Investigative Report on Ontology: Healthy Recipe Recommender

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Abstract- **The healthy recipe recommender ontology is planned to improve tailored nutrition advice by establishing knowledge about recipes, ingredients, nutrients, dietary restrictions and cooking methods into an organized framework. It is known that an unhealthy diet, intermittent life and work density can result in several health problems where diabetes, ulcers and gastro-enteritis are eternally around. In order to lessen the impact, it is essential that we follow recommendations for healthy eating. This report primarily aims to offer an ontology-based healthy recipe recommender that can accurately inform the user about nutrition. An accurate and nutritious recipe based on the user's input preference is suggested by the inference engine. We looked at the ontology consistency and scalability issues, among others, and proposed a number of improvements for the future, including integration with other systems. The focus of this design is on the impact of ontologies on healthy recipe recommendation and related fields, such as nutrition and health.**

Keywords- Ontology, Protégé, Inference, Semantic Reasoning, (DL) Queries, Healthy Recipe Recommender, Knowledge-based Systems.

I. INTRODUCTION/PROBLEM DESCRIPTION

The primary objective of a healthy recipe is to get a balanced diet in everyday life and reduce the likelihood of adverse health issues. One of the most important ways to encourage people to eat healthily is to provide them with recipes that they may like. Recommendations for healthy recipes have become an essential part of the argument for encouraging people to eat better [1]. It could be difficult to come up with nutritious meal suggestions and ingredients due to the large number of food products that need to be gathered, linked, and reasoned about [1]. The food we eat affects many other parts of our lives, including our ethnicity, socioeconomic status and long-term preferences; these factors, in turn, affect our chances of leading a healthy life. A balanced diet must include vitamins, minerals, protein, fat, water and carbs [2, 3]. Here, we provide an ontology for the food domain, along with a nutritious cuisine that satisfies dietary restrictions such being vegan, gluten-free, low in sodium and suitable for diabetics. By using semantic technologies, the project was able to formalise the definition of concepts like food ingredients, recipes, nutrients, cooking style, and dietary restriction in this specific area. To determine users' health state and provide dietary suggestions appropriately, reasoning methods were used. Together, these elements form a knowledge-based recommender system that ensures recipes are nutritious. In a nutshell this study makes the following primary contributions: We provide the Ontology of Healthy Recipe Recommendations (OHRR), a conceptual model that can be shared and includes maximum relevant mechanisms in the field of food recommendations, such as recipes, ingredients, nutrients, dietary restrictions and cuisine types. A knowledge base built upon the OHRR ontology was used to facilitate the recommendation process. The knowledge base was supplied with data on recipes and ingredients sourced from scholarly articles and other references. Recipes are extracted from two recipe sources website [16, 17]. These websites provide the specified recipe.

II. ASSOCIATED WORK

According to prior research, people seek out explanations and proof for any questions they may have about healthy recipes, nutrition, and food [4, 5, 6, 7, 8]. On the flip side, those statements are backed by testimony and reasoning that users become more involved with. Skills in logic, reasoning, and querying connected to food and recipe arts have been acquired through resources like RecipeDB's correlated information and food categorisation [10] and the fact that different sources of information have not been combined [11, 12]. We differ from these studies because we use more explicit and semantic information about recipes, foods, and related semantically annotated data to suggest healthy products or recipes and answer specific questions about dietary restrictions. Some ontologies [14] and conceptual frameworks [13] have attempted to portray explanations from the user's point of view. We intend to ground these more general efforts in the realm of food.

III. METHADOLOGY AND IMPLEMENTATION

A. Ontology Conceptualization

Given the vast amount of food items that must be compiled, connected, and considered, it may be challenging to develop nutrient-dense meal ideas and components [1]. Class, property, relation, individual, rule, and axiom categories are common in ontologies. A class can be defined conceptually. Attributes are the characteristics that an object in a class have. Relationships between individuals may be described by certain characteristics. Individuals or classes are connected to one another via relations. The fundamental objects are instances, which are connected to classes by properties. If-then statements are used in rules to explain logical thinking. Certain logical claims are known as axioms.
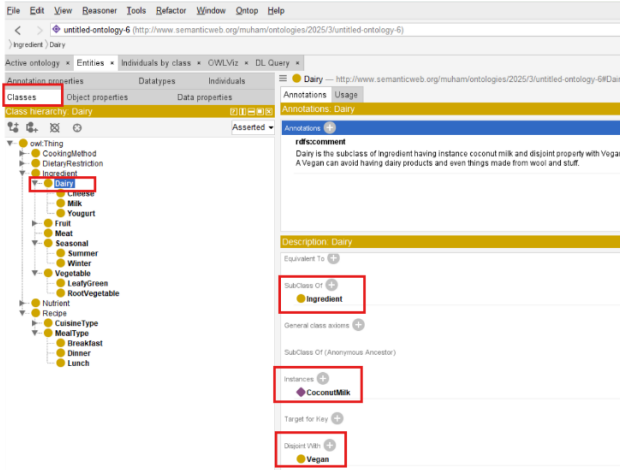
Figure 1: An Example Ontology structure

Figure 1 highlights classes and subclasses, with Dairy being the subclass of Ingredients used in recipe preparation. Now, the dairy product in question is coconut milk which is an individual. In addition, there is a disjoint property for the recipe, thus vegans should rigorously avoid the diary ingredients. Herein lies the role of the ontology's conceptualisation. In Table 1, the classes and subclasses are described.

TABLE I.   CLASSES AND SUBCLASSES

#	Class	Subclass	Subclass
	Healthy Recipe Recommender Ontology		
1	Recipe	Cuisine Type	Indian Italian Mediterranean
		Meal Type	Breakfast Dinner Lunch
2	Ingredient	Dairy	Cheese Milk Yogurt
		Fruit	Berry Citrus
		Meat	None
		Seasonal	Summer Winter
		Vegetable	Leafy Green Root Vegetable
3	Cooking Method	Baked Fried Grilled	None
4	Nutrient	Carbs Fiber Low Fat Protein	None
5	Dietary Restriction	Diabetic Friendly Gluten Free Low Sodium Vegan	None

The hierarchical explanation of the root concepts/classes and their subclasses is provided in Table 1. Recipes are categorised by Cuisine Type and Meal Type in the Recipe class. Subclasses of Cuisine Type include Indian, Italian, and Mediterranean, while subclasses of Meal Type include Breakfast, Dinner, and Lunch. In addition to having a preference based on time, a recipe must reflect the kind of cuisine based on taste, such as breakfast, lunch, or dinner. The implementation in protégé is shown in Fig. 1(a).
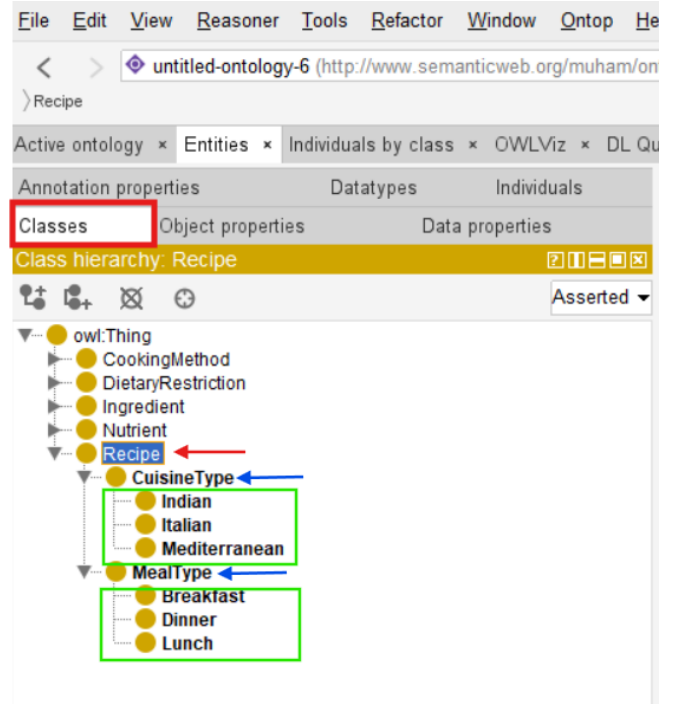

Fig. 1(a): Recipe and its subclasses

The ingredients are divided into five categories: dairy, fruit, meat, vegetables and seasonal. Cheese, milk, and yogurt are subclasses of dairy products. Citrus and berry are subclasses of fruit. Although there is currently no category for meat, one might be developed for chicken, beef, and shellfish. Summer and Winter are the two subclasses of the seasonal idea. Additionally, there are two subcategories of vegetables: root vegetables and leafy green vegetables. By choosing the right subclass, an ingredient must represent the kind of ingredient it is. For example, what items are needed to make avocado toast if a customer desired the recipe? Fig. 1(b) illustrates the implementation in protégé.
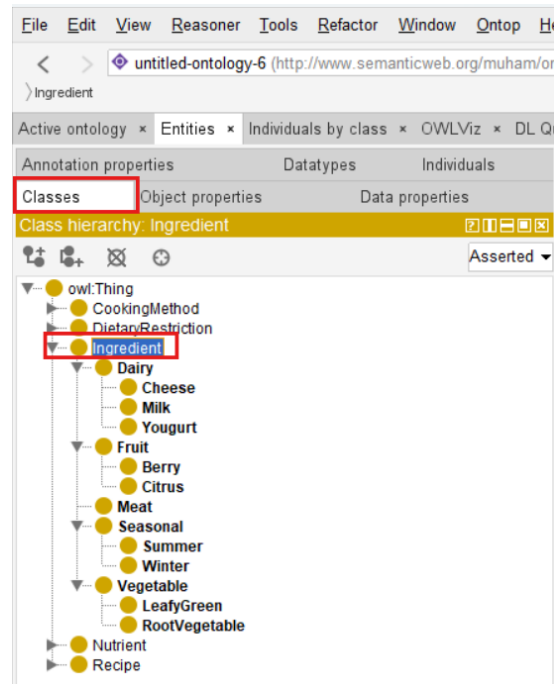

Fig. 1(b): Ingredient and subclasses

Since the rationale is based on recommendations for healthy recipes, a recipe may contain dietary restrictions. Thus, the subclasses of dietary restriction are vegan, low-sodium, gluten-free, and diabetic-friendly. A recipe may be tailored for a group of users based on these associations, such as those who are vegan or diabetic. Based on dietary restrictions, a knowledge system must deduce that a vegan can never consume the recipe's animal ingredients. The implementation in protégé is shown in Fig. 1(c).
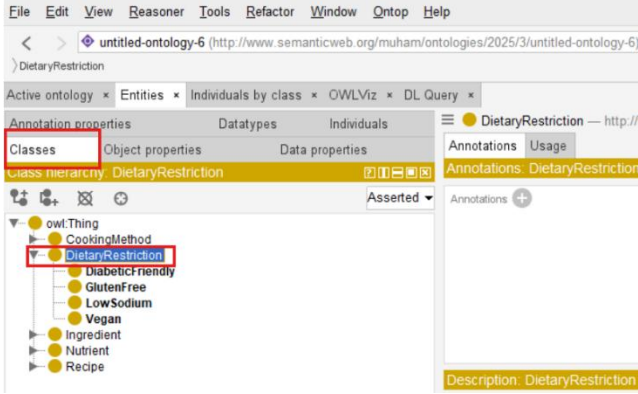

Fig. 1(c): Dietary Restriction and Subclasses

Nutrients are very significant for a balanced and healthy recipe. The amount and scale is has immense impact on overall ingredients of the recipe. Carbs, Fiber, Low Fat and Protein are the subclasses of Nutrient where the amount of each and every nutrient is mandatory per serving of the recipe. For example, citrus is a high source of vitamin C and if user's choice is based on meat then they can have the chicken and egg which are high in protein. Therefore, while inference engine will evaluate the amount of your nutrients based on users requirements. The implementation in protégé is shown in Fig. 1(d).
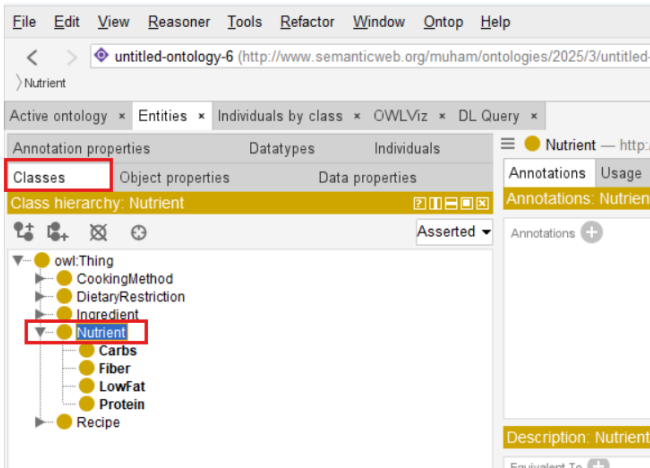

Fig. 1(d): Nutrient and Subclasses

Cooking method is necessary while making a recipe, so the subclasses of the Cooking method concept are Baked, Fried and Grilled. It is therefore highly recommended that the required cooking method and style is relevant to the healthiness of any recipe. There could be a difference if a salmon fish is grilled or it is being fried using oil. Cooking at higher temperatures and longer durations results in more lipid oxidation, thereby reducing lipid content; this effect is proportional to the product of these two variables [18]. Fig. 1(e). shown the implementation using protégé.
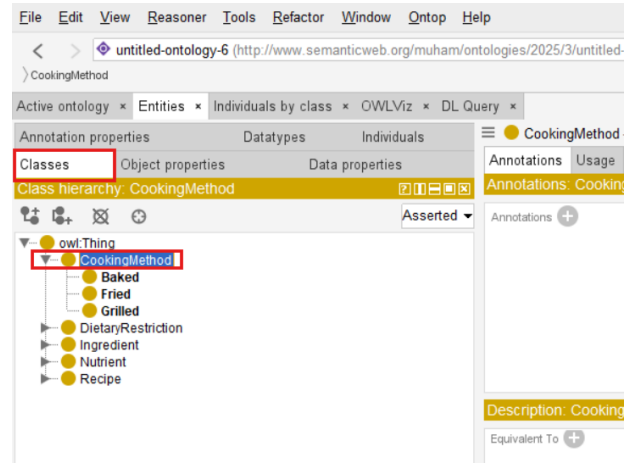

Fig. 1(e): Cooking Method class and Subclasses

B. Relations/Properties) and Relation Heirarchies

Things and relationships have qualities, which are known as properties. Object properties indicate the relationship between instances, data properties indicate the relationship between instances and data values which must have some datatypes and annotation properties provide metadata and comments. One or more properties may have the following attributes: functional, transitive, symmetric, disjoint or equivalent. Due to dietary restrictions in both recipes and ingredients, a vegan_diet1 is an instance of the Vegan concept with a characteristic that is not associated with the Meat class. Inference now leads one to conclude that a vegan is unable to use meat as an ingredient in any recipe. There is a clear provision for the linkages in Fig. 2.
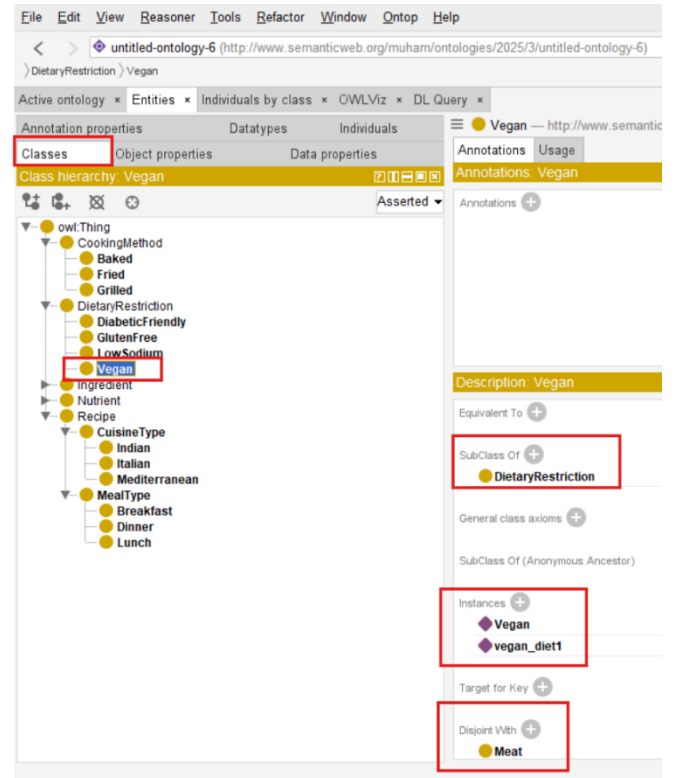

Fig. 2: Properties, instances and heirarchy

Instances: Ingredient classes may also have several instances, as seen in another example. The implementation in protégé is shown in Figure 2(a).
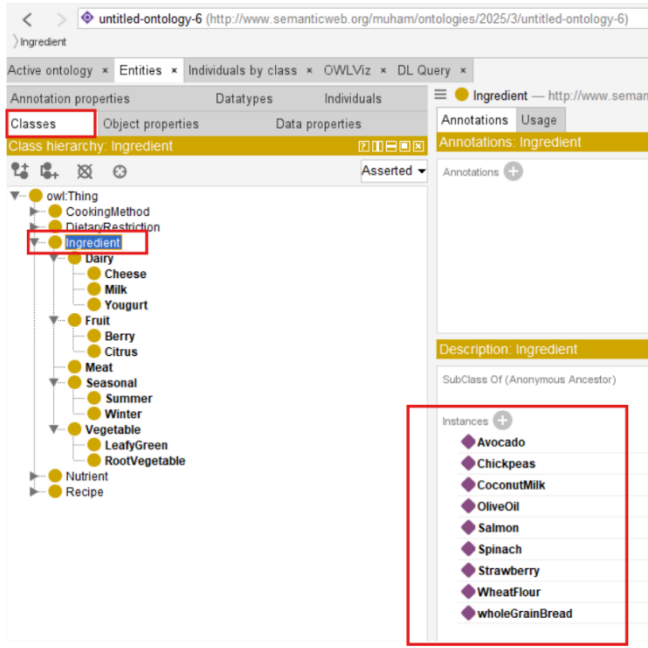

Fig. 2(a): Provision of Instances

Object Properties: In addition to Domain and Range, object attributes also define the connection between the two. Figure 2(b) shows an example of a relationship between Ingredient (Domain) and the Recipe (Range) using the isIngredientOf relation. As an example, we need to whip up a batch of Avocado Toast, which calls for avocados as an ingredient. Then, in this scenario, we may use relations to determine that avocados are an ingredient in avocado toast. To use an inference engine, we first need to assert some facts, and then, using our existing body of knowledge, the engine will take care of the rest. In addition to the hasIngredient connection, there is an inverse property. Now we can state that avocado is necessary to produce avocado toast by using the isIngredientOf connection, and we can also say that avocado toast needs the component avocado by utilising the hasIngredient relation.
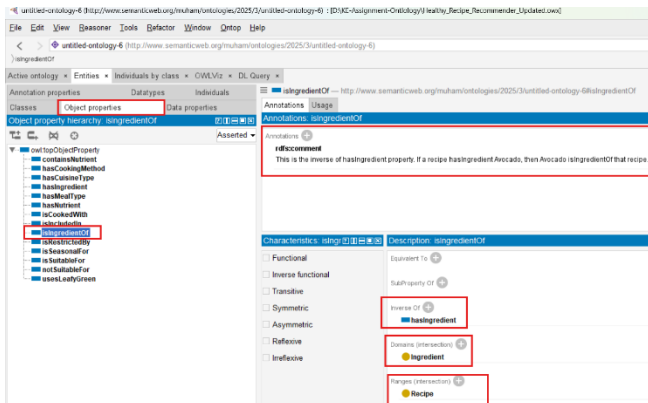

Fig. 2(b): Provision of Instances

Data Properties: Instead of associating objects with other objects, data attributes connect instances to literal values such as strings, numbers, bools, datetime, doubles, floats, and integers. They stand for the quantifiable or descriptive properties of the materials and recipes. Figure 2(c), illustrates

the data attributes of a domain type recipe and a range as xsd:decimal. It includes the data property hasCost, which is understood as providing a price or cost in the appropriate currency which will be a decimal value.
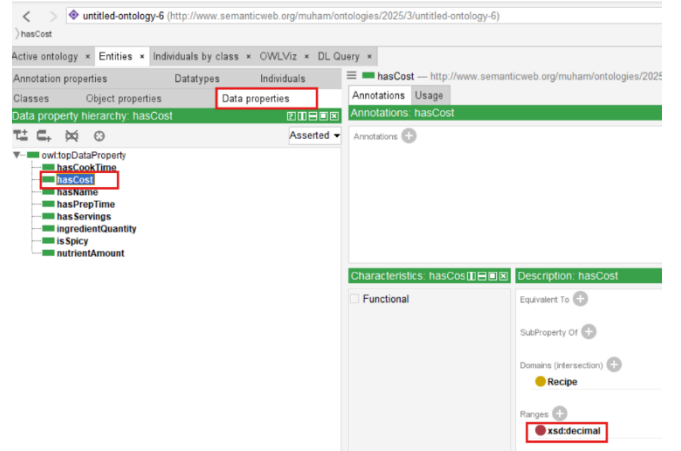
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Fig. 2(c): Data properties of range as xsd:decimal.

Individuals: An instance or individual represents specific, concrete examples of the defined classes. Individuals would include actual recipes, ingredients and dietary restrictions profiles. Fig. 2(d) describes the recipe itself, Avocado Toast (Individual), the type of recipe (Class/Concept), the object property assertions (hasCookingMethod: Baked, hasCuisineType: Mediterranean, hasIngredient: Avocado, hasMealType: Breakfast), and the data property assertions (hasCookingTime: 5 minutes, hasName: Avocado Toast, isSpicy: False).
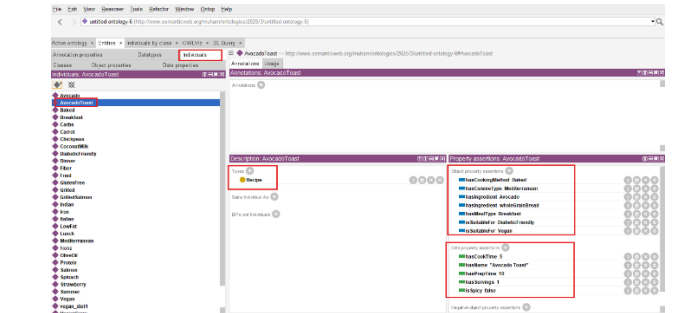

Fig. 2(d): Individuals, data properties and object properties assertions

IV. VALUATION AND DL QUERIES

The capacity to extract inferred knowledge (using reasoning) and answer meaningful enquiries using DL enquiries. A reasoner, HermiT, verifies the coherence of reasoning and deduces further facts. Some of following DL Queries are discussed below:

1. List ingredient(s) which are having a dietary restriction, gluten free.

DL Query: Ingredient and isRestrictedBy value GlutenFree.

Query is implemented and result is shown by the inference engine, see Fig. 3(a).
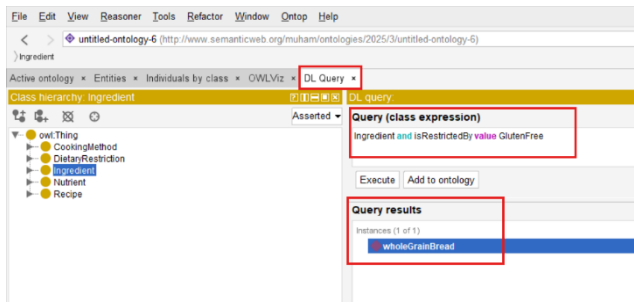
Fig. 3(a): DL Query 1

2. List Recipe(s) which has been made with cooking method, grilled.

DL Query: Recipe and hasCookingMethod value Grilled. Query is implemented and result is shown by the inference engine, see Fig. 3(b).
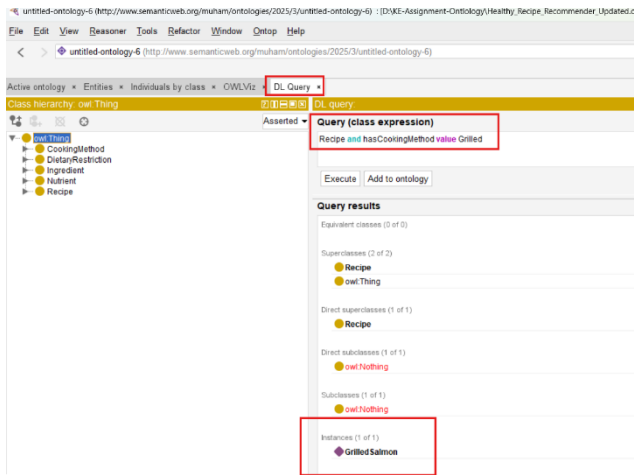

Fig. 3(b): DL Query 2

3. List Recip(s) which is suitable for diabetic patients.

DL Query: Recipe and isSuitableFor value DiabeticFriendly. Query is implemented and result is shown by the inference engine, see Fig. 3(c).
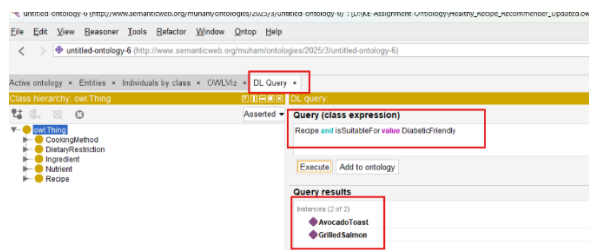

Fig. 3(c): DL Query 3

4. Show me recipe(s) and has nutrient in ingredients and that must be proteinaceous.

DL Query: Recipe and (hasIngredient some (hasNutrient value Protein)). Query is implemented and result is shown by inference engine, see Fig. 3(d).
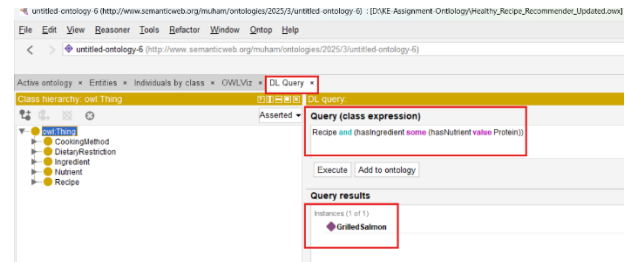

Fig. 3(d): DL Query 4

5. Filtering Recipes by Fried Cooking Method and Spinach Ingredient.

DL Query: Recipe and (hasCookingMethod value Fried) and (hasIngredient value Spinach). Query is implemented and result is shown by the inference engine, see Fig. 3(e).
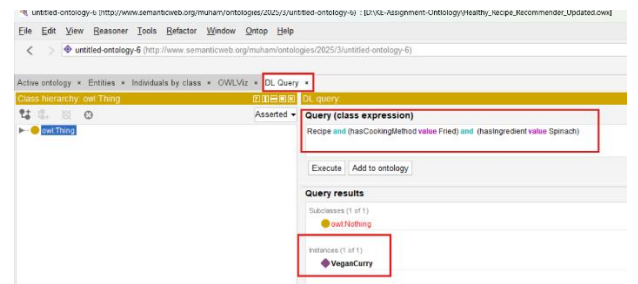

Fig. 3(e): DL Query 5

Abbreviations and Acronyms

OHRR (Ontology of Healthy Recipe Recommender), FOL (First Order Logic) and DL (Description Logic).

V. CONCLUSIONS

In this research, we have examined the design of an ontology-based healthy recipe recommendation system (OHRR). The system can analyse the user's dietary record, preferences, and personal circumstances to determine whether the user has a balanced diet. It can then offer recipes that are suited for the user's diet. Furthermore, the personal recipe ontologies will be constructed by extending the ontology architecture to include user dietary preferences. Users' privacy about their own recipes should be proactively protected by the healthy recipe recommender. For the sake of future generations' health, I want to piece together solutions that transcend gender and cultural boundaries.

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APPENDIX

Down below, please find the Ontology Healthy Recipe Recommender's object file.

Healthy_Recipe_Reco
mmender_Updated.ow