Personalized Nutrition Recommender System for Hypercholesterolemia Patients Using Ontology and SWRL Approaches

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***Abstract*—Hypercholesterolemia is a condition characterized by elevated levels of low-density lipoprotein (LDL) cholesterol in the blood, increasing the risk of cardiovascular diseases such as coronary heart disease and stroke. Effective management requires a personalized diet that considers individual preferences, dietary restrictions, and medical needs. While previous studies have utilized ontologies and Semantic Web Rule Language (SWRL) in nutrition recommender systems, few have specifically addressed hypercholesterolemia. To fill this gap, this study presents a personalized nutrition recommender system leveraging ontology and SWRL to provide tailored dietary recommendations for hypercholesterolemia patients. The system models patient data including demographic profiles, health conditions, and dietary preferences within an ontology framework, enabling logical reasoning through SWRL rules to infer suitable dietary plans. Additionally, the system integrates with a Telegram chat-bot to offer a user-friendly and accessible interaction platform. Performance evaluation was conducted using data from 15 patients and involved validation by nutritionists. The system generated 135 menu recommendations, achieving a precision of 0.889, recall of 1, and F-Score of 94.1%, indicating high accuracy and relevance of the recommendations. Some limitations were observed, including false positives due to incomplete nutritional data in the ontology, particularly regarding fat content in certain foods. The study highlights the need to expand datasets to encompass diverse cultural preferences and nutritional needs to improve system robustness. Future work will focus on incorporating real-time patient feedback through the chat-bot interface, enhancing dataset diversity, and improving system adaptability to dynamic health conditions. These enhancements aim to optimize the system's effectiveness in managing hypercholesterolemia and pave the way for broader applications in personalized nutrition management and chronic disease care.**

Keywords*—*nutrition recommender system, ontology, semantic web rule language, chatbot based recommender system.

I. INTRODUCTION

Health is a section of human life that defines quality. Among several challenges in this field, the most common is called hypercholesterolemia. Hypercholesterolemia can be defined as a medical condition of having an abnormally high level of LDL or Low-Density Lipoprotein cholesterol in the blood, a state that easily increases the risk for atherosclerotic cardiovascular disease and stroke [1], [2]. Hypercholesterolemia is a serious concern in global public health. According to the World Health Organization (WHO), around 39% of adults worldwide have total cholesterol levels exceeding normal limits, even exceeding 50% in some developed countries [3]. The number of cases of hypercholesterolemia is still growing worldwide, so proper management is very important [4].

Unhealthy lifestyles, physical inactivity, and a nutritionally imbalanced diet, particularly those rich in high-fat food ingredients, represent the most direct causative factors for hypercholesterolemia. On the other hand, poor knowledge about healthy nutrition among members of the public is one of the reasons why the incidence of the disease has also continued to increase. As expected, good nutrition knowledge imparts highly positive changes in attitudes and behavior related to food choices and hence is directly reflected in health [5]. Patients with hypercholesterolemia are recommended to follow a healthier diet supported by structured dietary guidelines [6].

Along with technological development, technology-based solutions have made a significant contribution to the improvement of healthcare services, including nutrition and diet management. The recommender system is one of the most applied technological approaches to assist users in making choices that suit their needs [7]. One of the fundamental bases in the development of a nutritional recommender system is ontology. Ontology is a formal representation of a knowledge domain that includes concepts, entities, and the relationships among those entities [8]. Ontology allows the system to identify specific nutritional preferences and needs based on individual profiles [9].

The success of using ontology and SWRL in developing a recommender system has been proven in some previous works. Mckensy-Sambola et al. [10] proposed an ontology-based recommender system along with semantic rules to help obese patients choose the right kind of diet. This system takes as input parameters like weight, height, and body mass index in order to come up with a list of recipes that would meet dietary constraints and nutritional needs. For instance, El Massari et al. [11] developed a cardiovascular disease prediction system using ontology and SWRL. The semantic rules integrate the information about patients into ontologies. Al-Nazer et al. [9] also developed an ontology-based personalized food and nutrition recommendation framework for users' health profiles, improving user satisfaction.

Taçyıldız & Ertuğrul [12] designed a decision support system for managing obesity in children and adolescents. Chi et al. [13], while building a dietary consultation system for patients with chronic diseases by using OWL and SWRL ontology, are able to recommend the portions of food intake with high accuracy. Various related studies proved that ontology and SWRL would have the potential to give personalized and effective solutions to society in nutrition recommender systems.

Beyond this, Rahmawati et al. [14] propose an ontology-based conversational recommender system with an explanation facility that allows semantic reasoning in order to arrive at a personalized product recommendation. Their model evidences explanation facilities along with semantic reasoning and develops effectiveness and accuracy. Though applied on the smartphone domain, this conveys important insights on how to make a nutritional recommender system whereby explanations of chosen food would enhance user confidence and decision-making, especially among the pool of patients dealing with hypercholesterolemia.

Various studies have explored technology-based nutrition recommendation systems, but few have specifically focused on hypercholesterolemia patients. Research that combines ontology and SWRL to provide personalized nutrition recommendations is also very limited. Therefore, this study aims to fill the gap by developing an ontology and SWRL-based nutrition recommendation system specifically designed for hypercholesterolemia patients. The system not only considers the patient's medical data, such as age, gender, weight, height, and activity level, but also considers the patient's food preferences and allergic restrictions. By utilizing these data, the system can provide relevant and practical food and nutrition recommendations. In addition, the system is implemented on the Telegram chat-bot platform to facilitate patient interaction and accessibility, thereby improving user experience in effectively managing hypercholesterolemia conditions.

II. Related Work

Today, most recommender systems use ontology and SWRL for personalized and practical solutions to find goods according to their needs. Ontology is widely used to represent knowledge in knowledge-based recommender systems, such as tourism recommendations [15] and laptop recommendations based on the product's functional needs [16]. Beyond general applications in domains such as tourism and electronics, ontology and SWRL have shown significant potential in health-related systems, particularly nutrition and disease management.

In health domains, various works have been done to improve nutrition and health management systems using ontology and SWRL. McKensy-Sambola et al. [10] proposed an ontology-based nutrition recommendation system for global obesity with 87% accuracy on 2,111 records. However, the precision was very low at 0.34 because of the deviations from nutritionist recommendations. Al-Nazer et al. [9] proposed a semantic framework for personalized food recommendation with 90% precision. However, its average recall of 76% reflects the limitations in covering a wide range of dietary needs.

Ontology-based reasoning has also been used in medical applications, such as cardiovascular disease prediction. El Massari et al. [11] integrated ontology with decision tree models, achieving an accuracy of 75.5% compared with standard models. Similarly, Amith et al. [17] integrated scattered data for the nutrition domain in fast foods into one semantic framework using developed ontologies with a 76.1% agreement among evaluators to improve accessibility by both consumers and medical professionals.

In obesity management, Taçyıldız and Çelik Ertuğrul [12] developed an ontology and SWRL-based decision support system, achieving 99.4% accuracy, 95.4% precision, and 98.9% recall across 749 recommendations. Similarly, Chi et al. [13] applied SWRL in dietary consultation systems for chronic disease management, integrating knowledge sources to provide accurate and context-specific meal and diet plan recommendations.

Rahmawati et al. [14] demonstrated the use of ontology-based conversational recommender systems with semantic reasoning and explanation features to provide personalized product recommendations. Their approach can be adapted to nutritional recommender systems for hypercholesterolemia patients, ensuring transparent and user-friendly guidance.

Previous studies have established the effectiveness of using ontology and SWRL in the development of personalized and context-aware recommender systems. However, most of these studies focus on generalized health conditions like obesity and chronic diseases, rather than tailored solutions for hypercholesterolemia. The limitations identified in these studies have been addressed in this paper, which presents a nutrition-based personalized recommender system for hypercholesterolemia patients using ontology, SWRL, and a friendly chat-bot user interface to improve recommendation accuracy, ease of use, and cater to the specific needs of patients.

III. Methodology

Our proposed nutrition recommender system for hypercholesterolemia patients is built using ontology and SWRL to represent knowledge and perform inference. Ontology structures relationships between nutritional data, such as food composition, calorie content, and nutritional values, alongside specific dietary requirements for hypercholesterolemia patients, including cholesterol levels, BMI, and activity levels. This structured knowledge enables the system to understand how health parameters and food attributes interact to provide personalized dietary recommendations.

SWRL complements the ontology by enabling logical reasoning and inferring new insights from user data, such as weight, age, and cholesterol levels. By applying rules, the system calculates BMI and BMR, which serve as the basis for tailored dietary advice. This integration enhances the system's ability to generate recommendations aligned with individual health conditions and nutritional needs.

The system incorporates a Telegram chat-bot interface, ensuring ease of interaction and accessibility for users. Unlike traditional systems that rely on static data, this dynamic system adapts to user preferences and dietary restrictions. Ontology and SWRL enhance the system's ability to understand the interplay between patient profiles, nutritional needs, and dietary guidelines.

This approach provides precise and adaptive recommendations that adjust to changes in a patient's condition over time, contributing to effective cholesterol management for hypercholesterolemia patients.

A. Ontology

The system would be designed to capture, through ontologies, the interrelationship between nutritional knowledge data-like food composition, calorie content of food-with the dietary requirement specifics of the hypercholesterolemic patient. Ontology thereby acts as the knowledge base containing information about patient profiles, dietary restrictions, and the attributes of food. Through its use, specific recommendations of dietary advice may be developed related to particular data provided for a patient, which would include cholesterol level, BMI (Body Mass Index), and calorie requirements per day.

This system takes several factors into consideration when making recommendations, including the patient's activity level, gender, age, height, weight, cholesterol levels, and allergies. First, it will be necessary to calculate the patient's daily calorie needs using the Basal Metabolic Rate (BMR) formula and then multiply by the Activity Factor. BMR reflects basic energy consumption for simple physiological life-sustaining activities, breathing and thermoregulation of the human body, while AF denotes correction for a patient's calorie needs based on physical activity [18]. This equation is fundamental in making a personalized dietary prescription, as this will normalize the intake of calories to the patient's lifestyle and energy utilization. The BMR formula for males based on the Mifflin-St Jeor method is given in (1):

$$BMR_{male} = (10\times Weight\ (kg))+(6.25\times Height\ (cm)) - (5\times Age\ (year))+5 \tag{1}$$

And for females, the BMR formula is presented in (2) :

$$BMR_{female} = (10\times\ Weight\ (kg))+(6.25\times\ Height\ (cm)) - (5\times Age\ (year))-161 \tag{2}$$

The integration of the BMR calculation in the system will make the dietary recommendations even closer to the needs of a patient with hypercholesterolemia in order to manage cholesterol levels and maintain good health.

The results of this BMR are then multiplied by the physical activity factor to obtain the patient's daily calorie needs, as shown in Table I [19]. Activity Factor (AF) is a factor that modifies the calorie requirement according to the activity level of the individual. For example, a sedentary person has an AF of 1.2, while a very active person has an AF of 1.725. It gives more personalized dietary recommendations, taking into consideration not only metabolic needs but also lifestyle, since the total daily calorie needs are calculated by multiplying the BMR with the appropriate AF. This makes sure that dietary guidance is appropriately tailored for managing cholesterol levels and overall health.

TABLE I. ACTIVITY FACTOR

Activity Level	Activity Factor (AF)
Sedentary	1.2
Lightly Active	1.375
Moderately Active	1.55
Very Active	1.725
Extra Active	1.9

Moreover, the BMI can be calculated to assess the patient's weight status and provide personalized dietary recommendations. It is computed as:

$$BMI = \frac{Weight(Kg)}{Height(m)^2} \tag{3}$$

As shown in (3), once the BMI is calculated, the values are categorized into five main groups based on standard classifications: Underweight, when the BMI is less than 18.5, means a weight below normal. The normal range of BMI is between 18.5 and 22.9, which reflects an ideal weight. Furthermore, the overweight category includes individuals whose BMI is within the range of 23 to 24.9 and signifies an overweight condition. Whereas, for BMI ranging from 25 to 29.9, the category would be Obesity I, and the one exceeding a mark of 30 would fall in the category of Obesity II, with a higher obese rate. This categorization provides a clear basis upon which one can evaluate a patient's weight status and formulate nutritional recommendations relevant to their condition.

In addition, the system also processes the cholesterol level data of the patient to determine the status of risk. Cholesterol level data are categorized as shown in Table II [20], which helps to determine the severity of hypercholesterolemia. This classification will make it possible for the system to provide dietary guidance in accordance with the cholesterol levels of the patient. For example, the "High" or "Very High" will be advised on cholesterol reduction, while the "Normal" will be advised on how to maintain their present health status.

TABLE II. PATIENT CHOLESTEROL LEVELS

Cholesterol Levels	Categories
<100	Normal
100-129	Normal range
130-159	High range
160-189	High
>190	Very High

B. System Design

Fig. 1 shows the flow of the proposed nutrition recommender system. This starts with information gathering that includes user data and food data. The various stages of the workflow include the following:

- Information Collection: It acquires information from two major sources, namely, user data that includes weight, height, age, gender, activity level, allergies, and cholesterol level, and food data. This acts as the core basis for giving personalized recommendations.
- Ontology Generation: The collected data are processed to develop an ontology structure. Ontology in this system is a formal representation of knowledge that maps the relations between user data, nutritional needs, and food attributes. It defines concepts such as "cholesterol levels," "BMI," and "food composition" in a way that the system will understand how these factors influence dietary recommendations. Ontology would therefore help the system relate the particular conditions of the patients with the correct food items suitable for their conditions.
- Ontology Validation: The created ontological structure will be validated for correctness and appropriateness with regards to nutritional needs of patients suffering from hypercholesterolemia. The validation step ensures interrelations between the food attributes and user data that are correct, hence the appropriateness of recommendations set forth by the system. That said, this also involves validation checks of input data as well as the performance or otherwise of SWRL rules utilized on the system, especially when it concerns certain inferences about the subject under investigation-for instance, associating with diet restrictions, and most useful associations between different types of food in improving or regulating cholesterol.
- Recommendation Generation: By means of the already validated ontology, the system identifies certain recommendations on food, appropriate to the case

under consideration. Indeed, suggestions including meal time distribution like breakfast, lunch, and dinner will be proposed to the patient by taking his needs, preferences, and restrictions into account.The system ensures that the dietary plan meets the health requirements of the patient, including managing cholesterol levels effectively.

- Evaluation: This is necessary for the assurance that the recommendations meet nutritional standards and the needs of the patient. It will involve a nutritionist who will validate the result of recommendations so that what the system produces is accurate and medically sound.

This is in pursuit of personalized recommendations, more precise and relevant to the patients with hypercholesterolemia, which will prove to be effectively feasible in managing the diet of such patients. Such an incorporation would ensure that ontology and SWRL will enable deeper insight into the representation of user health status, food preference, and requirement, increasing overall quality in personalized diet guidance.

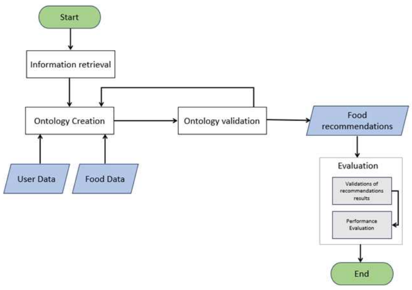

Fig. 1. Workflow of the nutrition recommender system using ontology.

C. System Flow

This study developed a chat-bot for user interaction via the Telegram platform, accessible from several devices and places [21]. Users and systems can engage using the chat-bot interface on the Telegram platform. Users may input their data, which will subsequently be transmitted as a query to the handler. The system will provide suggestions utilizing ontology-based SWRL based on this query. Subsequently, the outcomes of the current recommendations will be displayed on the chat-bot interface. This process is illustrated in the graphic form in Fig. 2.

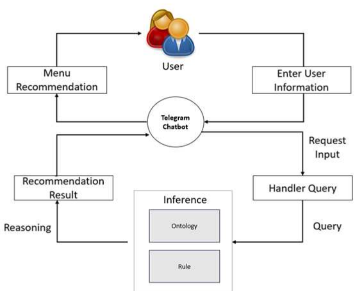

Fig. 2. System flow of the Telegram-based nutrition recommender chat-bot.

D. Implementation of Ontology and SWRL

In this paper, a nutritional recommender system for patients with hypercholesterolemia was developed based on the ontology-based approach designed using *Protégé software*, version 5.6.4. The proposed ontology consists of many classes that provide clear and rich representation of nutritional data, patient preferences, and health needs. Ontology implementation consists of a top-down approach that ranges from major classes to sub-classes. Fig. 3 below illustrates the hierarchy of ontology.

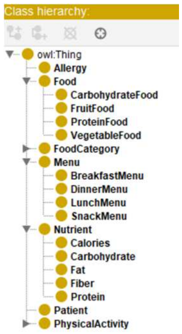

Fig. 3. Class hierarchy of the ontology in the nutrition recommender system.

Fig. 3: An excerpt of the hierarchy of the ontology used in the nutritional recommender: main classes such as *Patient*, *Food*, *Menu*, *Nutrient*, and *PhysicalActivity*. *Food* sub-classes are *CarbohydrateFood*, *FruitFood*, *ProteinFood*, and *VegetableFood*, while *Menu* is divided into classes like *BreakfastMenu*, *LunchMenu*, *DinnerMenu*, and *SnackMenu*. *Nutrient* class attributes include *Calories*, *Carbohydrate*, *Fat*, *Fiber*, *Protein*, etc. The relationship provides personalization in food recommendations related to cholesterol level, BMI, and activity level of a patient. Data and object properties for structuring the knowledge base exist in every class. Object properties such as *avoidedBy*, *BelongsToCategory*, and *hasAllergyRestriction* link food to allergies, categories, and nutritional content. Data properties, such as *hasHeight*, *hasWeight*, *hasBMI*, and *hasCholesterolLevel*, enable the system to personalize recommendations based on patient data. Other nutrient properties, such as *hasCalorieNeed*, *hasFatNeed*, and *hasProteinNeed*, further refine the nutritional needs. This structure conveys appropriate and specific dietary recommendations for hypercholesterolemia management.

For the realization of inference, it uses SWRL rules to process data about patients' status and recommend diets. A few examples of such SWRLs implemented are shown below.

- Calculation of BMI
  Rules calculating BMI of a patient depending on the value of the patient's weight and height.

$$\begin{aligned}&Patient(?p) \wedge hasHeight(?p,?h) \wedge hasWeight(?p,?w) \wedge \\ &swrlb{:}divide(?heightMeter,?h,100.0) \wedge \\ &swrlb{:}multiply(?htSquare,?heightMeter,?heightMeter) \wedge \\ &swrlb{:}divide(?bmi,?w,?htSquare) \;\text{->}\; hasBMI(?p,?bmi)\end{aligned}$$

- BMI Classification:
  Categorization of patients in regard to their BMI value.

$$\begin{aligned}&Patient(?p) \wedge hasBMI(?p,?bmi) \wedge swrlb{:}greaterThanOrEqual(?bmi,18.5) \wedge \\ &swrlb{:}lessThanOrEqual(?bmi,22.9) \;\text{->}\; hasBMICategory(?p,\text{"Normal"})\end{aligned}$$

- BMR Calculation:
  Rule to calculate the BMR by patient gender, age, weight, and height.

$$\begin{aligned}&Patient(?p) \wedge hasGender(?p,\text{"Pria"}) \wedge hasAge(?p,?a) \wedge hasWeight(?p,?w) \wedge \\ &hasHeight(?p,?h) \wedge swrlb{:}multiply(?wFactor,?w,10.0) \wedge \\ &swrlb{:}multiply(?hFactor,?h,6.25) \wedge swrlb{:}multiply(?aFactor,?a,5.0) \wedge \\ &swrlb{:}add(?bmrStep1,?wFactor,?hFactor) \wedge \\ &swrlb{:}subtract(?bmrStep2,?bmrStep1,?aFactor) \wedge \\ &swrlb{:}add(?bmr,?bmrStep2,5) \;\text{->}\; hasBMR(?p,?bmr)\end{aligned}$$

- Calculation of Daily Calorie Needs:
  Physical activity level-based assessment of daily calorie requirement.

```
Patient(?p) ^ hasActivityLevel(?p, "Aktif") ^ hasBMR(?p, ?bmr) ^
swrlb:multiply(?calorieNeed, ?bmr, 1.55) ->
hasCalorieNeed(?p, ?calorieNeed)
```

- Cholesterol Consumption Limit
  Limitation put up for patients, not to exceed 200 mg/day cholesterol intake.

```
Patient(?p) ^ hasCholesterolLevel(?p, ?cholesterol) ^
swrlb:greaterThan(?cholesterol, 200) ^ Food(?f) ^
hasCholesterol(?f, ?foodCholesterol) ^ swrlb:greaterThan(?foodCholesterol, 200)
-> ex:avoidedBy(?f, ?p)
```

The meal suggestion distribution is based on the individual's daily calorie needs: 30% for breakfast, 50% for lunch, and 20% for dinner. Suggested menu items will be kept in their respective properties based on how to get suggestions from the full menu. Here is an example of calculating breakfast suggestions.

- Per Day Calorie Distribution:
  Split daily calorie needs into various meal timings.

```
Patient(?p) ^ hasCalorieNeed(?p, ?calorieNeed) ^
swrlb:multiply(?breakfastCalorie, ?calorieNeed, 0.30) ->
hasBreakfastCalorie(?p, ?breakfastCalorie)
```

- Recommended Menu:
  Suggests food items according to the calorie requirement.

```
Patient(?p) ^ hasBreakfastCalorie(?p, ?breakfastCalorie) ^
Food(?f) ^ hasNutrientCalorie(?f, ?calorie) ^
swrlb:lessThanOrEqual(?calorie, ?breakfastCalorie) ->
hasBreakfastRecommendation(?p, ?f)
```

IV. Experimental Result

The evaluation procedure for the food recommender system involves a nutritionist who is responsible for validating the results of the system's recommendations. This validation is carried out by comparing the food menu generated by the system with the manual evaluation of nutritionists using the collected patient data. The data is then used to calculate True Positives (TP), False Positives (FP), and False Negatives (FN), which serve as the basis for calculating the Precision, Recall, and F1-Score evaluation metrics.

Validation was performed on patient data registered at Klaten Islamic General Hospital, with the criteria that patients were over 20 years old. A total of 15 patient datasets were collected and used as test samples. These datasets include information such as gender, age, weight, height, physical activity levels, and allergies.

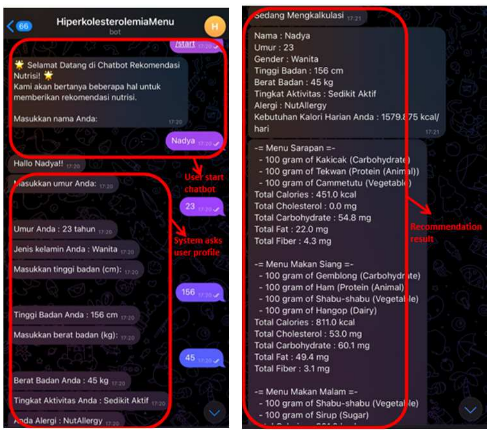

Fig. 4. Interaction between patient and chat-bot.

As shown in Fig. 4, the system generates daily food recommendations, including breakfast, lunch, and dinner. For the 15 patients involved, the system provided a total of 135 food recommendations. The evaluation results are as follows:

- True Positives (TP): 120 foods that match nutritionist validation.
- False Positives (FP): 15 foods that the system recommends but are not approved by nutritionists.
- False Negatives (FN): 0 foods that nutritionists recommend but are not recommended by the system.

The system's performance was evaluated using Precision, Recall, and F1-Score metrics, calculated as follows:

Precision is calculated as shown in (4):

$$Precision = \frac{TP}{TP+FP} = \frac{120}{120+15} = \frac{120}{135} = 0.889 \quad (4)$$

Recall is calculated as shown in (5):

$$Recall = \frac{TP}{TP+FN} = \frac{120}{120+0} = 1 \quad (5)$$

F1-Score, based on Precision and Recall, is calculated as shown in (6):

$$F1\_Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{0.889\times1}{0.889+1} = 94.1\% \quad (6)$$

The results show that the system performs well, with a Precision of 0.889, Recall of 1, and an F1-Score of 94.1%. This indicates that 88.9% of the recommendations are relevant, and the system successfully identifies 100% of the relevant food items. The F1-Score demonstrates a balanced performance, confirming the system's reliability. However, 15 recommendations were not approved by the nutritionists, indicating areas for improvement.

The false Positives are considered those foods suggested by the system that were not approved by the nutritionists. Based on the validation, some of the foods classified as false positives were staple foods not fit for carbohydrates. For instance, some of the suggested breakfast, lunch, or dinner menus utilized cakes as the primary source of carbohydrates. This was not appropriate because cakes tend to not keep the stomach full for a long period and are highly loaded with sugar or fat. In addition, some of the suggested foods were high in fat, such as "*nasi rames*" and dishes containing coconut milk, which is not suitable for patients with hypercholesterolemia. These may be due to possible weaknesses in the ontology. Their information concerning nutritional values such as saturated fat, unsaturated fat, and trans fat may be lacking in some of these foods, which then made the system fail in recognizing high-fat foods as "invalid" recommendations. These might be due to possible weaknesses in the ontology. If such weaknesses are improved in the ontology, these types of false positives may decrease, and thus improve the overall accuracy of the system.

These results suggest that the system is effective in managing hypercholesterolemia, with high Precision and Recall providing confidence in its ability to generate relevant and accurate recommendations. Future developments should focus on enhancing the ontology, incorporating real-time data, and refining the system based on patient feedback to increase recommendation accuracy and reduce unapproved suggestions.

V. Conclusions

This research successfully developed a personalized nutrition recommender system for hypercholesterolemia patients using ontology technology and Semantic Web Rule Language (SWRL). Integrated with a Telegram chat-bot interface, the system effectively provides tailored food recommendations based on individual patient profiles, preferences, and dietary restrictions. The evaluation demonstrated strong performance, achieving a precision of 88.9%, recall of 100%, and an F1-Score of 94.1%, highlighting its capability in delivering accurate recommendations and promoting user engagement through interactive updates.

Despite the strong performance, there are still opportunities for further improvement. Expanding the dataset to include a broader range of food types, cultural preferences, and additional nutritional needs would enhance the system's applicability to a more diverse population. Incorporating real-time patient feedback through the chat-bot would allow the system to adapt dynamically to changes in patient conditions, further personalizing recommendations.

Future work will also focus on scalability by utilizing cloud infrastructure and parallel processing methods to efficiently handle a larger user base without sacrificing performance. Additionally, the system has potential applications in managing other chronic conditions such as diabetes, hypertension, and obesity by adapting the dataset and inference rules accordingly.

In conclusion, these improvements will significantly enhance the system's efficiency, responsiveness, and applicability, increasing its effectiveness in managing hypercholesterolemia and other chronic diseases.

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