DiabeticFoodBot: Food and Water Intake Recommender System for Diabetics

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Keywords: Food and Water Intake, System for Diabetics.

Abstract: Diabetes is a non-communicable disease which is one of the highest causes of death in the world. Diabetics need to arrange the schedule, amount and type of food and water consumed every day from a nutritionist to regulate blood sugar levels so that complications do not occur. A recommender system for food and water intake that has been validated by nutritionists is needed to assist diabetics in determining the nutrients consume. In this study we develop Artificial Intelligence (AI) telegram chatbot called as DiabeticFoodBot. This system can provide food recommendations and water intake for diabetics. There are many previous works that developed recommender systems for diabetics. However, this study has not considered the amount of water intake for diabetics. In addition, our research uses household size in presenting the results of recommendations to make it easier for users to determine serving sizes without using a scale. We develop our system using ontologies with Semantic Web Rule Language (SWRL) because they are considered capable of providing better performance. The DiabeticFoodBot validation result of 94.7 percent shows that our system can provide good recommendation results for users.

1 INTRODUCTION

Diabetes is a non-communicable disease that causes 1.5 million deaths every year and affects 422 million people worldwide. Most of people with diabetes live in low to middle income countries (W.H.O., 2022). In Indonesia, the highest mortality from chronic disease is caused by diabetes mellitus (Office, 2022). Diabetes is divided into four types, including IDDM (Insuline Dependent Diabetes Mellitus) or type 1 diabetes caused by autoimmune Langerhans beta cell damage, NIDDM (Non Insuline Dependent Diabetes Mellitus) or type 2 diabetes caused by relative failure of Langerhans beta cells and resistance insulin, gestational diabetes occurring during pregnancy, and specific diabetes (Rahman et al., 2018; Hardianto, 2020). Diabetes can strike anyone regardless of age or race. and more common in obese people. Diabetes can cause complications in the heart, nerves, kidneys and eyes (Ministry, 2013).

To help control the blood sugar and minimize complications, diabetics must maintain the amount, type, and schedule of meals every day (Jahidin, 2019). Face-to-face consultation with a nutritionist is needed to get food recommendations that is suitable for diabetics is not possible to do every day. Although now telemedicine has developed which can help diabetics get consultation with a nutritionist online, this is not effective and efficient if done every day and costs a lot (Simatupang, 2020). Therefore, diabetics need to develop a food recommender system that has been validated by a nutritionist and can provide recommendations automatically to manage their daily meal menu.

We found a lot of research that built a food recommender system for diabetics. However, these studies have not considered the water intake for diabetics. Even though we found research in India that applied hydrotherapy as a therapy to regulate blood sugar for diabetics. Water is also a medium for delivering nutrients and other substances into the body's cells and removing toxic substances so that the water consumed will affect the patient's blood sugar (Lim et al., 2011). Therefore, we are considering building a recommender system that also regulates the amount of water intake of users.

Ontology is used as a knowledge domain to represent various types of food and the amount of mineral water served for users. The Semantic Web Rule Language (SWRL) search method is an option in inducing food menus and mineral water intake to users because it can provide more expressiveness compared to using a relational database which cannot produce

Firmansyah, I., Baizal, Z. and Dharayani, R.
DiabeticFoodBot: Food and Water Intake Recommender System for Diabetics.
DOI: 10.5220/0012639000003848

In *Proceedings of the 3rd International Conference on Advanced Information Scientific Development (ICAISD 2023)*, pages 314-320
ISBN: 978-989-758-678-1

output if the data sought is not found. Several studies have also used ontology and SWRL to recommend food menus (Cahn, 2017).

There is study that uses conversational systems to interact with users. However, the flexibility in conversional systems that use chatbots is better, so it needs to be considered (Baizal et al., 2020). Chatbots have the ability to interact with users without the need for a third person to provide feedback by utilizing Artificial Intelligence (AI). Chatbot through Telegram social media is used to make it easier for users to interact with the system through applications that are worldwide and familiar to users and can be downloaded for free on their smartphones (Editor, 2019; Arjun and Baizal, 2022; Nurani et al., 2022). Based on the problems discussed in this study, we developed DiabeticFoodBot using the Telegram Chatbot based ontology and SWRL. This system was developed to make it easier for diabetics to determine the amount, type and time of food consumption based on the validation results of nutritionists. This recommender system provides information regarding the amount of water consumption required by the user. Our research also uses matrix unit serving sizes and household measurements in presenting recommendations to make it easier for users to determine food portions.

1.1 Related Work

Several researchers have conducted study related to determining the diet for diabetics. The goal of their study is to automatically provide dietary recommendations for diabetics using ontology. At the testing stage, the researchers collected data from diabetics. The data obtained is used as a query object. The results displayed are in the form of a food menu arrangement with units of calories or weight units in grams (Mckensy-Sambola et al., 2021; Arwan et al., 2013; Farman Ali et al., 2017; Rachman and Nurjannah, 2019).

Research using ontology design has problems in displaying results that must be in accordance with the database. If the database does not contain the information the user wants, then the recommender system cannot display the results. This problem is answered in a research article that optimizes the recommender system application using SWRL. SWRL is still able to provide the information the user wants if similar results are not found in the database by reviewing the available database similarities. The results of the accuracy of these studies can still be improved (Baizal et al., 2020; Nurani et al., 2022; Arwan et al., 2013).

The use of chatbots in a food recommender system for diabetics has also been used in Thailand and has received a positive response to the user experience due to its attractive appearance, easy use, fast performance, and clear content. However, this research only uses the Google Sheet system as a database (Thongyoo et al., 2020). The use of Google Sheets as a database has drawbacks such as error-prone in data input, slow loading speed, limited data types that can be stored, limited number of record storage, less structured, and less speed in searching for data (Weir et al., 2010). The use of chatbots with SWRL analysis on telegrams is also used in film recommender systems, but does not apply ontologies (Nurani et al., 2022).

Based on previous research studies, the development of a food recommender system for diabetics can be optimized by representing ontology and SWRL using a telegram chatbot. The addition of a mineral water intake recommendation feature was also added in this study to maximize the user's blood sugar control.

1.2 Related Theory

The total daily calorie requirement is determined using the Basal Metabolic Rate (BMR) formula multiplied by the Activity Factor (AF) in daily activity. BMR is the calories needed by the body to perform basic functions (Sihombing, 2017; Harris and Benedict, 1918).

$$\begin{aligned} Male\ BMR = 88,362 + (13,397 weight\,[kg]) + \\ (4,799\ x\ height\,[cm]) - \\ (5,677\ x\ age\,[years] \end{aligned} \tag{1}$$

$$\begin{aligned} Female\ BMR = 447,593 + (9,247 weight\,[kg]) + \\ ((3,098\ x\ height\,[cm]) - \\ (4,330\ x\ age\,[years] \end{aligned} \tag{2}$$

The user's daily caloric needs are calculated using the Body Mass Index (BMI), Basal Metabolic Rate (BMR), and input data regarding the user's daily activity intensity. BMI is used to interpret the user's weight status. While the user's activity intensity is used as a supporting factor to determine daily caloric needs (Harris and Benedict, 1918).

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

BMI interpretation Table is used to determine the user's weight status (Indonesia, 2018).

Users' daily activity intensity Table 2 is little or no exercise, light, moderate, and vigorous exercise (Mawartika and Guntur, 2021).

Table 1: Body mass index.

BMI	Weight Status
< 18.5	Underweight
18.5-22.9	Normal (Ideal)
23-24.9	overweight (Overweight)
25-29,9	Obesity I
> 30	Obesity II

Table 2: Daily activity and activity Factor.

Daily Activity	Activity Factor (AF)	
	Man	Woman
Little or no exercise (Only light daily activities)	1.30	1.30
Light exercise (1-3 days a week or light daily activities)	1.56	1.55
Moderate exercise (3-5 days a week or moderate daily activity)	1.76	1.70
Vigorous exercise (6-7 days a week or doing strenuous daily activities)	2,10	2.00

The recommended formula for daily calorie needs uses:

$$Daily\ Calories = BMR\ x\ AF \pm Calories\ BMI \quad (4)$$

BMI calories for the normal level are increased by 0 calories, the underweight level is increased by 500 calories, the overweight level is reduced by 300 calories, and the obese levels 1 and 2 are reduced by 500 calories. This calculation is used to improve the accuracy of the calculation based on the intensity of the activities carried out and considering the user's BMI level.

The calculation of the mineral water intake needed by the user is (Gunardi, 2022):

$$Water\ Intake = \frac{Weight(kg)x30}{1000} \quad (5)$$

The unit used in this calculation is liters. Calculation of daily nutritional needs is obtained through the formula Percent Daily Value.

$$\%DV = \frac{NutritiononFood(g)}{Daily\ Value}x100 \quad (6)$$

The author uses the FDA-approved 2022 Daily value Table 3 to calculate the user's daily requirement (F.D.A., 2020).

Meal portions each day are divided into 25% of daily calories for breakfast, 25% of daily calories for lunch, 20% of daily calories for dinner, and 30% of daily calories for snacks according to what has been agreed upon by a nutritionist.

Table 3: Daily value.

Nutrition	Daily Values
Carbohydrate	300g
Proteins	50g
Fat	78g

2 METHODOLOGY

2.1 System flow

In this research, we developed a chatbot on the Telegram platform that can be accessed by users via laptops, mobile phones or computers. The system receives input from the user in the form of user information such as height, weight, daily activity, age, gender, and user's allergy history. This information is sent to the handler to be changed in the form of a query. Based on this query, the system performs reasoning on system knowledge (Ontology and SWRL Rules) to be able to provide recommendations. The recommendation results are sent to the user via the chatbot interface. This flow is shown in Figure 1.

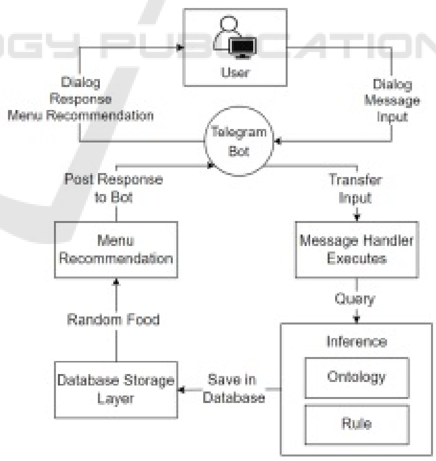

Figure 1: Chatbot system flow.

2.2 System development

2.2.1 Knowledge development (Ontology and SWRL)

There are four main classes that will be applied to the ontology design. The main class is BMI, User, Allergy, and Menu. The main ontology shown in Figure 2.

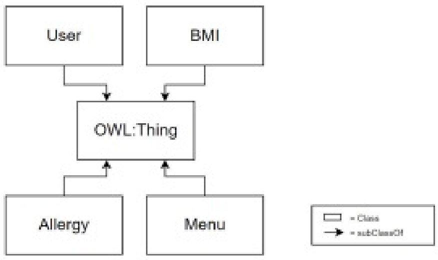

Figure 2: Chatbot system flow.

BMI class hierarchy is classification based on calculated values from user input using height and weight as parameters. The subclasses of the BMI class are obesityI, obesityII, overweight, normal and underweight Figure 3.

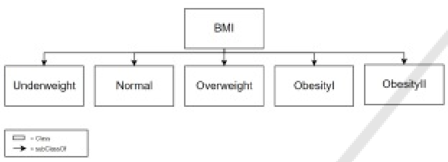

Figure 3: The hierarchy of BMI class.

The User class stores user characteristic information. Meanwhile, the Menu Class stores information regarding the types of drinks and food. The subclasses of the Menu class are Drink, Snack, and Food. The Food subclass stores data about fruits, carbohydrates, proteins, and vegetables Figure 4.

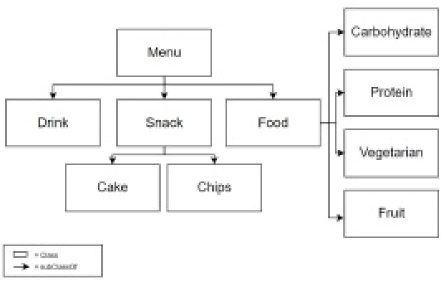

Figure 4: The hierarchy of Menu class.

The snack subclass stores data about snack such as chips and cake. The Allergy class will store the various types of allergies considered such as, nuts, diary, oats, chicken, and seafood. Rule development is adjusted to the calculation of the necessary needs. An example of this calculation is the determination of BMI and BMR values.

2.2.2 Information Retrieval

Information retrieval is the initial stage to obtain information from users. This process is carried out by requesting data input from the user in the form of functional requirements that act as properties in the class, including information about the user's height, weight, daily activity, age, gender, and allergy history, which is stored in the User Class.

2.2.3 Knowledge Validation

The validation process in this study was carried out by nutritionists. Nutritionists validate datasets for ontology development. They also validate SWRL.

3 RESULTS

3.1 Implementation of Ontology and SWRL

We use protégé version 5.5.0 for composing the ontology. We use the top-down (tree) technique which is defined by forming classes, continuing into subclasses and ending with instances. The hierarchy of class is shown in Figure 5.

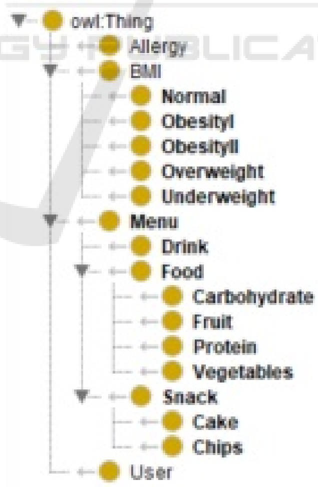

Figure 5: The hierarchy of class in ontology.

Each class in the ontology has a data property. This Data Property serves to complete the information of each class. In addition to data properties, object properties are also defined to link between instances of each class through semantic relations. Figure 6 shows the data properties and object properties that are used to create hierarchies and conceptual relationships between instances.

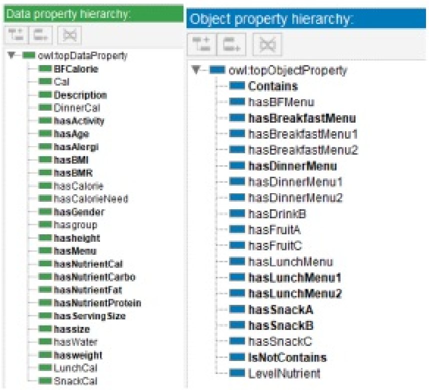

Figure 6: Data properties and object properties.

The User class has a data property:

- hasBMI: the property that store the BMI calculation result data.
  $User(?p)^{h}asweight(?p,?w)^{h}asheight(?p,?h)^{s}wrlb$: $multiply(?wh,?w,10000)^{s}wrlb$: $multiply(?hm,?h,?h)^{s}wrlb$: $divide(?bmi,?wh,?hm)->hasBMI(?p,?bmi)$
  BMI calculation will be obtained to classify user level BMI. For example, if the user's BMI is less than 18.5, it is considered underweight.
  $User(?p)^{h}asBMI(?p,?bmi)^{s}wrlb$: $greaterThan(18.5,?bmi)->underweight(?p)$
  Recommendations are given to users in the form of 5 menus (Figure 5), that are breakfast menu, morning snack, lunch, afternoon snack and dinner. The process is built using object properties as can be seen in figure 5. LevelNutrient is a property used to see whether the food is included in the appropriate nutritional category to be recommended to users based on the nutrients in the food. The calculation is obtained based on the daily value with the SWRL rule example as follows:

- High fat
  $Menu(?f)^{h}asNutrientFat(?f,?n)^{s}wrlb$: $divide(?h,?n,78)^{s}wrlb$: $multiply(?DV,?h,100)^{s}wrlb$: $greaterThanOrEqual(?DV,20)->LevelNutrient(?f,HighFats)$

- Low Carb
  $Menu(?f)^{h}asNutrientCarbo(?f,?n)^{s}wrlb$: $divide(?h,?n,300)^{s}wrlb$: $multiply(?DV,?h,100)^{s}wrlb$: $greaterThanOrEqual(5,?DV)->LevelNutrient(?f,LowCarbo)$

The Menu class has a data property:

- hasServingSize: the property that will define the food in terms of serving size measures. Described in string form.
- hasWater: property to store the recommended amount of mineral water intake. The following is the SWRL rule formula for hasWater:
  $User(?p)^{h}asweight(?p,?w)^{s}wrlb$: $multiply(?wt,?w,30)^{s}wrlb$: $divide(?water,?wt,1000)->hasWater(?p,?water)$

3.2 DiabeticFoodBot Prototype

The recommender system provides a recommendation menu according to user information. The chatbot development process is carried out using the Python language. For database development and queries, we use sqlite3. Furthermore, to connect the program to Telegram, we use the provided Telegram API. The system receives input in the form of user information, that is gender, age, activity intensity, weight, height, temporary blood sugar, diabetes symptoms, diabetes complications, and allergies. The system recommends food menus and mineral water intake, including information about nutrition and when to consume food. The conversation flow process is shown in Figure 7.

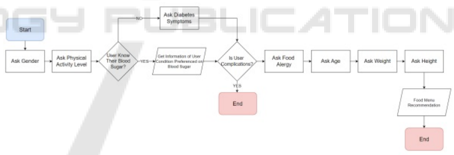

Figure 7: The hierarchy of BMI class.

The language used in this chatbot is Indonesian. An example of a chatbot conversation is shown in Figure 8.

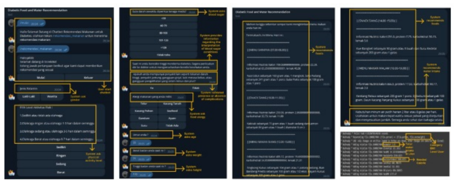

Figure 8: Interaction between user and DiabeticFoodBot on telegram.

3.3 DiabeticFoodBot Testing

There are two steps to the testing process, that is testing during training and system testing. Testing during the training process is carried out by testing the phrases on the system and checking the response system. If the answer is incorrect, then additional training testing is required. After the system development is complete, system testing is carried out. Simulation by trying to provide input in the form of user information, for example by looking at whether the BMI results are true or false based on user information. If the testing system is appropriate, the researcher continues to enter the final stage, that is testing the results of recommendations to nutritionists.

4 EXPERIMENT

The testing process of the recommendations by DiabeticFoodBot involves nutritionists. The nutritionist validates the food list from the results of our recommender system in Spreadsheet. Nutritionist validation results are used to obtain true positive, false positive, and false negative values. Based on these values, F-Score, precision, and recall calculations can be performed to see the accuracy of the recommended results.

Sample user data for the validation process were obtained from diabetics who filled out a Google form with a minimum age limit of 12 years. The number of sample user data obtained is 60 samples, but three sample cannot be included because the user is a diabetic with complications. Therefore, the total samples used for validation were 57 user samples and produced 285 samples of food recommendations and mineral water intake. Of the 285 food samples and mineral water intake approved by nutritionists, there were 31 food samples that were inappropriate.

$$Precision = \frac{TP}{TP+FP} = \frac{285}{285+31} = 0.901 \quad (7)$$

$$Recall = \frac{TP}{TP+FN} = \frac{285}{285+0} = 1 \quad (8)$$

Recall is the ability of the system to retrieve the appropriate document, while precision is used to measure the effectiveness of a system to find information. If the recall and precision values are close to 1 then the results are good.

Precision and Recall are used to obtain the F-Score, which is the average value of precision and recall. This value can be obtained by the following equation:

$$F-Score = 2x\frac{PrecisionxRecall}{Precision+Recall} = 2x\frac{0.901x1}{0.901+1} = 94.7\% \quad (9)$$

Table 4: Information of confusion matrix.

	Information
TP (True Positive)	The total results of food recommendations that are in accordance with the recommendations of nutritionists
FP (False Positive)	The total results of food recommendations that are recommended by the system but not recommended by nutritionists
FN (False Negatives)	The results of food recommendations that are not recommended by the system and not recommended by nutritionists

F-1 Score illustrates the comparison of the average precision and recall listed. The level of accuracy is shown from the F-1 Score presentation which is close to 100%.

5 CONCLUSIONS

DiabeticFoodBot is a chatbot that recommends food menus and mineral water intake for diabetics without complications. Based on the validation that has been carried out, the results obtained that the accuracy level of this chatbot is 94,7 percent so that this chatbot is able to provide food and mineral water recommendations according to the user's nutritional needs and can be used as a solution to assist users in implementing good eating and drinking patterns for sufferer diabetes.

The limitation of this research is the limit on the server and database which hinders the speed performance in displaying output results to users. In addition, researchers have also not assessed user opinions regarding the displayed chatbot features. This chatbot also cannot be used for diabetics who have certain complications because diabetics with complications have different food and mineral water intake rules, depending on the type of complications they are suffering from.

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