Ontology-Based Low Glycemic Index Menu Recommender System for Patients with Diabetes

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***Abstract*—Diabetes is a growing chronic health issue driven by lifestyle changes, urbanization, and poor dietary habits. Managing diabetes requires not only medical intervention but also significant lifestyle adjustments, particularly through a healthy and balanced diet. However, existing menu recommender systems often fail to consider the importance of a low glycemic index (GI) in meal planning, and they typically lack detailed information such as ingredients, recipes, and nutritional facts. This study seeks to address these shortcomings by developing an ontology-based menu recommender system using the Ontology Web Language (OWL) to improve dietary adherence and reduce complications associated with diabetes through personalized low glycemic index menu recommendations. By modeling food data with OWL, the system organizes information about food items, glycemic index values, and nutritional properties to generate personalized recommendations. Evaluation metrics showed a precision of 0.767, recall of 1.0, accuracy of 0.767, and an F1-score of 0.869, demonstrating the system's effectiveness in recommending low-GI foods. These results indicate the system's potential in supporting diabetes management by improving dietary adherence and reducing complications.**

***Keywords*—glycemic index, food recommender system, ontology, ontology web language, recommender system**

I. Introduction

Lifestyle changes have significantly impacted people's behaviors and habits, ultimately leading to the emergence of chronic health problems. The number of diabetes cases is increasing due to factors such as population growth, aging, urbanization, rising obesity rates, and a lack of physical activity [1]. Diabetes, particularly Type 2 diabetes, has become one of the major health challenges in many countries. Younger individuals diagnosed with diabetes lose more years of life compared to those diagnosed at an older age [2]. This highlights the need for a holistic approach to diabetes management that focuses on both medical treatment and adopting a healthy lifestyle. Diet quality is a key factor influencing the risk of diabetes. Regular, healthy eating habits can reduce the risk of progressing from prediabetes to diabetes by 40–70% [7].

In efforts to achieve a healthy lifestyle, diet plays a crucial role in diabetes management by stabilizing blood sugar levels and preventing complications. A low glycemic index (GI) diet has proven particularly beneficial for diabetic patients. However, selecting foods that meet the glycemic and nutritional needs of diabetic patients is complex. Food recommender systems have emerged as valuable tools to address this challenge by helping diabetic patients make informed food choices tailored to their health conditions. These systems help users navigate individual preferences, dietary restrictions, and glycemic needs, providing a practical solution for daily diabetes management.

Previous studies have explored ontology-based approaches for dietary recommendations. Ali et al. [11] successfully implemented a type-2 fuzzy ontology for food menu recommendations, demonstrating significant improvements over traditional methods. However, their system faced challenges such as incomplete data from wearable sensors and a lack of focus on glycemic index considerations. Building on this work, our study integrates low-GI data and detailed nutritional information to enhance the relevance and accuracy of dietary recommendations for diabetic patients. Similarly, Sicilia et al. [5] developed a chatbot-based food recommender system with a high F1-score of 0.97, providing food suggestions personalized to user details such as age, gender, and medical history. While effective for obesity prevention, this system did not address glycemic index-specific needs, leaving a gap for diabetes management.

This study addresses these gaps by developing an ontology-based menu recommender system specifically designed for diabetic patients. The system utilizes the Ontology Web Language (OWL) to model relationships between food items, glycemic index values, and user-specific dietary needs. By using OWL, the system ensures that recommendations are structured, personalized, and nutritionally balanced. In addition to glycemic index-based recommendations, the system provides detailed information on ingredients, recipes, and nutritional facts, enhancing the user experience by making the food selection process intuitive. The evaluation was conducted through an interview with the nutritionist, where the expert was asked to assess and approve the system's recommendations based on their suitability and alignment with the dietary needs of individuals with diabetes, with the ultimate goal of improving dietary adherence and reducing complications associated with diabetes.

II. Related Work

Exploration of menu recommender systems using ontologies has been conducted in several previous studies. Baizal et al. [6] developed an ontology-based system integrated with SWRL to represent food consumption and define relationships between food composition (including nutritional content) and patient needs. Similarly, Mckensy-Sambola et al. [8] also utilized ontology and applied semantic rules to process users' height, weight, and BMI. However, the system achieved a lower precision of 0.7 due to false positives, where menus recommended by the system were not validated by experts.

Agapito et al. [9] introduced DIETOS, a system that recommends diet menus based on users' health conditions. By processing questionnaire results, the system creates user health profiles to personalize recommendations effectively. Further advancements in ontology-based menu recommender systems include Espín et al. [11] who developed NutElCare, a system designed to assist elderly users in planning diets based on nutritional guidelines. It uses ontology and semantic technologies to handle nutritional data and provide relevant dietary suggestions. Cioara et al. [12] created an expert system for older adults, which uses a Nutrition Care Process Ontology to identify unhealthy feeding patterns and detect risks of malnutrition. Both systems demonstrate how ontology can support nutrition planning, although their focus on elderly care limits their application to diabetes management.

S. Alian et al. [14] developed an ontology-based system that processed user data such as age, height, weight, CPM (Choices Per Meal), EER (Estimated Energy Requirement), and BMI. The system achieved 100% accuracy in generating recommendations approved by nutrition experts, showcasing its potential for high precision. However, it did not address glycemic index considerations or meal balancing, which are essential for diabetes management.

Ontology is a collection of terms along with detailed specifications of their definitions, including the conceptual structure and relationships within a domain, as well as potential limitations in interpreting these terms [21]. Its core components are concepts (categories), relationships (interactions), instances (examples), and rules (values assigned to these relationships), forming a knowledge base. Ontology-based systems often face limitations when the database lacks sufficient information, preventing users from receiving desired results. Research has shown that OWL can address this issue by offering alternative outputs based on the similarity of existing data in the database [17].

Although many recommender systems have been built using ontology [6, 8, 13], they often lack consideration of specific factors such as low glycemic index food, integration of glycemic data with nutritional requirements, and reasoning capabilities for diabetes-specific dietary needs. Building on prior research, this study utilizes OWL (Web Ontology Language) to process data, considering BMR (Basal Metabolic Rate) and balanced daily nutritional needs, while recommending foods with a low glycemic index. This approach improves the system's ability to provide relevant and accurate recommendations, addressing the challenges of diabetes management.

III. METHODOLOGY

The first step to be taken is to estimate the total calories and nutrients required (carbohydrates, proteins, and fats). The estimate for daily caloric needs can be calculated using the Harris-Benedict Equation, by multiplying the Basal Metabolic Rate (BMR) by the Activity Factor (AF) [18].

$$\begin{aligned}\text{BMR (Male)} = 66.47 + (13.75 \times \text{weight}) \\ + (5.0 \times \text{height}) - (6.75 \times \text{age})\end{aligned} \tag{1}$$

$$\begin{aligned}\text{BMR (Female)} = 655.1 + (9.56 \times \text{weight}) \\ + (1.85 \times \text{height}) - (4.67 \times \text{age})\end{aligned} \tag{2}$$

$$\text{Daily Calories Requirement} = \text{BMR} \times \text{AF} \tag{3}$$

AF is the total number of calories burned in one day from all sources of physical activity, including work and exercise. AF is essential for determining daily caloric needs and maintaining energy balance in the body. There are several option for AF as shown in the Table I [18]. In the case of individuals with diabetes, the distribution of macronutrients from total calories can be divided into 60% carbohydrates, 15% protein, and 25% fat [20].

TABLE I
ACTIVITY FACTOR BASED ON LIFESTYLE AND INDIVIDUAL ACTIVITIES

Lifestyle and Individual Activities	**Activity Factor (AF)**
Little or no exercise	1.200
Light activity (1-3 days per week)	1.375
Moderate activity (3-5 days per week)	1.550
Heavy activity (6-7 days per week)	1.725
Very heavy activity (2x per day, extra intense training)	1.900

The Glycemic Index (GI) is a ranking system that classifies carbohydrate-containing foods based on their effects on blood sugar levels. GI categorizes foods into three classes: low GI (< 55), medium GI (56–69), and high GI (> 70) [19]. Glycemic Load (GL) helps determine the blood sugar levels after consuming specific foods.

A. Dataset

The dataset used in this study was collected by scraping data from the website https://glycemicindex.com/, which offers information on low glycemic index (GI) menus. It consists of 219 rows of data, each representing a different food item, with various attributes including the name of the dish, its ingredients, the method of preparation, and detailed nutrition information such as calories, carbohydrates, and protein content. This data provides a comprehensive view of each food item's nutritional composition, which is crucial for understanding its impact on blood glucose levels. In addition to the food data, the system also collects personal information from users to generate dietary recommendations. The user data includes the name, age, and gender of the patient, alongside their height (in centimeters) and weight (in kilograms), which are essential for calculating Basal Metabolic Rate (BMR) and understanding individual energy expenditure. Moreover, the user's activity level is recorded to determine their physical activity and energy expenditure, which influences dietary needs. This combination of 219 low GI food data and user-specific information enables the system to offer personalized recommendations that account for both dietary preferences and individual health conditions.

B. System Workflow

The system is designed to provide food menu recommendations tailored to the nutritional needs and preferences of individuals with diabetes. This system utilizes ontology and OWL (Web Ontology Language) to generate personalized recommendations by considering calories provided, low glycemic index menu, and micronutrients. Each user has a profile that reflects their individual characteristics, preferences, and limitations.

The system uses ontology to represent domain knowledge about food types, glycemic values, fiber content, carbohydrates, and other nutritional information. OWL is used to define the relationships between concepts within the ontology, as well as the logical rules that govern the system's behavior. The system evaluates food nutrition based on factors such as glycemic index, fiber intake, and carbohydrates to provide food options that meet the user's nutritional needs and dietary restrictions. Based on the user's profile and the rules defined in OWL, the system generates food menu recommendations that take the aforementioned factors into account.

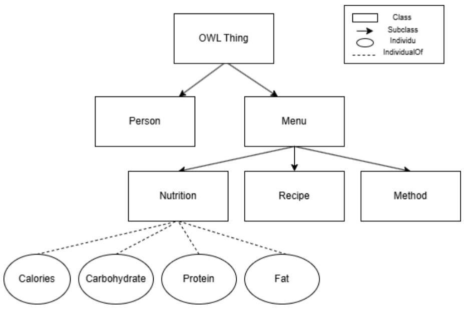

Fig. 1. Ontology design

The system is designed to provide food menu recommendations that match the nutritional needs and preferences of individuals, especially those with specific health conditions like diabetes. Using an ontology and OWL (Web Ontology Language), the system organizes its structure around key components such as Person, Menu, Nutrition, Recipe, and Method. This structure ensures that the recommendations are clear and based on individual characteristics and food details.

As shown in Fig. 1, the ontology acts as the foundation of the system. At the top is the OWL Thing class, from which all other components, such as Person and Menu, come. The Person class represents users and connects to the system through their personal data. The Menu class lists food options and breaks them into details like Nutrition, Recipe, and Method. Each Menu includes nutritional information (Calories, Carbohydrate, Protein, Fat) shown as individual elements. The links between the components show their relationships. These relationships, combined with user-specific input, allow the system to provide menu recommendations that fit the user's profile and nutritional needs. This setup makes it easy to connect general food options to detailed nutritional information.

Table II provides a detailed summary of the properties defined in the system, which play a crucial role in enabling this personalized approach to dietary management. This systematic process ensures the system is robust, scalable, and capable of delivering recommendations that are both practical and beneficial for users managing diabetes or other health-related dietary needs.

TABLE II
ONTOLOGY PROPERTIES

Property	Domain	Range	Description
hasBMR	Person	Decimal	BMR via Harris-Benedict Equation
hasAge	Person	Integer	Person's age.
hasWeight	Person	Decimal	Weight (kg).
hasHeight	Person	Decimal	Height (cm).
hasGender	Person	String	Gender (M/F).
hasCalories	Nutrient	Decimal	Calorie needs.
hasProtein	Nutrient	Decimal	Protein needs (g).
hasCarbohydrates	Nutrient	Decimal	Carb needs (g).
hasFat	Nutrient	Decimal	Fat needs (g).
hasIngredients	Menu	String	Menu ingredients.
hasMethod	Menu	String	Prep steps.
hasNutrient	Menu	Nutrient	Links to nutrition data.
hasRecommendation	Person	Menu	Links person to menus.

For example, properties such as 'hasBMR', 'hasAge', and 'hasWeight' capture the individual's profile, while 'hasCalories', 'hasProtein', and 'hasCarbohydrates' provide detailed information about the nutritional requirements. Additionally, 'Menu' properties such as 'hasIngredients' and 'hasMethod' are extracted from RDF data, allowing for structured representation of recipes and their preparation methods. The relationship between 'Person' and 'Menu' is established using 'hasRecommendation', linking a user's profile to menu items that meet their calculated nutritional needs. This structure ensures a personalized recommender system that is both dynamic and scalable.

```
SELECT ?food ?label
WHERE {
    ?food rdf:type nutrition:Food .
    ?food nutrition:hasCalories ?calories .
    ?food nutrition:hasProtein ?protein .
    ?food nutrition:hasCarbohydrates ?carbs .
    ?food nutrition:hasFat ?fat .
    BIND (?protein * 4 AS ?proteinCalories)
    BIND (?carbs * 4 AS ?carbCalories)
    BIND (?fat * 9 AS ?fatCalories)
    FILTER (?proteinCalories >= 0.1 * ?calories && ?proteinCalories <= 0.2 * ?calories)
    FILTER (?carbCalories >= 0.5 * ?calories && ?carbCalories <= 0.6 * ?calories)
    FILTER (?fatCalories >= 0.2 * ?calories && ?fatCalories <= 0.3 * ?calories)
}
```

Fig. 2. Rule example

TThe SPARQL query in Fig. 2 is implemented to enforce nutritional balance rules for food recommendations based on macronutrient contributions to total calories. The query structure begins with selecting food entities, where properties such as hasCalories, hasProtein, hasCarbohydrates, and hasFat define the nutritional attributes of each item. Using the BIND function, caloric contributions of protein, carbohydrates, and fat are calculated based on their standard calorie-per-gram values (4 for protein and carbohydrates, and 9 for fat). Logical constraints are applied through FILTER statements, specifying the percentage of each nutrients. These constraints act as rules to ensure that only nutritionally balanced food items are selected. While the rules are not embedded directly into the ontology, they function as practical constraints within the query execution to provide accurate and health-specific food recommendations,

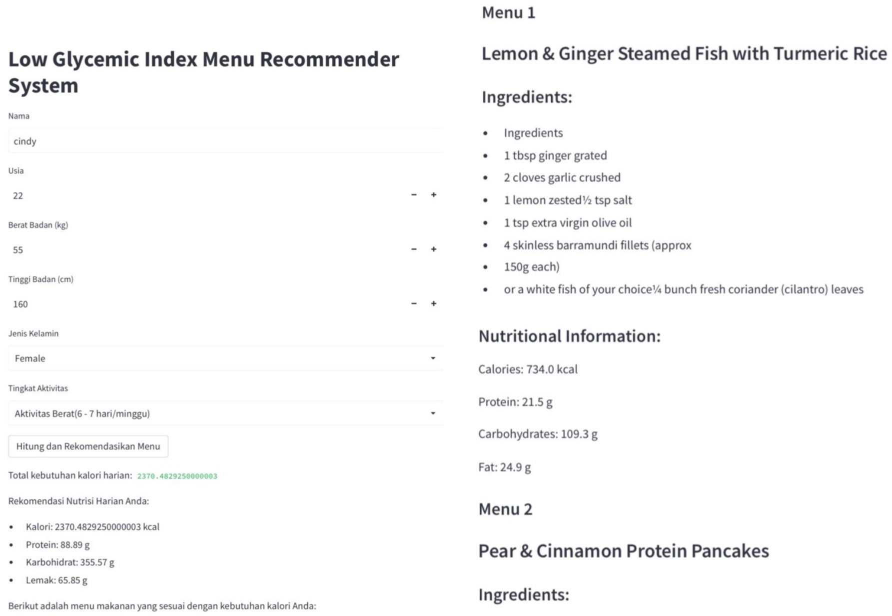

Fig. 3. The streamlit UI

particularly useful in scenarios such as managing dietary requirements for diabetes patients.

C. Recommendation Generation

Fig. 3 shows the Streamlit-based user interface of the system. This interface allows users to enter personal details such as name, age, gender, weight, height, and activity level. Based on this information, the system calculates their daily calorie needs and provides information about their nutrition. It also recommends menus with low glycemic index foods that are suitable for their health. The design is simple and easy to use, helping users to manage their diet effectively. The recommendation generation process involves several steps to ensure the system provides meal plans that match the user's nutritional needs and preferences. The process begins by calculating the user's Basal Metabolic Rate (BMR) and daily calorie requirements using their age, weight, height, gender, and activity level. These calculations are based on the Harris-Benedict equation, which is adjusted for the user's physical activity level. Once the total calorie needs are determined, the system distributes these calories into macronutrient targets, allocating 15% for protein, 60% for carbohydrates, and 25% for fat. The macronutrient values are converted into grams to provide precise dietary recommendations for daily intake. The system extracts menu data from an RDF dataset using SPARQL queries. This data includes details such as ingredients, preparation methods, and nutritional information. The extracted data is organized and analyzed to match the user's nutritional requirements. Menu recommendations are generated by selecting meal options that collectively meet at least 95% of the user's total calorie requirements. The system ensures a balanced intake of protein, carbohydrates, and fat by evaluating the difference between the actual and target nutrient values. Randomization is applied to the menu selection process to avoid repeating the same recommendations.

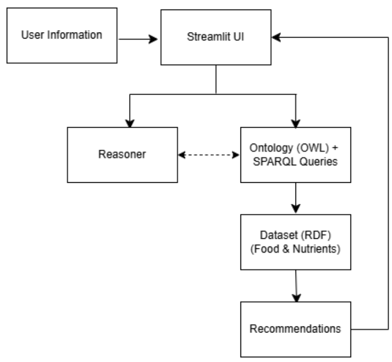

Fig. 4. System design overview

The architecture of the system, as illustrated in Fig. 4, begins with the user entering personal details such as age, weight, height, activity level, and any specific health conditions through an intuitive user interface. These inputs are processed by a series of functions, including a reasoner, which calculates the user's caloric and nutritional requirements. The system utilise a knowledge base that integrates an ontology modeled using the OWL standard, specifically implemented via the OWLready2 library in Python, and a set of predefined rules to enhance reasoning and inference capabilities. The rules also use SPARQL queries to process the data by using simple mathematical expressions within the query. The ontology structures relationships between various data points, such as nutrients, food types, and dietary needs, while the rules guide the reasoning process to ensure accurate and context-aware insights. These functions also interact with a dataset containing nutritional information for various food items, querying and combining this data with the ontology to generate personalized menu recommendations. The recommendations are tailored to the user's preferences and health requirements and are displayed on the user interface, completing the recommendation process.

IV. Result and Discussion

The testing process for this recommender system involved a qualified nutritionist who played a key role in validating the dietary recommendations generated by the program. The nutritionist's task was to evaluate whether the nutrients and menus suggested by the system were suitable and aligned with the dietary needs of individuals with diabetes. To ensure the system's accuracy and reliability, a sample of 30 users was selected for testing. Upon reviewing the recommendations, the nutritionist confirmed that the system provided accurate and appropriate results for 23 out of the 30 samples, meeting the specific nutritional guidelines required for diabetic individuals. However, the remaining 7 samples contained recommendations that did not fully align with the nutritionist's expert evaluation, indicating that the suggested menus or nutrient content did not completely adhere to the desired standards. A detailed analysis of the 7 incorrect samples suggests potential causes for discrepancies. In some cases, user input data such as activity level may have been not accounted for correctly, leading to recommendations that deviated from the required nutritional standards. Additionally, gaps in the database, such as incomplete information on specific foods, could have contributed to errors. To address these issues, improving the handling of input data by introducing validation steps during data entry and expanding the database with more comprehensive food and nutrient details are necessary.

TABLE III
User Sample

User	**Category**	**Value**
Cindy	Gender	Female
	Age	22 Years
	Height	160 cm
	Weight	55 kg
	Activity Factor	Heavy Activity
Output	Calorie	2370 kcal
	Protein	88.89 g
	Carbohydrate	355.7 g
	Fat	65.85 g

Table III shows the input and output data for a sample user, Cindy, processed through the recommender system. The input provided by the user includes gender, age, height, weight, and activity factor. Based on these inputs, the system calculates the user's daily caloric needs using the Basal Metabolic Rate (BMR) formula adjusted by the activity factor. The system outputs a detailed breakdown of daily nutritional recommendations, including total calorie intake, along with the required amounts of macronutrients such as protein, carbohydrates, and fat. These recommendations are designed to meet the physical requirements of the user based on their input data.

$$\text{Precision} = \frac{23}{23+7} = 0.767 \tag{4}$$

$$\text{Recall} = \frac{23}{23+0} = 1.000 \tag{5}$$

$$\text{Accuracy} = \frac{23}{23+7} = 0.767 \tag{6}$$

$$\text{F1-Score} = 2 \times \frac{0.767 \times 1.000}{0.767 + 1.000} = 0.868 \tag{7}$$

Evaluation metrics reveal a precision of 0.767, indicating 77% of recommendations were approved by the nutritionist, and a recall of 1.000, showing all valid recommendations were identified. The accuracy matches the precision at 0.767, while the F1-Score of 0.868 indicates that all valid recommendations identified by the nutritionist were captured by the system and reflects how well the system maintains precision and recall together. These metrics provide a quantitative measure of the system's performance in making and identifying appropriate recommendations. When compared to related studies, such as Mckensy-Sambola et al. [8], whose system achieved a lower precision of 0.7, the results of this study indicate progress in providing more accurate dietary recommendations. This improvement highlights the benefits of incorporating detailed glycemic index data and structured nutritional modeling. However, the perfect recall coupled with a lower precision suggests that while the system successfully captures all correct recommendations, it also generates some incorrect ones, pointing to areas for refinement.

V. Conclusion

This system uses a low glycemic index (GI) menu dataset to provide dietary recommendations for individuals with diabetes. The dataset is organized using an ontology (OWL), which structures and categorizes data, enabling the system to generate recommendations that align with nutritional guidelines. The recommendations were validated by a qualified nutritionist to ensure their suitability and effectiveness. The evaluation results show a precision of 0.767, recall of 1.000, accuracy of 0.767, and an F1-score of 0.868, demonstrating the system's potential to provide accurate and relevant suggestions for diabetes management.

The key contributions of this study is the use of an ontology-based system for generating low glycemic index recommendations. By structuring the data with OWL, the system offers a more focused approach to supporting dietary management for diabetic patients. However, this research has some limitations. The dataset used in the system was scraped from a website with a fixed set of menu items, limiting the variety of recommendations and occasionally leading to repetitive suggestions. Additionally, the system's reliance on input data requires careful handling to avoid errors caused by misclassification or missing information. Future work should focus on expanding the dataset to include a broader range of menu items and integrating more advanced data validation techniques to address these process-related weaknesses.

While the system demonstrates promising results, further refinement is necessary to enhance its precision and variety. Expanding the database, incorporating dynamic updates, and improving data processing could help ensure the system's recommendations remain diverse, accurate, and suitable for real-world applications. This study provides a starting point for developing ontology-based recommender systems that support dietary management for diabetic patients.

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