constraints of certain religions in order to prevent receiving unsuitable dietary advice. It's critical to recognize the dietary constraints of certain religions to prevent receiving unsuitable dietary advice. It is not acceptable to suggest any cuisine containing pork or alcohol to Muslims, for instance, as these items is forbidden in the Islamic faith.

3.4.2. Developing User Profiles with a Focus on Health and Nutrition

What a user likes and doesn't like is reflected in their profile. It aids in comprehending the user's query's context more clearly. It's required to make the suggestions more unique. It can be shown in several ways, such as a keyword profile that gives each keyword a weight according to the user's preferences. Additional information about other approaches can be found. Since this work is connected to other sections of a larger project that are based on conceptual ontologies, we have chosen to represent the profile as ontology. This makes it simpler to connect it with the ontologies for the health and nutrition domains and facilitates the reasoning of the data using semantic dialects like SPARQL.

First, we use a form to gather the user description, which includes food preferences, health information, cultural background, and socioeconomic level. Then, by examining how the user interacted with the results, the profile was changed, which improved subsequent results. For example, if the user consistently chose a particular food from the results, the profile was updated to reflect the user's preference for that particular dish. We describe the user profile and apply the ontology notion to the search query.

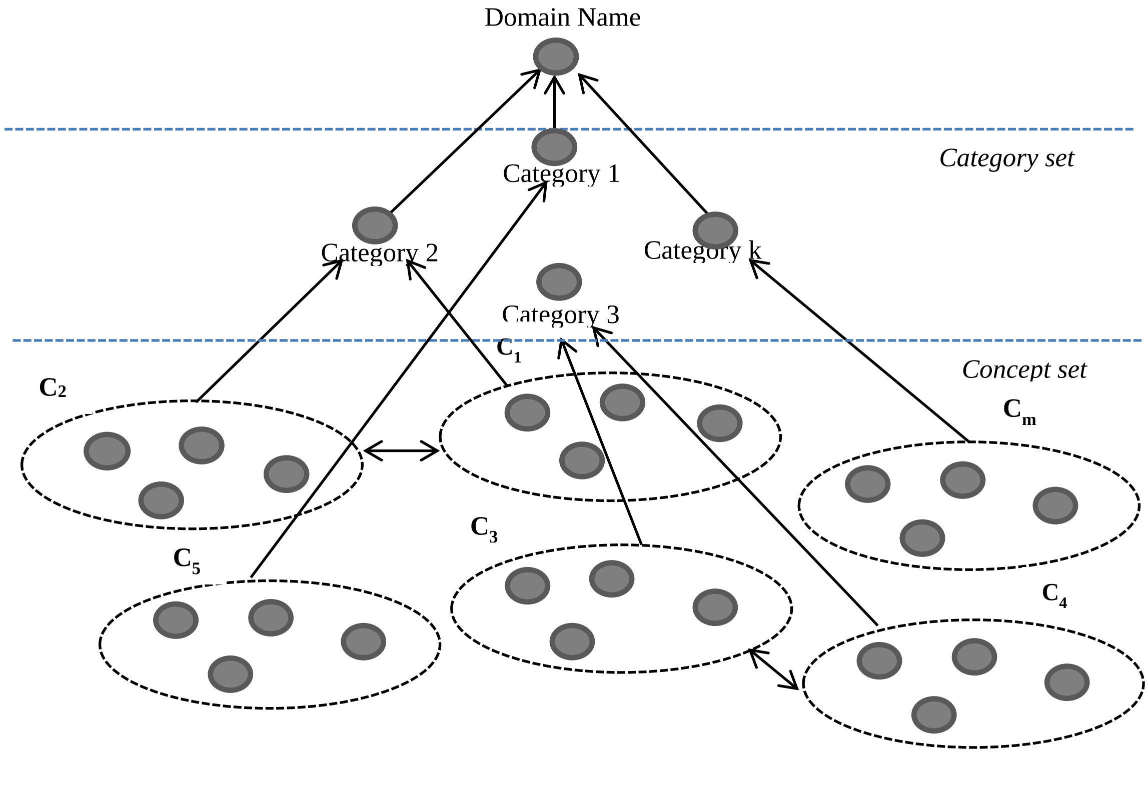

Fig. 3.2. Organization of the domain ontology

For instance, because concepts C1 and C2 are related to category 2, there is a unidirectional arrow between them. We apply the domain ontology's structure to the food ontology, depicted in Figure 3.2, utilizing its structure. This ontology is named "six food categories" on its domain name. Within the category layer are the following groups: grains and carbohydrates, vegetables, fruits, dairy products, meat and protein molecules, and lipids.

A footnote with the Daily Values (DVs) based on a 2000-calorie diet is included in the nutrition facts along with product-specific information such as serving size, calories, and nutritional information, corresponding to the nutrition facts label of every food item. The building of the food ontology in this study takes into account the grams of fat, protein, and carbohydrates per portion in addition to the number of calories per meal. As a result, specific product data like "calories" and "nutrient information (carbohydrates, amino acids, and oil)" are contained in the nutrient facts sub-layer of the idea. For example, the dietary information for each portion of the "Fruit" is 32 kcal, with 8.31 g of carbohydrates, 0.42 g of protein, and 0.1 g of fat, correspondingly.

4. Implementation and Experimental Results

4.1 Multi-agent ontology-based approaches for evaluating nutritious food

The ontology-based multi-agents for healthy diet assessment are introduced in this part. A brief description of the OMAS structure and its three agents—a fuzzy inference agent, an individual understanding agent, and an ontology generation agent—are given in part 4.1.

4.1.1. The ontology-based multi-agents design

I.Building Stage:

(1) Food nutrition data is obtained in Taiwan via handy stores and the Internet. There are two types of domain experts involved in the experiments presented in this paper: those who specialize in ontology and those who specialize in healthcare. Building ontology and establishing rules is under the purview of the ontology domain experts. The suggested approach's effectiveness is to be assessed by the specialists in the healthcare domain. (3) After that, the ontology domain specialists create the food ontology using the Portege application (4), which includes information on each food's nutritional value, including its calorie, nutritional content, and portion size. The personal profile ontology is also constructed by domain experts with brief user personal profiles that include information on age, gender, elevation, and nutrition. (5) The OMAS information repository and rule base are constructed by domain experts using the FML compiler.

II.Utilization Stage:

The following tasks are carried out by the OMAS. (1) Locate the individual user profile. (2) Gain the essential dietary knowledge by examining the nutritional information for the items consumed, figuring out the proportion of calories from vitamins and minerals, and determining the intended dietary objective. (3) Assume a healthy eating pattern. (4) Produce and provide to the user semantic statements. (5) The healthy diet condition repository houses the created semantic descriptors for the foods consumed. (6) The performance of the suggested method is assessed by the specialists in healthcare. (7) Lastly, giving people access to the output so they can adopt healthier habits.

The personal knowledge agent is involved in the extraction of personal profile information from the personal profile ontology, including gender, year of birth, elevation, and body weight. Using this data, the user's BMI and the anticipated daily calorie intake can be calculated by the individual's agent using the Harris-Benedict formula.

The food ontology is also used by personal knowledge agents to further investigate the grams of fat, protein, and carbohydrates for a single portion of the gathered meal data. It also obtains the number of calories in a single portion. The personal knowledge agent uses the calorie counts of the items ingested to convert the nutritional data into real calories, percentages of calories from protein, carbs, and fat. To compute the calorie difference between actual and intended caloric intake, the personal knowledge agent lastly collects the planned daily calorie consumption. The algorithm used by the personal knowledge agents is listed in Table 1.

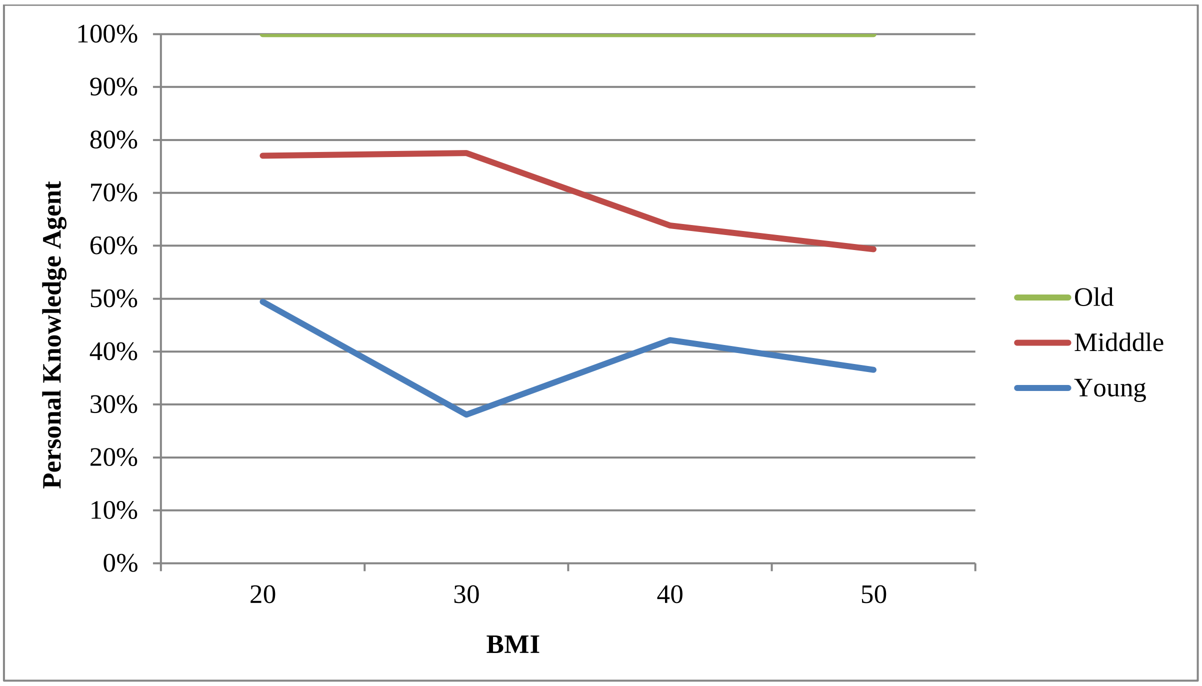

Fig. 4.1. Membership functions with trapezoidal shape for fuzzy parameters

Table 1. The Harris-Benedict Formula

Gender	BMR
Female	77+(15.8*weight)+(6*height) – (7.9*age)
Male	776+(6.8*weight)+(2.6*height) – (3.9*age)

4.2 Outcomes of an experiment

ASP.Net (Web Inference), Microsoft C# (OMAS), and Java (FML and Visual Editor) were used to create the OMAS framework. This study focuses on individuals with average levels of physical activity who are between the ages of 20 and 60. For around a month, the subjects documented their supper meals every Monday through Friday. Consequently, a total of 400 dietary records—20 for each subject—were gathered [15]. The subjects' personal information is listed in Table 2. In the experiments that follow and are displayed in this section, two different types of domain experts are involved: ontology domain specialists and medical domain experts. Together, the ontology domain experts and the medical domain experts developed the fuzzy rules and carried out the experimental assessments.

Table 2. Personal details of those concerned

No	Femininity	Stage	Tallness (Cm)	Heaviness (Kg)
1	Male	30	180	65
2	Female	29	170	72
3	Male	28	166	74
4	Female	27	155	86
5	Male	28	153	69
6	Female	29	171	76
7	Male	30	182	77
8	Female	29	142	78
9	Male	28	156	69
10	Female	29	163	70

The semantic generating agent obtains the inferred results produced by the fuzzy inference agent based on phrase patterns and then uses semantic descriptions to turn these inferred results into information to offer a healthy dietary condition. The formulas (2), (3), and (4), respectively, compute the accuracy, precision, and recall. Figure 4.1 displays the accuracy curves based on several thresholds limited in the interval [0.06, 0.80].

The algorithm for the semantic generating agent is displayed in Table 2. For instance, the OMAS indicates that, when a 25-year-old woman consumes two portions of strawberries chocolate and one portion of Coca-Cola, the level of an appropriate dietary state for such a meal is very detrimental when the person is young and underweight, the percentage of energy from fat, protein, and carbohydrates is low, and the caloric variance is inappropriate.

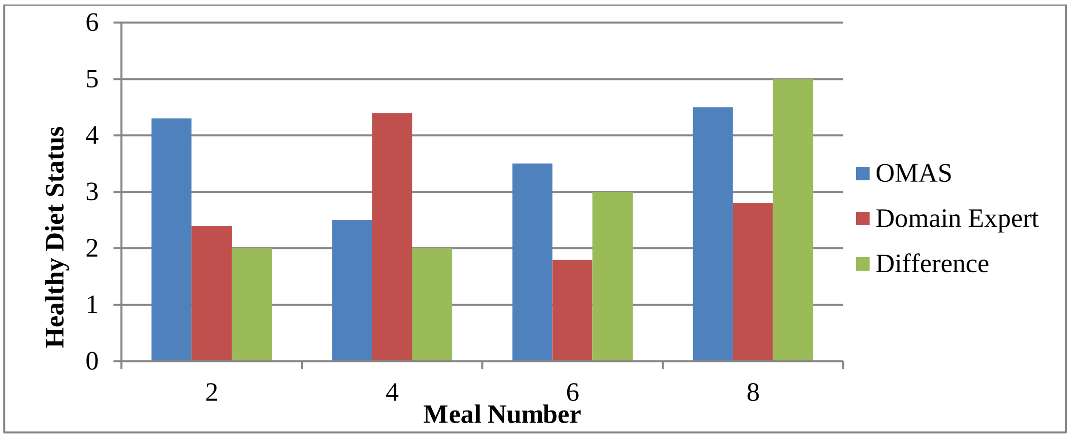

Fig. 4.2. Charts indicating the state of eating nutritious food

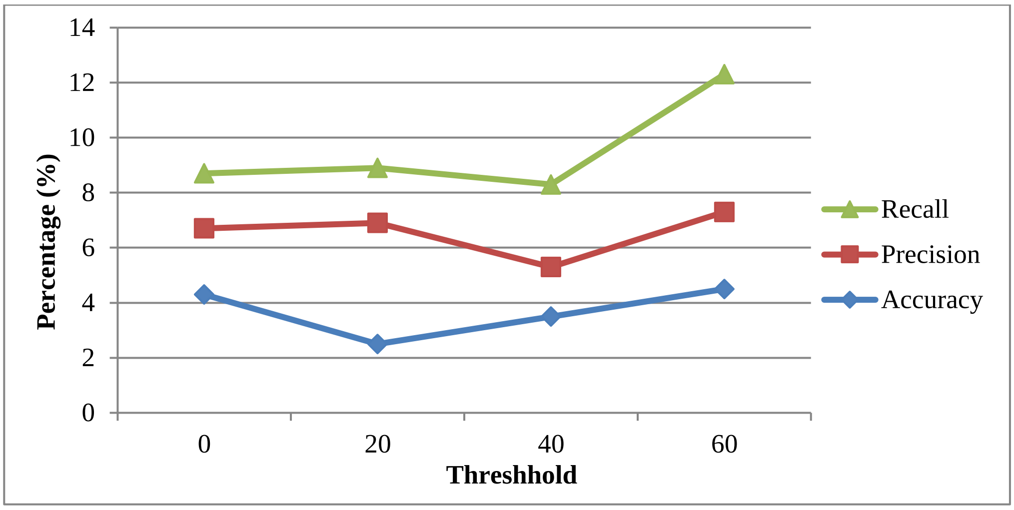

Fig. 4.3. Curves representing recall, precision, and accuracy

$$Accuracy = \frac{TP+TN}{FN+TN+TP+FP} * 200\% \qquad (1)$$

$$Recall = \frac{(FP+TP)}{FP} * 200\% \qquad (2)$$

$$Precision = \frac{(FN+TP)}{FN} \qquad (3)$$

The OMAS's performance

The mean square error (MSE), which is determined by Equation 4 [16], is assessed in the subsequent comparison between the field's expert's and the OMAS's results. Figure 4.2 displays the probability curves for a healthy diet status that the domain experts anticipate; all MSEs are less than 0.6.

$$MSE = \frac{2}{m}\sum_{j=2}^{m} f_j^3 \qquad (4)$$

Where M the disparity in the outcome between the OMAS and domain expert is denoted by FP, and n is the total participants.

5. Conclusion

This research proposes an intelligent multi-agent system that consists of a personal profile agent, nutritional information analysis agent, knowledge analysis agent, discovering agent, fuzzy inference agent, and semantic subsequent generation's agent. It explains how fuzzy rules and fuzzy lists can be employed to convey conceptual data based on an individual's physical characteristics and diet opinion. The outcomes of the experiments indicate that the suggested approach facilitates intelligent behavior capable of producing a healthier diet that is better appropriate for a particular individual. Furthermore, the suggested multi-agent system becomes significantly more intelligent when integrated with the ontology. With the use of the suggested agent, a person can reduce their burden as a medical domain specialist while simultaneously maintaining a healthy diet and physical fitness.

A fuzzy inference person, an understanding generation agent, and an individual knowledge agent make up the three sub-agents of the proposed OMAS. According to experimental findings, the suggested system allows users to behave intelligently to choose a healthy diet that is appropriate for them based on a constructed ontology. In addition to lightening the duty of medical professionals, the suggested agent helps people maintain a healthy diet and physical fitness. Furthermore, nutritionists believe that determining the food group balance is crucial in determining the overall healthfulness of the food consumed. Thus, one of the upcoming research projects will be to incorporate the food category balance into the suggested OMSA. Further thoughts will be given to the idea of a type-2 fuzzy collection and an instructional system for subsequent studies.

References

[1] Musen, M. A. (1998). Modern architectures for intelligent systems: reusable ontologies and problem-solving methods. In *Proceedings of the AMIA Symposium* (p. 46). American Medical Informatics Association.

[2] Wang, M. H., Lee, C. S., Hsieh, K. L., Hsu, C. Y., & Chang, C. C. (2009, August). Intelligent ontological multi-agent for healthy diet planning. In *2009 IEEE International Conference on Fuzzy Systems* (pp. 751-756). IEEE.

[3] Lee, C. S., Wang, M. H., Acampora, G., Hsu, C. Y., & Hagras, H. (2010). Diet assessment based on type-2 fuzzy ontology and fuzzy markup language. *International Journal of Intelligent Systems*, *25*(12), 1187-1216.

[4] Lee, C. S., Wang, M. H., Acampora, G., Hsu, C. Y., & Hagras, H. (2010). Diet assessment based on type-2 fuzzy ontology and fuzzy markup language. *International Journal of Intelligent Systems*, *25*(12), 1187-1216.

[5] Chakraborty, S., & Gupta, S. (2014). Medical application using multi agent system-a literature survey. *International Journal of Engineering Research and Applications*, *4*(2), 528-546.

[6] Bukhari, A. C., & Kim, Y. G. (2012). Integration of a secure type-2 fuzzy ontology with a multi-agent platform: a proposal to automate the personalized flight ticket booking domain. *Information Sciences*, *198*, 24-47.

[7] De Nicola, A., & Villani, M. L. (2021). Smart city ontologies and their applications: a systematic literature review. *Sustainability*, *13*(10), 5578.

[8] Borri, D., Camarda, D., Grassini, L., & Patano, M. (2014). Learning and Sharing Technology in Informal Contexts. A Multiagent-Based Ontological Approach. *TeMA-Journal of Land Use, Mobility and Environment*.

[9] Pazienza, M. T., Sguera, S., & Stellato, A. (2007). Let's talk about our “being”: A linguistic-based ontology framework for coordinating agents. *Applied Ontology*, *2*(3-4), 305-332.

[10] Lee, C. S., Wang, M. H., Acampora, G., Loia, V., & Hsu, C. Y. (2009, March). Ontology-based intelligent fuzzy agent for diabetes application. In *2009 IEEE Symposium on Intelligent Agents* (pp. 16-22). IEEE.

[11] Lee, C. S., Wang, M. H., Hagras, H., Chen, Z. W., Lan, S. T., Hsu, C. Y., ... & Cheng, H. H. (2012). A novel genetic fuzzy markup language and its application to healthy diet assessment. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, *20*(supp02), 247-278.

[12] Prakash, K., & Sivakumar, R. (2013). Ontology-based intelligent multi-agent for diet food recommendation. *International Journal of Scientific & Engineering Research*, *4*(1), 1-8.

[13] Wang, M. H., Lee, C. S., Hsieh, K. L., Hsu, C. Y., Acampora, G., & Chang, C. C. (2010). Ontology-based multi-agents for intelligent healthcare applications. *Journal of Ambient Intelligence and Humanized Computing*, *1*, 111-131.

[14] Al-Nazer, A., Helmy, T., & Al-Mulhem, M. (2014). User's profile ontology-based semantic framework for personalized food and nutrition recommendation. *Procedia Computer Science*, *32*, 101-108.

[15] Nagy, M., & Vargas-Vera, M. (2010). Towards an automatic semantic data integration: Multi-agent framework approach. *Semantic web*, 107-134.

[16] R. Vidhya, T. Padmapriya, S. Selvakumar, R. Mary Victoria, & M. Anand. (2023). Multidimensional Parity Algorithms to Escalate the Security of Intelligent Mobile Models in Education. *International Journal of Interactive Mobile Technologies (iJIM)*, *17*(04), pp. 4–20. https://doi.org/10.3991/ijim.v17i04.37769