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Personalized Ontology-based Food Menu Recommender System for Bodybuilders using SWRL Rules

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Abstract−Bodybuilding requires precise and careful food planning to promote muscle growth and optimize body composition. However, creating personalized meal plans that meet the unique dietary needs of bodybuilders is challenging. This study introduces a customized food recommender system specifically designed for bodybuilders, addressing this problem by utilizing an ontology-based approach combined with Semantic Web Rule Language (SWRL) and a Telegram chatbot. The objective is to provide personalized nutritional guidance that aligns with individual bodybuilding goals. The system employs ontologies to represent key concepts such as user profiles, nutritional needs, and food attributes. SWRL rules generate tailored meal plans based on the user's input, which includes personal information and bodybuilding objectives submitted through the chatbot. The system was evaluated with 15 user profiles, producing 180 food recommendations. The results demonstrated high accuracy, with a precision value of 0.866, a recall value of 1, and an F-Score of 0.928. Although the system effectively delivers personalized nutritional advice, it currently lacks the ability to address specific dietary restrictions. Future work could involve incorporating a wider range of dietary considerations and enhancing the system's applicability. This study highlights the potential of semantic technologies in advancing personalized diet and fitness planning.

Keywords: Bodybuilding; Ontology-Based Recommendation; Personalized Nutrition; Semantic Web Rule Language (SWRL); Telegram Chatbot

1. INTRODUCTION

Bodybuilding is a highly specialized sport where athletes are evaluated based on the aesthetic qualities of their physique, including muscle size, definition, and proportion [1]. Achieving an optimal physique requires bodybuilders to meticulously plan their nutritional intake to support muscle growth while minimizing body fat and preserving muscle mass [2]. A well-structured nutritional plan is essential for bodybuilders to balance muscle growth with fat reduction and overall physical aesthetics. This balance is crucial not only for achieving competitive success but also for maintaining long-term health and performance in the sport.

Bodybuilders face unique nutritional challenges compared to the general population due to their elevated physical activity levels and specific muscle-building goals [3]. Physical activity encompasses a broad range of bodily movements, including work, leisure, sports, and commuting, all of which involve energy expenditure [4]. For bodybuilders, this involves more than just routine exercise; it includes intensive and structured workouts designed to maximize muscle growth and strength. Consequently, their nutritional needs are significantly different from those of less active individuals. They require a higher intake of protein, calories, and carbohydrates to support their rigorous training regimens and to optimize muscle development [5]. Failure to meet these specific nutritional needs can result in suboptimal muscle growth and impaired recovery, ultimately affecting performance and progress [6]. Bodybuilders typically require a hyper-energetic diet with a caloric surplus of 10–20% and a protein intake of 1.6–2.2 g/kg body weight per day, evenly distributed throughout the day, including pre-training and post-training periods [7]. This precise nutritional strategy is vital for effective muscle protein synthesis and repair.

For novice bodybuilders, determining the optimal nutrient intake can be particularly challenging. These individuals often lack the necessary nutritional expertise and planning skills to create a customized meal plan that aligns with their specific training and physique goals. As a result, inadequate nutritional planning can hinder their progress and muscle development [7]. This challenge underscores the need for a tailored approach to nutritional guidance that addresses the unique requirements of bodybuilders, especially those who are just beginning their fitness journeys.

Recommender systems have been increasingly utilized in various domains, including food and nutrition, to assist individuals in optimizing their dietary intake. A study by [8] developed a chatbot capable of providing personalized food recommendations based on user preferences and nutritional values. This system offers detailed information on the calorie, carbohydrate, protein, and fat content of recommended foods. However, it does not specifically address the nuanced nutritional needs of bodybuilding programs, which require more precise macronutrient considerations tailored to muscle-building goals. Research by [9] introduced a personalized food recommendation system that considers general factors such as lifestyle and dietary patterns, offering a broad range of food options tailored to dietary needs and restrictions. Similarly, [10] demonstrated the effectiveness of ontology-based recommendation engines in providing customized diet and nutrition strategies for individuals with obesity. While these advancements represent significant progress, they fall short of addressing the specific dietary needs of bodybuilders, who require targeted macronutrient strategies to effectively build muscle mass.

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To bridge this gap, this research proposes the development of an ontology-based recommendation system specifically designed for bodybuilders in Indonesia. This system will leverage Semantic Web technologies, particularly the Semantic Web Rule Language (SWRL), which facilitates sophisticated logical reasoning within OWL knowledge bases by integrating Horn-based rules [11]. Ontologies play a crucial role in formalizing collective knowledge and are fundamental to the Semantic Web [12]. SWRL enhances ontologies by enabling the specification of intricate links and constraints, as demonstrated in recent studies. For instance, [13] utilized SWRL and ontologies to offer personalized meal suggestions based on user preferences, helping users adopt healthier eating habits. Similarly, [14] employed ontologies to construct a knowledge graph for content recommendations in social networks. Another study by [15] showcased an innovative approach using ontologies and SWRL to develop an intelligent system for predicting diabetes based on decision tree models, achieving high performance in prediction tasks.

These studies highlight the adaptability and potential of SWRL and ontologies in enhancing personalized health recommendations across various domains. Building on this foundation, this research focuses on creating a personalized, ontology-based food recommendation system tailored specifically for Indonesian bodybuilders. The proposed system will use Semantic Web technologies, incorporating ontologies to model key concepts, relationships, and constraints related to nutrition, bodybuilding, and user profiles. SWRL rules will define the logic for generating personalized food recommendations based on individual nutritional needs. By utilizing a Telegram chatbot, the system aims to efficiently provide tailored nutritional guidance, support muscle-building goals, and optimize the dietary intake of bodybuilders in Indonesia.

2. RESEARCH METHODOLOGY

2.1 Research Stages

This research follows several stages designed to address the problem of diet recommendations for bodybuilders. Initially, an ontology-based diet recommender system was developed utilizing a Telegram bot as the user interface. Ontology is used as a knowledge representation tool to manage information about various types of food and their nutritional compositions. The Semantic Web Rule Language (SWRL) is applied to establish rules or patterns for generating appropriate dietary suggestions. This system provides real-time feedback to users and recommends daily consumption needed to meet calorie and protein requirements essential for muscle growth and recovery.

Existing literature demonstrates the effectiveness of ontology-based systems in various domains. For instance, previous studies show that ontologies can model dietary recommendations and offer effective strategies for combating obesity, achieving an average accuracy of 87% in recommending suitable diets [10]. Similarly, ontology-based systems have been used to personalize course recommendations, enhancing user satisfaction by providing relevant course suggestions to prospective students [16]. Additionally, research has addressed the cold-start problem in new users within e-learning content recommender systems by incorporating learner characteristics into the recommendation process [17].

In the field of nutrition, ontologies have been employed to manage and integrate complex and heterogeneous data, such as food intake biomarkers [18]. In medicine, ontology-based models have been developed to predict cardiovascular diseases with high accuracy, demonstrating the potential of combining machine learning techniques with ontologies for early diagnosis and prediction [19]. Ontology rules have also been constructed to support research services in academic libraries, achieving high measurement accuracy and completeness [20].

Building on these findings, our research focuses on developing an ontology-based food recommender system tailored to bodybuilders in Indonesia. The system identifies dietary options based on the nutritional needs of bodybuilders. Users input their personal details and bodybuilding goals through a chatbot, which constructs a user profile stored in the ontology. This ontology includes various foods, their nutritional compositions, macronutrients, and calorie requirements for different bodybuilding goals, along with Basal Metabolic Rate (BMR) calculations. Using SWRL rules, the system determines nutritional demands based on the user's BMR and provides tailored meal recommendations, including portion sizes.

The system architecture, as shown in Figure 1, allows users to interact with the application through a Telegram chatbot. The system can be accessed and modified on multiple devices, including phones, PCs, and tablets. By providing personal details to the Telegram chatbot, the user initiates the conversation. The user-entered input is then received by the reasoning system as a query. The system uses ontology and SWRL (Semantic Web Rule Language) rules to generate food selections based on the query from Indonesian food composition data that meets the specified requirements. As a result, users can access and browse the recommendations to obtain dietary advice relevant to and consistent with the data they have already submitted.

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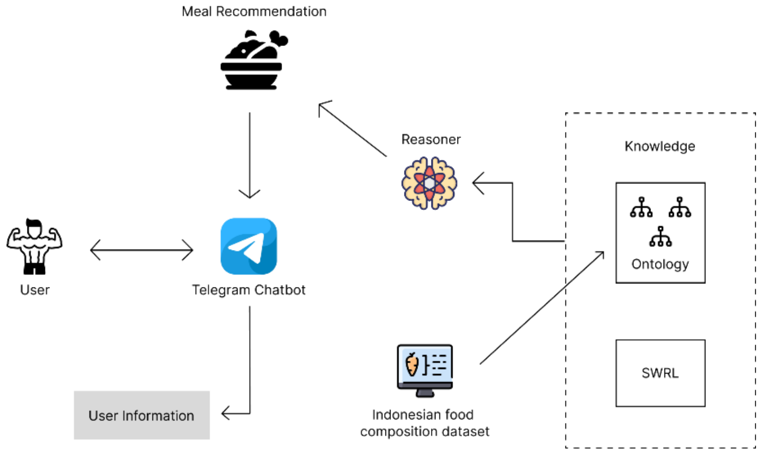

Figure 1. System Design

The recommender system generates a list of recommended foods based on the user's nutritional needs. The personal data that the system collects includes the name, gender, height, weight, level of physical activity, dietary preference, and age of the user. The dietary requirements of the user are determined using this data. The manner in which users engage with the chatbot is depicted in Figure. 2. This diagram illustrates how the user can communicate with the chatbot to receive recommendations for meals.

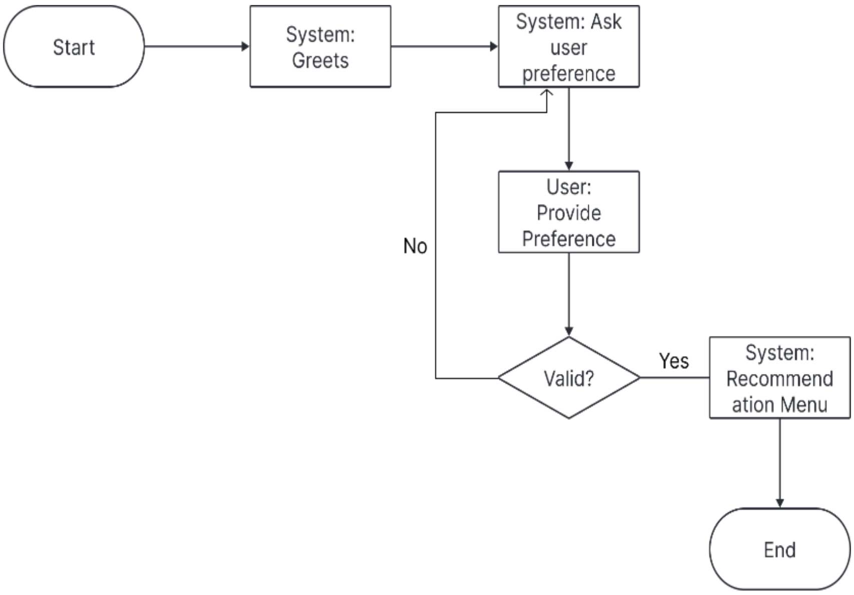

Figure 2. User Flow

2.2 Dataset

The 2017 Indonesian Food Composition Table provided the dataset for this investigation (TKPI). This dataset contains a variety of data including food names, fat, protein, and calorie content, among other things. The complete set of facts is shown in full in Table 1. The nutritional information in this dataset serves as a knowledge foundation for the ontology's growth.

Table 1. Indonesian Food Composition Dataset

Meal	Macronutrients / 100g					
	Calorie	Protein	Fat	Carbs	...	Fiber
Nasi putih	180	3	0.3	39.8	...	0.2
Dendeng sapi	301	55	9	0	...	0

2.3 Ontology Design

The ontology is depicted in Figure 3 is designed to support a food recommender system for bodybuilders. It consists of classes and subclasses, including Person, Menu, FoodGroup, Carbo, Protein, Vegetable, and Fruit. Person and Menu classes are the main classes in this ontology. Person class is used to store user information, such as name, age, gender, activity level, dietary preference, weight, and height. The Menu class is used to store details about a person's diet, including food name, food type, and nutrient content.

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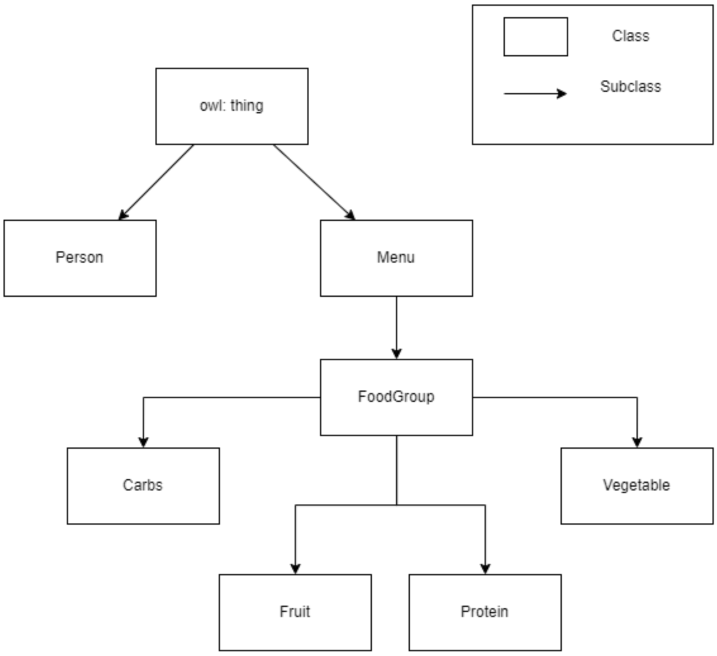

Figure 3. Ontology Design

The ontology includes object properties and data properties, as shown in Figure 4, to define relationships and attributes of the classes. Object properties link instances of two classes, specifying relationships between them. For example, an object property might link a specific food item to its food group. Data properties, on the other hand, link instances of classes to literal values. This includes details like a user's age, weight, and height, or the nutrient content of a particular food item.

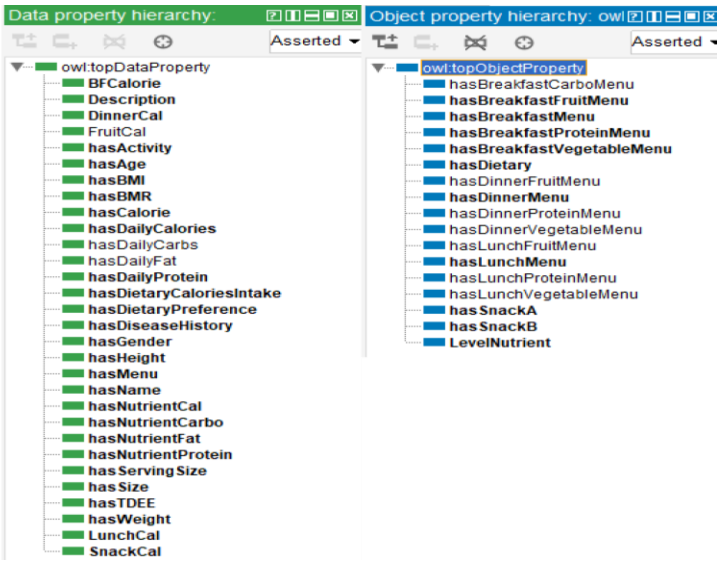

Figure 4. Data and Object Properties

2.4 SWRL Implementation

The reasoning for creating customized meal recommendations is defined by SWRL rules. To deliver personalized dietary recommendations, these rules integrate the user's input data and the ontology's knowledge base. These are a few of the SWRL guidelines needed to offer dietary suggestions based on user information. The Basal Metabolic Rate (BMR) for bodybuilders is determined by the Male and Female BMR rules in the ontology and SWRL, which take age, gender, weight, and height into consideration. These guidelines enable researchers to compute the bodybuilder BMR precisely based on these variables, which are essential for figuring out their caloric and nutritional requirements. The following calculations serve as the foundation for applying the male and female BMR criteria.

$$BMR_{male} = 13.7 \times Weight_{(kg)} + 5.0 \times Height_{(cm)} - (6.8 \times Age) + 66 \quad (1)$$

$$BMR_{female} = 9.6 \times Weight_{(kg)} + 1.8 \times Height_{(cm)} - (4.7 \times Age) + 665 \quad (2)$$

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These formulas enable a precise calculation of BMR, tailored to the specific needs of bodybuilder males and females based on their individual physical characteristics. To further refine the dietary recommendations, we incorporate the calculation of BMR based on activity levels, ensuring that the final recommendations are not only personalized but also dynamically adjusted to reflect the user's lifestyle and physical exertion. This approach ensures that dietary suggestions are accurately aligned with the bodybuilder's energy expenditure and nutritional requirements.

Gender considerations aside, the Activity Level Rule in the ontology and SWRL is intended to determine the calorie requirements by utilizing their BMR and degree of physical activity. The Rule, which is derived from the computation of calorie requirements, can serve as a foundation for suggesting the right amount of calories to older adults, accounting for their energy requirements and degree of physical activity. An illustration of the rules used to determine the activity level is provided in Table 2.

Table 2. BMR Rules

Activity Level	Rules
Little	ontology:Person(?p) ^ ontology:hasGender(?p, "Pria"^^rdf:PlainLiteral) ^ ontology:hasBMR(?p, ?bmr) ^ ontology:hasActivity(?p,"Little"^^rdf:PlainLiteral) ^ swrlb:multiply(?c, ?bmr, 1.30) -> ontology:hasDailyCalories(?p, ?c)
Light	ontology:Person(?p) ^ ontology:hasGender(?p, "Pria"^^rdf:PlainLiteral) ^ ontology:hasBMR(?p, ?bmr) ^ ontology:hasActivity(?p,"Light"^^rdf:PlainLiteral) ^ swrlb:multiply(?c, ?bmr, 1.56) -> ontology:hasDailyCalories(?p, ?c)
Moderate	ontology:Person(?p) ^ ontology:hasGender(?p, "Pria"^^rdf:PlainLiteral) ^ ontology:hasBMR(?p, ?bmr) ^ ontology:hasActivity(?p, "Moderate"^^rdf:PlainLiteral) ^ swrlb:multiply(?c, ?bmr, 1.76) -> ontology:hasDailyCalories(?p, ?c)
Heavy	ontology:Person(?p) ^ ontology:hasGender(?p, "Pria"^^rdf:PlainLiteral) ^ ontology:hasBMR(?p, ?bmr) ^ ontology:hasActivity(?p,"Heavy"^^rdf:PlainLiteral) ^ swrlb:multiply(?c, ?bmr, 2.10) -> ontology:hasDailyCalories(?p, ?c)

To ascertain the nutritional content of each menu item, SWRL rules have been developed in addition to these guidelines. The SWRL guidelines take into account a range of nutritional parameters, including macronutrients, to guarantee that every meal recommendation fulfills the individual dietary requirements of the user. To deliver individualized nutrient levels for every menu item, these rules combine information from the food ontology with user-specific needs. Bodybuilders' dietary tastes and objectives can be well-served by following the nutritional level standards, which guarantee that their meals are optimized to promote muscle building. Table 3 is an example of rules used in menu classification.

Table 3. Menu Classification Rules

Level Nutrient	Rules
HighProtein	ontology:Menu(?f) ^ ontology:hasNutrientProtein(?f, ?n) ^ swrlb:divide(?h, ?n, 50) ^ swrlb:multiply(?DV, ?h, 100) ^ swrlb:greaterThanOrEqual(?DV, 20) -> ontology:LevelNutrient(?f, ontology:HighProtein)
LowFat	ontology:Menu(?f) ^ ontology:hasNutrientFat(?f, ?n) ^ swrlb:divide(?h, ?n, 78) ^ swrlb:multiply(?DV, ?h, 100) ^ swrlb:greaterThanOrEqual(5, ?DV) -> ontology:LevelNutrient(?f, ontology:LowFat)

It is shown how ontology and SWRL may be applied to provide food menus that meet the specific needs of bodybuilders by creating rules for breakfast, lunch, and dinner. In order to support general health and muscle growth, these guidelines make sure that dietary recommendations are in line with each person's unique caloric and nutritional demands. The guidelines also consider dietary choices like bulking and reducing. Daily calorie intake is adjusted by 10% from the baseline computed BMR for bulking and by 10% for reducing. Table 4 provides an illustration of how these rules are applied to dietary recommendations.

Table 4. Menu Recommendation Rules

Menu	Rules
Breakfast Bulking	ontology:Person(?p) ^ ontology:hasDietaryPreference(?p, "Bulking"^^rdf:PlainLiteral) ^ ontology:hasNutrientCal(?f, ?nc) ^ ontology:Carbo(?f) ^ ontology:Vegetable(?f2) ^ ontology:BFCalorie(?p, ?c) ^ ontology:Protein(?f1) ^ ontology:Fruit(?f3) ^ ontology:hasNutrientCal(?f1, ?nc1) ^ ontology:hasNutrientCal(?f2, ?nc2) ^ ontology:hasNutrientCal(?f3, ?nc3) ^ swrlb:add(?tc, ?nc, ?nc1) ^ swrlb:add(?tc1, ?tc, ?nc2) ^ swrlb:add(?tc2, ?tc1, ?nc3) ^ ontology:LevelNutrient(?f1, ontology:HighProtein) ->

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Menu	Rules
Lunch Cutting	ontology:hasBreakfastMenu(?p, ?f) ^ ontology:hasBreakfastProteinMenu(?p, ?f1) ^ ontology:hasBreakfastVegetableMenu(?p, ?f2) ^ ontology:hasBreakfastFruitMenu(?p, ?f3) ontology:Person(?p) ^ ontology:hasDietaryPreference(?p, "Cutting"^^rdf:PlainLiteral) ^ ontology:hasNutrientCal(?f, ?nc) ^ ontology:Carbo(?f) ^ ontology:Vegetable(?f2) ^ ontology:LunchCal(?p, ?c) ^ ontology:Protein(?f1) ^ ontology:Fruit(?f3) ^ ontology:hasNutrientCal(?f1, ?nc1) ^ ontology:hasNutrientCal(?f2, ?nc2) ^ ontology:hasNutrientCal(?f3, ?nc3) ^ swrlb:add(?tc, ?nc, ?nc1) ^ swrlb:add(?tc1, ?tc, ?nc2) ^ swrlb:add(?tc2, ?tc1, ?nc3) ^ ontology:LevelNutrient(?f1, ontology:LowFat) ^ ontology:LevelNutrient(?f2, ontology:LowFat) -> ontology:hasLunchMenu(?p, ?f) ^ ontology:hasLunchProteinMenu(?p, ?f1) ^ ontology:hasLunchVegetableMenu(?p, ?f2) ^ ontology:hasLunchFruitMenu(?p, ?f3)
Dinner Cutting	ontology:Person(?p) ^ ontology:hasDietaryPreference(?p, "Cutting"^^rdf:PlainLiteral) ^ ontology:hasNutrientCal(?f, ?nc) ^ ontology:Carbo(?f) ^ ontology:Vegetable(?f2) ^ ontology:DinnerCal(?p, ?c) ^ ontology:Protein(?f1) ^ ontology:Fruit(?f3) ^ ontology:hasNutrientCal(?f1, ?nc1) ^ ontology:hasNutrientCal(?f2, ?nc2) ^ ontology:hasNutrientCal(?f3, ?nc3) ^ swrlb:add(?tc, ?nc, ?nc1) ^ swrlb:add(?tc1, ?tc, ?nc2) ^ swrlb:add(?tc2, ?tc1, ?nc3) ^ ontology:LevelNutrient(?f1, ontology:LowFat) ^ ontology:LevelNutrient(?f2, ontology:LowFat) -> ontology:hasDinnerMenu(?p, ?f) ^ ontology:hasDinnerProteinMenu(?p, ?f1) ^ ontology:hasDinnerVegetableMenu(?p, ?f2) ^ ontology:hasDinnerFruitMenu(?p, ?f3)

3. RESULT AND DISCUSSION

The system examines user data, including name, age, gender, activity level, medical history, height, and weight, to deliver individualized food recommendations with nutritional facts and ideal intake schedules. It was written and tested using Python and integrated with Telegram using its API. An expert bodybuilder with extensive experience conducts the testing, utilizing Sheets to verify the recommendations. By calculating true positives, false positives, and false negatives, this validation makes it possible to evaluate the recommendations' accuracy using precision, recall, and F-Score metrics.

3.1 Recomendation System (chatbot)

The recommendation system is designed to provide bodybuilders with personalized dietary advice tailored to their specific nutritional needs and goals. By leveraging the power of ontologies and the SWRL (Semantic Web Rule Language), the system integrates seamlessly with a chatbot interface, enabling efficient and user-friendly interactions. The chatbot not only collects essential user information such as name, age, gender, activity level, medical history, height, and weight, but also processes this data to generate precise food recommendations. The integration with Telegram via its API allows for real-time communication and immediate feedback, ensuring that users receive timely and accurate dietary suggestions. This subsection delves into the interaction flow of the chatbot, demonstrating how it effectively gathers user inputs and employs the underlying ontology-based system to offer customized nutritional guidance.

The user's interaction flow with the bodybuilding food recommendation chatbot is depicted in Figure. 5. The user gives the command "start" to initiate the process. Subsequently, the interface requests the user's name, gender, height, weight, age, degree of physical activity, and preferred diet. Using this data, food recommendations are customized according to the user's dietary requirements and medical circumstances.

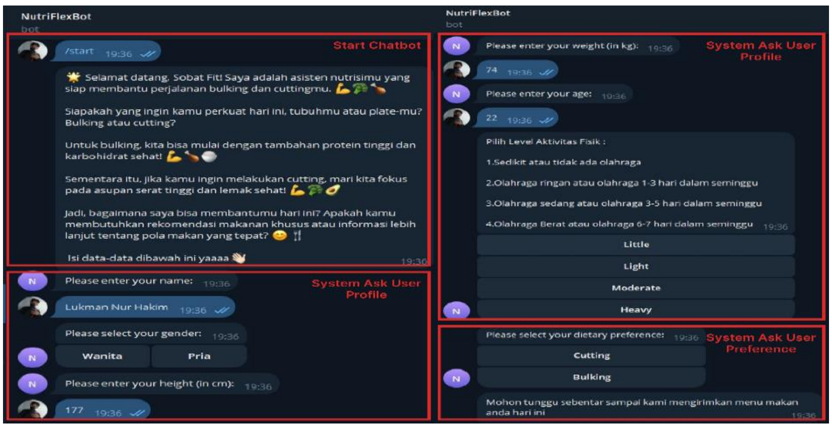

Figure 5. User Interaction with the System

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The recommendation results produced by the system based on the data users entered pertaining to their bodily state are shown in Figure. 6. The system processes the user's data to determine their Basal Metabolic Rate (BMR) after they enter their personal information and dietary preferences. This BMR is important since it establishes the daily energy needs, which change according to the user's degree of physical activity. Every activity level has a corresponding daily requirement for calories and protein. The system creates customized meal suggestions for bodybuilders for breakfast, lunch, and dinner based on the BMR computation and the supplied health data. A thorough description of the food's composition, nutritional value, and description is provided for each suggested meal.

Figure 6. Display of Recommendation

3.2 System Performance

The system was evaluated using 15 user datasets, which included gender, dietary preference, physical activity level, weight, name, age, and height. Based on this data, the chatbot processed and generated meal recommendations for breakfast, lunch, and dinner. In total, 192 food recommendation samples were produced. Out of these, 168 samples were accepted as valid, while 24 were rejected. The results were analyzed to assess the system's accuracy in generating suitable meal plans tailored to individual needs.

Information from 15 users, including gender, dietary preferences, degree of physical activity, weight, name, age, and height, was used to assess the effectiveness of the meal recommender system. Based on this information, the system produced 180 recommendations for breakfast, lunch, and dinner. Of these, 24 were found to be invalid, and 156 were determined to be legitimate. Several important metrics were computed in order to evaluate the recommendations' accuracy:

a. True Positives (TP): Suggestions that were accurately determined to be appropriate.
b. False Positives (FP) are recommendations that are mistakenly classified as appropriate when they are not.
c. False Negatives (FN) are recommendations that the system ought to have recognized as appropriate but overlooked.

The following metrics were calculated using these values:

$$Precision = \frac{TP}{TP+FP} = \frac{168}{168+24} = 0.866 \quad (3)$$

$$Recall = \frac{TP}{TP+FN} = \frac{168}{168+0} = 1 \quad (4)$$

$$F - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{0.866 \times 1}{0.866+1} = 0.928 \quad (5)$$

While recall assesses a system's capacity to precisely retrieve pertinent documents from all documents available, precision gauges a system's effectiveness in identifying information. If the precision and recall levels are near to 1, it is a sign of high quality. This indicates that the algorithm can identify the majority of relevant documents, with very few pieces of data being mislabeled as relevant. The F-Score combines both precision and

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recall into a single metric, providing a balanced evaluation of the system's performance. A high F-Score indicates that the system performs well in both identifying and retrieving relevant recommendations..

3.3 Discussion

A personalized food recommendation system for bodybuilders was developed in this study, utilizing an ontology-based approach combined with SWRL rules and a Telegram chatbot. The ontology modeled relevant nutritional and user data, while SWRL rules enabled dynamic meal recommendations based on user profiles. The Telegram chatbot facilitated user interactions and provided instant feedback.

The system was tested with predefined user profiles, and the recommendations were validated against expert opinions, showing high accuracy as evidenced by strong precision, recall, and F-Score metrics. These results suggest that the system provides reliable and personalized dietary suggestions beneficial for bodybuilders. However, the study has limitations, including the exclusion of specific dietary restrictions like food allergies and a focus solely on bodybuilding, which may limit its applicability to other dietary needs. Future work should consider incorporating diverse dietary requirements and expanding the system's use to broader health goals. Additionally, integrating machine learning could enhance personalization, and improvements in the chatbot's natural language processing could further optimize user interaction

4. CONCLUSION

This study developed a personalized food recommendation system specifically designed for bodybuilders, addressing the critical need for precise and tailored nutritional guidance in promoting muscle growth and optimizing body composition. Utilizing an ontology-based approach combined with Semantic Web Rule Language (SWRL) and a Telegram chatbot, the system effectively provides customized meal plans that align with individual bodybuilding goals. By representing key concepts such as user profiles, nutritional needs, and food attributes through ontologies, and leveraging SWRL rules to generate meal recommendations, the system has shown promising results. The evaluation with 15 user profiles resulted in the generation of 180 food recommendations, with validation metrics indicating a precision value of 0.866, a recall value of 1, and an F-Score of 0.928. These findings underscore the system's high accuracy and effectiveness in delivering personalized nutritional advice tailored to the specific needs of bodybuilders. This demonstrates the potential of semantic technologies in advancing personalized diet and fitness planning, providing a reliable tool for users aiming to optimize their bodybuilding outcomes. However, the study has some limitations. The system currently does not account for specific dietary restrictions such as food allergies, and its focus on bodybuilding may limit its applicability to other dietary needs. Future work should address these limitations by incorporating more diverse dietary options and expanding the system's utility to cater to different fitness and health goals. Enhancements like integrating machine learning for adaptive recommendations and improving chatbot interactions could further increase the system's effectiveness and user satisfaction.

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