Ontology-Based Food Menu Recommender System for Patients with Coronary Heart Disease

Najla Nur Adila[1), Z. K. A Baizal[2)*]
[1)2)]School of computing, Telkom University Bandung, Indonesia
[1)]najlanuradila@student.telkomuniversity.ac.id, [2)]baizal@telkomuniversity.ac.id

Abstract: Coronary heart disease is one of the leading causes of death. Knowledge of dietary patterns and proper food selection is an effort to address the risk and support coronary heart disease's healing process. Therefore, this study developed a food menu recommender system as a reference for patients with coronary heart disease. The recommender system is crucial in creating a proper dietary pattern for managing personalized meal plans. The system calculates the required nutritional needs of users. Ontology is used to represent knowledge about nutrition data and food intake. The ontology base with Semantic Web Rule Language (SWRL) enables the system to identify the most suitable foods for patients with coronary heart disease. We use SWRL rules to generate recommendation conclusions based on the existing ontology. Using this language enhances the descriptive logic capabilities, as the rules can overcome the limitations of the ontology language. Therefore, the system is built to find food menu options that match the required nutrition for patients. The nutritionist knowledge will be used to measure the system's performance compared to the recommendations made by nutritionists. From the user data sample, 150 recommended food menu data were obtained. The validation performance results obtained a precision 0.893, recall 1, and F_Score 94.3%.

Keywords: recommender system; coronary heart disease; ontology; Semantic Web Rule Language; chatbot

INTRODUCTION

Lifestyle changes have led to shifts in societal behaviour, ultimately resulting in a transition of disease patterns from infectious to chronic conditions. One of the chronic illnesses currently faced by the community is cardiovascular disease. Cardiovascular disease is a leading cause of death globally (Mozaffarian, 2017). It encompasses coronary heart disease and stroke, which accounted for 17.8 million deaths in 2017, representing about one-third of all fatalities (Kaptoge et al., 2019). Many cardiovascular diseases, especially coronary heart disease, have behaviors such as unhealthy eating patterns, unbalanced nutrition in food, obesity, lack of physical activity, smoking, and alcohol consumption, which can cause increased behavioral risk factors. (Anderson et al., 2017).

Health factors such as cholesterol levels and blood pressure also play an important role in influencing cardiovascular health. There is evidence of the benefits of a healthy diet for various cardiovascular health outcomes and other diseases, by the US Dietary Guidelines Advisory Committee. They state that a healthy diet is dominated by consuming vegetables, fruits, low-fat or non-fat dairy products, whole grains, and nuts (Tsao et al., 2022). Unhealthy eating patterns such as consuming too much red meat and its processed products and consuming foods and drinks with high sugar, high salt, and low vegetable intake will increase the risk of coronary heart disease (Benjamin et al., 2018). Patients with higher health knowledge will find it easier to face lifestyle and dietary challenges with a more confident attitude (Tian et al., 2019). However, patients with a lower level of health knowledge need easily accessible sources of information to understand the proper lifestyle and diet. Therefore, we need a recommender system for selecting food menus to help determine the proper diet for patients with coronary heart disease.

In previous research, it was proven that ontology has an important role as a means of representing knowledge in recommender systems. The results also show that combining ontology knowledge in the recommendation process can improve results that are more accurate and efficient, as well as help overcome weaknesses that often

*name of corresponding author

occur in conventional recommender systems, such as data limitations and cold-start problems. Recommendation systems that adopt ontology are recommendation systems that depend on aspects of knowledge, where ontologies represent knowledge about items and users while providing recommendations (Tarus et al., 2018). In addition, the performance evaluation of the dietary recommendation system using the ontology of each individual was compared with the recommendations provided by health advisors, achieving an average accuracy of 87% (Mckensy-Sambola et al., 2021). (Aditya et al., 2023) used ontology with SWRL in developing a recommender system creating food recommendations based on what users like in helping users implement appropriate healthy eating patterns.

In this study, we developed a recommender system based on ontology and SWRL using the Telegram chatbot for patients with coronary heart disease to make it easier for sufferers to determine the appropriate food menu and water requirements. The developed system can determine the amount, type, and time of consumption based on nutritionist advice. This system can also provide information regarding the daily calories needed per meal and the amount of water consumption the user requires.

LITERATURE REVIEW

(Toledo et al., 2019) states that an unhealthy diet causes early heart disease, diabetes, cancer, and others. Therefore, a food recommender system model was developed in this context, incorporating nutritional information and user preferences. The researchers provided advice regarding dietary intake adjusted for individual profile data. The method involves optimization-based stages and multi-criteria decision analysis at the pre-filtering stage to produce food recommendations that match the user's daily nutritional needs.

Using ontologies in recommender systems allows for modeling recipes, ingredients, and diet classifications to help obese patients. The results of the ontology-based dietary system recommendations are compared with the advice given by health advisors resulting in an average accuracy rate of 87%. In addition, researchers also utilize semantic technology to provide precise and accurate information regarding allergies in obese patients. Research conducted by (Mckensy-Sambola et al., 2021) applies semantic rules and ontology to the recommendation-making menu. This process involves several measurements, such as user's weight, height, and BMI level. Using this approach, the system can identify the diet that best suits the user's preferences and compiles a list of recipes so that their ingredients and nutritional values are within the recommended dietary limits.

(El Massari et al., 2022) implemented a decision tree algorithm to differentiate patients with cardiovascular disease from those without cardiovascular disease using specific patterns and rules. In this study, SWRL enters the identified regulations so that the ontology has relevant information about the patient's condition.

(Calvaresi et al., 2021) chatbots developed using intelligent agents allow users to integrate and improve diets effectively. This chatbot can also record the user's weight regularly and provide evaluation statistics and visualization data collected to provide real-time feedback to the user. According to (Gupta et al., 2021), chatbots have a positive value in providing diagnostic support with just a button. In addition, chatbots offer the advantage of cost-efficiency aspects for usage. Test results (Casas et al., 2018), 82% of users who were used as system tests felt that the Rupert chatbot could help users think and identify the proper diet. According to (Palanica et al., 2019), 54 out of 100 doctors (54%) believe that chatbots have a role that can help improve nutritional quality and improve diet.

METHOD

Several studies have used ontology as a representation of knowledge, SWRL is used as specific rules or patterns to get recommendations, and chatbots are used as a system display that can provide direct feedback to users. Based on research (Mckensy-Sambola et al., 2021), we contributed to developing a food recommender system for people with coronary heart disease by representing ontology and SWRL using a telegram chatbot. Hence, users get direct feedback, and we added a water intake recommendation feature for minerals needed by each individual.

The system built aims to find food menu choices that are by the nutrients needed by patients with coronary heart disease. At first, the user enters the patient's data. The personal data includes weight, height, age, gender, and level of physical activity. Then, the data will be used by the system to understand the patient's health condition. Furthermore, the system will provide recommendations in the form of a list of food menus by the daily nutrition needed by the patient.

The knowledge ontology contains information regarding patient profiles, *Body Mass Index* (BMI), and a list of available food menus. Existing knowledge will be implemented into a logical rule with a specific pattern the computer can understand. Knowledge of the ontology with the semantic rules used will be a helpful suggestion for the user. The following will summarize the main study topics agreed upon during system development.

*name of corresponding author

Ontology Knowledge

Using ontology to represent food intake data aims to clearly define the relationship between nutritional data (food composition) and patient needs. This study uses ontology as a knowledge base for food intake data for patients with certain diseases to obtain nutrition according to user preferences. To provide appropriate food recommendations, the system we build considers several elements, including activity level, gender, age, height, and weight of the individual.

Over the last few years, the application of ontology has increased along with the advancement of Semantic Web technology. Given the amount of information available, ontology is very important to categorize each piece. This categorization process aims to help machines understand information and facilitate information search (Noy et al., 2001).

The total daily calorie requirement is determined using the BMR multiplied by the *Activity Factor* (AF) formula. BMR (*Basal Metabolic Rate*) is the amount of energy or calories needed by the body to maintain basic body functions in a state of complete rest, such as breathing, heart beating, internal organ function, and maintaining a stable body temperature. BMR is measured in the number of calories needed per day, and each individual will have a different number because several factors, including age, weight, height, body composition, and level of physical activity, influence it. BMR calculations for men and women differ (Harris & Benedict, 1918). The following is a BMR calculation using the Harris-Benedict formula.

$$\text{BMR}_{male} = \left(13.7 \ \times \text{Weight}_{(kg)}\right) + \left(5.0 \ \times \text{Height}_{(cm)}\right) - (6.8 \ \times \text{Age}) + 66 \tag{1}$$

$$\text{BMR}_{female} = \left(9.6 \ \times \text{Weight}_{(kg)}\right) + \left(1.8 \ \times \text{Height}_{(cm)}\right) - (4.7 \ \times \text{Age}) + 665 \tag{2}$$

Calculating a user's daily calorie needs involves using *Body Mass Index* (BMI), *Basal Metabolic Rate* (BMR), and data related to daily activity level. BMI is used to assess the user's weight status, while the user's activity level is a supporting factor in determining daily caloric needs (Harris & Benedict, 1918).

Table 1 BMI Classification

BMI	Weight Status
<18.5	Underweight
18.5-22.9	Normal
23-24.9	Overweight
25-29.9	Obesity I
>30	Obesity II

BMI category (Table 1) shows body weight based on the user's *Body Mass Index* (BMI) value.

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

Rule of SWRL

To get the right diet for people with coronary heart disease, it is important to thoroughly understand the right diet and nutrition according to their needs. Besides consulting nutritionists, we have also taken existing data and information from publicly accessible documents and websites with a trusted reputation. However, for knowledgeable and time-constrained users, sifting through all of the available information that is currently easily accessible and determining what information is relevant to their situation can be difficult. Therefore, based on our research, we have developed general recommendations to provide an appropriate diet and nutrition for coronary heart disease patients. SWRL is a W3C standard for ontology-based production rules. Conclusions from recommendations can be obtained with the use of SWRL rules. Rules compiled to get appropriate food recommendations, including daily calorie rules, BMI categories, and food recommendations.

*name of corresponding author

System Flow

In this study, we created a chatbot that can be used to interact with users through the Telegram platform, which can be accessed from various devices and anywhere. Users and systems can be able to interact through the chatbot interface on the Telegram platform. Users can enter their data, such as weight, height, age, gender, and activity level, which will then be sent as a query to the handler. Based on this query, the system will generate suggestions using ontology-based SWRL. After that, the results of existing suggestions will appear on the chatbot interface. You can see a visual representation of this process in Figure 1 for more details.
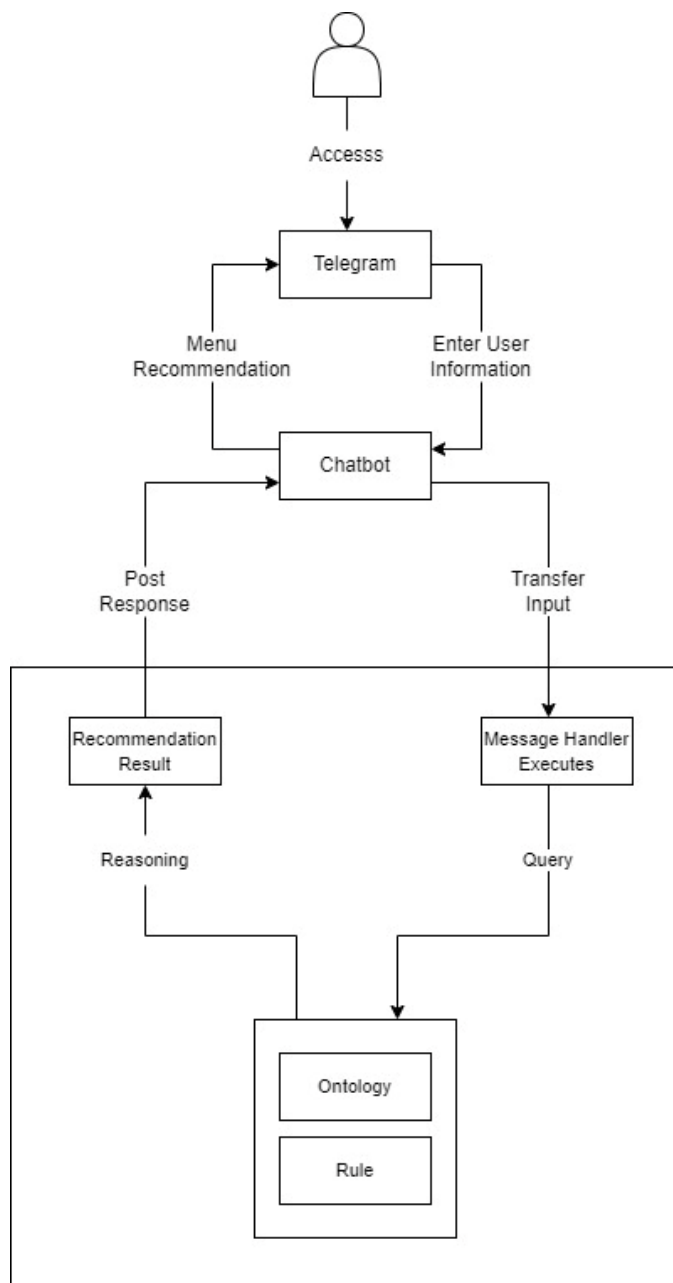
Fig. 1 Chatbot System Flow

Implementation of Ontology and SWRL

We have utilized the Protégé application in version 5.6.1 to create the ontology. We have a design ontology in Figure composed of 3 main classes: *Person*, *BMI Level*, and *Menu*. Classification of users based on BMI is included in *BMI Level* Class. There are four levels of users, namely Normal, Underweight, Overweight, and Obesity. *Person* class is used to store user information. Information regarding individual meals is entered into the *Menu* Class.
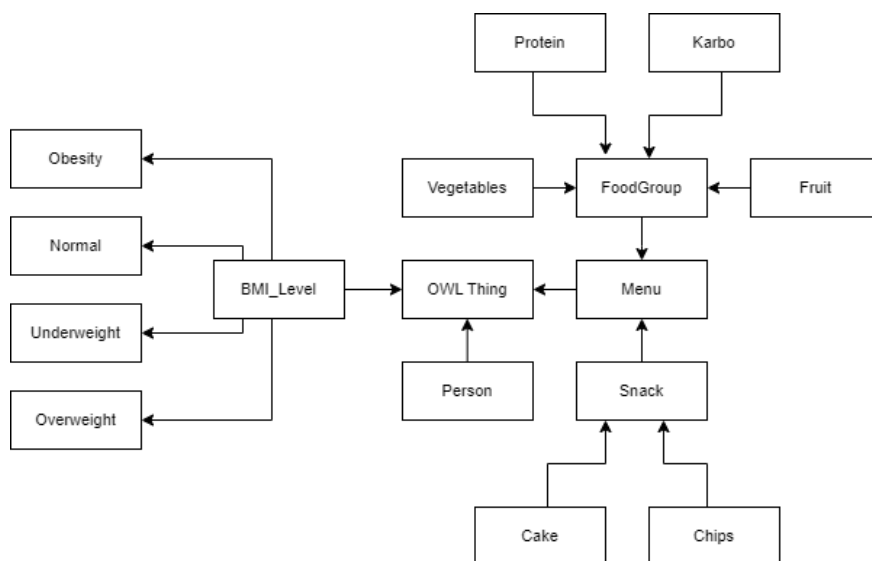
*name of corresponding author

Fig. 2 Ontology Class Design

Data properties and object properties are used in creating Ontology, as shown in Figure 2. Data properties provide values and store attributes about entities or individuals in an ontology. In contrast, property objects describe the relationship between two entities or classes in an ontology.
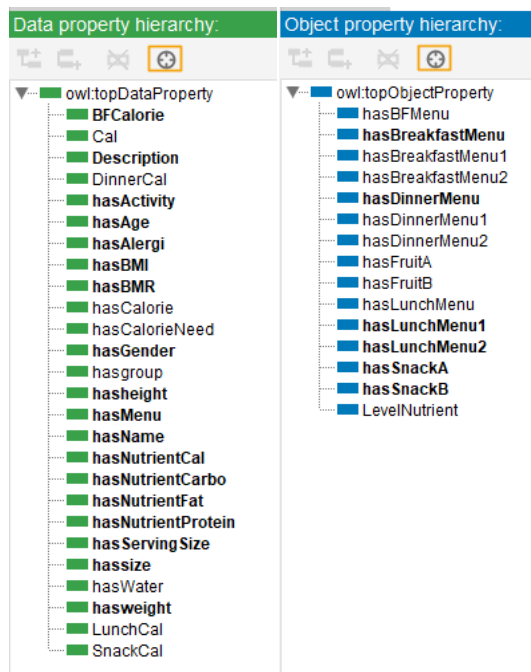

Fig. 3 Data Properties and Object Properties

Several SWRL rules are made to get food recommendations according to user preferences.
- hasBMI: a property that stores BMI calculation results. In this study, there are four categories, namely normal, underweight, overweight, and obesity.
  patient(?p), hasHeight(?p, ?t), hasWeight(?p, ?b), multiply(?tb, ?b, 10000), multiply(?m, ?t, ?t), divide(?bmi, ?tb, ?m) -> hasBMI(?p, ?bmi)

*name of corresponding author

- hasCalorieNeed: a property that stores the required calorie calculation data based on BMR and physical activity. The following is an example of calculating calories for women with moderate activity levels.
  patient(?p), hasGender(?p, "Wanita"), hasActivity(?p, "Moderate"), hasBMR(?p, ?hasBMR), multiply(?k, ?hasBMR, 1.70) -> hasCalorieNeed(?p, ?k)

- hasWater: a property to store each individual's recommended amount of mineral water intake.
  patient(?p), hasWeight(?p, ?b), multiply(?wt, ?b, 30), divide(?water, ?wt, 1000) -> hasWater(?p, ?water)

- Menu recommendation
  The distribution of food recommendations is based on the calorie needs of each individual, with a percentage of 25% for breakfast, 25% for lunch, 20% for dinner, 15% for snacks during the day, and 15% for snacks in the afternoon. The recommended menu items will be stored in their individual properties according to the rules to get recommendations from the entire menu item. The following is an example of calculating breakfast recommendations for normal-weight individuals.
  patient(?p), normal(?p), Karbo(?n), hasNutrientCaloriel(?n, ?nc), add(?tc, ?nc, ?nc1) , subtract(?bba, ?c, ?pcf1), Vegetables(?f2) , roundHalfToEven(?pf1, ?bba), greaterThan(?tcf, ?pf1), greaterThan(?pf, ?tcf), hasNutrientCalorie(?f1, ?nc1), hasNutrientCalorie(?f2, ?nc2), add(?tc1, ?tc, ?nc2), BFCalorie(?p, ?c), roundHalfToEven(?tcf, ?tc1), multiply(?pcf1, ?c, 0.005), Protein(?f1), add(?ba, ?pcf1, ?c), roundHalfToEven(?pf, ?ba) -> hasBreakfast(?p, ?n), hasBreakfast(?f, ?f1) , hasBreakfast(?f1, ?f2)

The recommendation system is able to generate a list of menu recommendations based on the data entered by the user. The chatbot development process uses Python, and the available Telegram API connects the program to Telegram. The system receives input from user data, such as the user's gender, height, weight, age, and activity level. The system recommends food menus and consumption of mineral water, including information about the nutrients in each food menu. For more details, Figure 4 describes user interaction flow with chatbot.
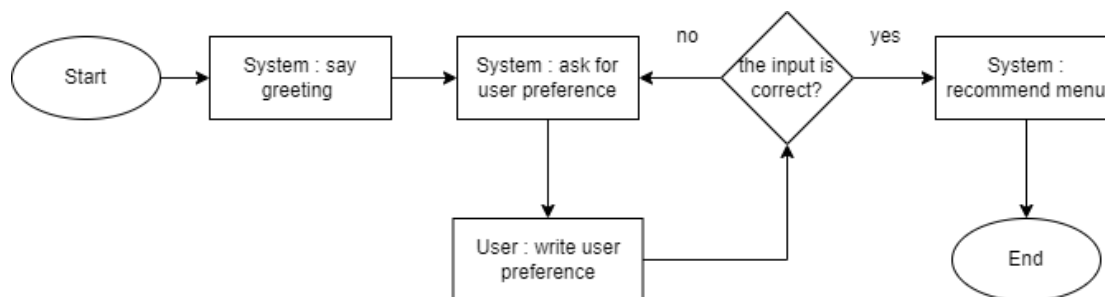

Fig. 4 User interaction with chatbot

RESULT

The testing process on food recommendations involves a nutritionist. Nutritionists validate food from the results of our recommender system in Sheets. Nutritionist validation results are used to obtain true positive, false positive, and false negative values. Based on this value, precision, recall, and *F_Score* calculations can be performed to see the accuracy of the recommended results.

The validation process was obtained from information on heart disease patients recorded at Bhayangkara TK Hospital. II Sartika Asih Bandung, and the patient is over 20 years old. A total of 30 sample user data were successfully collected for this purpose. The data samples tested consisted of name, gender, age, weight, height, and level of physical activity. Then the user data will be processed in the chatbot to produce food recommendations. Food recommendations include breakfast, lunch, dinner, and two snacks. This results in 150 food recommendation samples. Of the 134 food samples that several nutritionists approved, there were 16 that nutritionists did not approve.
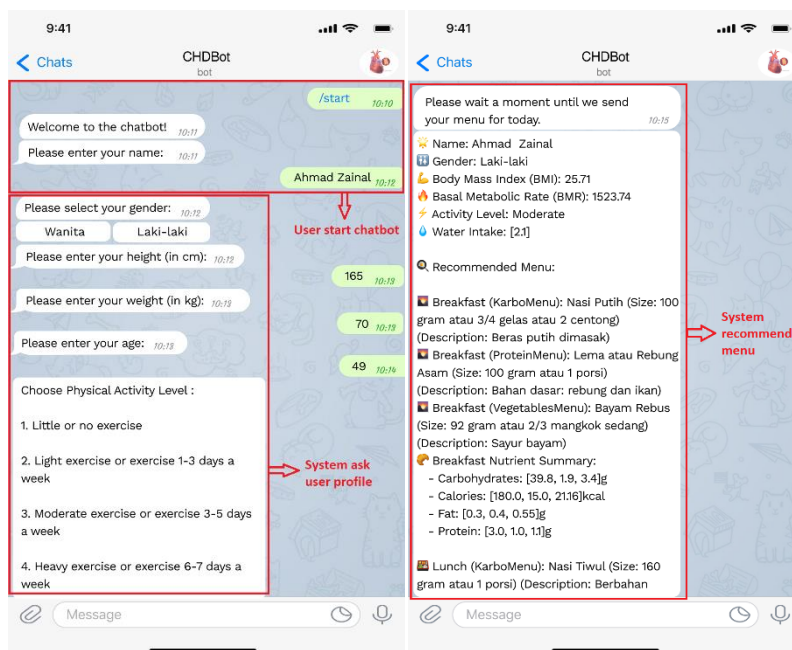
*name of corresponding author

Fig. 5 Interaction user and the chatbot Telegram

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{134}{134 + 16} = 0.893 \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{134}{134 + 0} = 1 \tag{5}$$

True Positive (TP) is a food recommendation by a nutritionist. *False Positive* (FP) is a food recommendation by the system except by nutritionists. *False Negative* (FN) results from food recommendations not supported by the system and nutritionists.

Precision is used as a metric to measure the efficiency of a system in identifying information, while recall measures the ability of the system to retrieve relevant documents from all available documents accurately. An indication of good quality is if the precision and recall values are close to 1. This means the system can recognize the most relevant documents, with only a few data incorrectly identified as relevant.

The results of recall and precision calculations are used to obtain the *F_Score*. The *F_Score* is the average value of the recall and precision calculation results. Calculation of the *F_Score* can be calculated using the formula below:

$$F\_Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{0.89333 \times 1}{0.89333 + 1} = 94.3\% \tag{6}$$

The results of comparing the average recall and precision values are listed in the *F_Score*. The level of accuracy of the *F_Score* shows a presentation that is close to 100%.

DISCUSSIONS

In this study, we designed an ontology using protégé version 6.5.1. We use the SWRL rules in the SWRLTab protégé to make inferences and state some of the logical rules used in the ontology that we have created. We built a system using the Python-based Telegram chatbot. This chatbot will interact with users through the Telegram platform. To verify the optimal performance of our chatbot, we ask questions to experts in the field and test the system using predefined questions. The validation process by experts provides valuable feedback to us, helping to increase the effectiveness of our ontology, SWRL rules, and chatbot implementations. As a result, after combining several methodologies, data, tools, and suggestions from experts in the field, the knowledge-based system we have developed has managed to get accurate and validated results.

*name of corresponding author

Limitations of this study involve restrictions on user profiles, and it should be noted that chatbots can only be used for patients with coronary heart disease and cannot be used in other cases. In addition, user allergies to certain foods have not been considered in this study.

CONCLUSION

We discuss our research on dietary recommendations, especially for patients with coronary heart disease. Based on the tests, the system has succeeded in providing food recommendations consisting of breakfast, lunch, dinner, and two snacks for lunch and evening. This recommender system can use an ontology basis to provide users with recommendations according to their profiles. Validation by nutritionists resulted in 134 menus that were accepted and 16 that were not recommended. According to the evaluation, the accuracy obtained by the system is 0.893 precision, recall of 1, and F_Score of 94.3%. From the results obtained, a food menu recommender system for patients with coronary heart disease can be proposed to assist users in implementing the right diet.

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