

Ontology-based Nutrition Recommender System for Stunting Patients

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Abstract: Stunting is a growth disorder that occurs in early childhood. This condition occurs because the child has a chronic nutritional problem which triggers the child to have a height below normal. The indicator used as a standard for whether a child is stunted or not is height for age. If a child has a z-score value less than -2 standard deviations, then the child is said to suffer from stunting. Poor nutritional intake is one of the factors causing children to suffer from stunting. Most Indonesian people think that the genetics of both parents causes children to be shorter than their age, but genetics is a minimal factor that causes stunting. In 2020, Indonesia ranks second in the prevalence of stunting in Southeast Asia, according to the Asian Development Bank (ADB) report. Based on the results of the Indonesian Nutritional Status Survey (SSGI) in 2021, the stunting prevalence rate in Indonesia 2021 is 24.4%, but in 2022, the stunting prevalence rate will drop to 21.6%. One way to treat stunting in children is by providing daily nutritional intake according to the child's condition. In this study, we used the Telegram chatbot with an ontology and the rules Semantic Web Rule Language as a knowledge base. The accuracy performance of our system is 93.3% which shows that our system can provide nutritional recommendations for stunting patients.

Keywords: Stunting disease, Ontology, Semantic Web Rule Language, Nutritional intake, recommender system

INTRODUCTION

Nutritional problems in toddlers are still a severe problem that needs to be addressed in every country, including stunting. In the year 2020, as reported by the World Health Organization (WHO), Africa recorded a stunting prevalence rate of 31.7%. In the same year, according to the Asian Development Bank (ADB), Timor Leste has the highest prevalence in Southeast Asia with a value of 48.8%, and Indonesia is in second place with a prevalence value of 38.8% (Nasution & Susilawati, 2022). Many Indonesians think that the influence of a short child's body is a genetic influence from the child's parents. In fact, genetics has a negligible impact compared to environmental factors and access to health care. Some people may not understand the term stunting. Stunting is a chronic malnutrition disease caused by a lack of nutritional intake for a long time, resulting in impaired growth in children's height is lower than the standard age. Stunting is assessed as a nutritional condition by considering the toddler's height, age, and gender (Sutarto et al., 2018). The general indicator used to measure children suffering from stunting is the height for age (TB/U), which according to anthropometric standards, a child can be said to be stunted if the measurement results are at a threshold (z-score) <-2 Standard Deviation (SD) up to -3 Standard Deviation (SD) (Rahmadhita, 2020). Based on the research of the Indonesian Nutritional Status Survey (SSGI) in 2021, the stunting prevalence rate in Indonesia in 2021 is 24.4%, while in 2022, the stunting prevalence rate will be 21.6%. Therefore, one of the government's current focuses is stunting prevention, regulated in Presidential Regulation 72 of 2021 concerning Accelerating the Reduction

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of Stunting. This effort aims to enable children in Indonesia to grow and develop optimally and maximally.

The natural causes of stunting are nutritional intake and infectious diseases. In contrast, the indirect causes are education, family economic status, nutritional status of the mother during pregnancy, water, and environmental sanitation, Low Birth Weight (LBW), and knowledge from the mother and family (Ramdhani et al., 2021). The essential understanding required by healthcare professionals and the community regarding the underlying factors of stunting holds significance, as it is anticipated to play a role in stunting prevention and the reduction of stunting prevalence within the community (Yanti et al., 2020). Information regarding the handling of stunting in children is something that is needed by parents in the treatment and prevention of stunting for their children. Information can be easily obtained in the era of modern technology, and one way to do this is by developing a recommender system (Rachman & Nurjanah, 2019).

Mckensy-Sambola defined Ontology as an explicit specification of a conceptualization (Mckensy-Sambola et al., 2021). Apart from being a representation of knowledge, another capability of ontology is its ability to be reused as a knowledge base in other systems and can be used for decision-making. For machine readability, W3C proposes Ontology Web Language (OWL). Based on the limited ability of OWL expression, Semantic Web Rule Language (SWRL) is presented as a model rule to expand the expressiveness of OWL.

Several previous studies have demonstrated using ontology as a knowledge base for a recommendation system. Ontology-based recommendations only experience some problems associated with conventional recommender systems, such as cold-start, rating sparsity, and overspecialization problems, because ontology-based recommendations rely more on domain knowledge than ratings (Tarus et al., 2018). Research conducted by (Chen et al., 2010), represents knowledge of anti-diabetic drugs using an ontology and defines the rules for giving drug recommendations using SWRL. In the experiment, Chen combined SWRL and Java Expert System Shell (JESS) to analyze the diabetes condition, and then the most appropriate medicine is suggested. A decision support system based on an anti-diabetic drug ontology was further developed to recommend the most appropriate hypoglycemic agent and to alert physicians to what to monitor and contraindicate. Another study, namely an ontology-based diet recommendation system for each individual compared to the results of nutritionists, achieved an average accuracy of 87% (Mckensy-Sambola et al., 2021). Namahoot developed ontology to present information about food and nutrition and optimizing SWRL rules for selecting food ingredients suitable for hospital patients resulting in an accuracy value of 35% (Namahoot et al., 2016).

This study focused on designing ontologies and SWRLs using Telegram to provide nutritional recommendations for stunting patients. SWRL is used to expand ontology as a support for giving recommendations. System recommendations are generated from data on height, weight, activity level, and age of stunting sufferers. Meanwhile, the results of the recommendations are the number of calories, fat, carbohydrates, protein, calcium, fiber, and iron needed by stunting patients in one day derived from the advice of nutritionists.

LITERATURE REVIEW

The nutritional intake are important for young children because it will affect their growth and development process in adulthood (Ramlah, 2021). Nutrition is a supporting factor that influences the growth of intelligence and health development of children. The nutritional intake of children in developing countries are insufficient that affected children development. Based on the previous research, The government, TNP2K, established specific nutritional intervention to pregnant woman and sensitive nutritional intervention to prevent children malnutrition in their golden age. This program intentionally prevent the stunting cases in Indonesia (Nisa, 2018).

Several researchers have researched using ontology. Spoladore researched HeNuAL, an ontology-based Telehealthcare System (TS) that aims to encourage healthy eating and an active lifestyle in older adults with chronic illnesses. The system is built based on the formalization of the user's health condition, which can be obtained by utilizing existing standards. The validation of the HeNuAL system enables it to provide meal recommendations classified as suitable for individuals

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with respiratory disorders and diabetes mellitus, indicating whether the meals are healthful, appropriate, or unsuitable (Spoladore et al., 2021). Meanwhile, in a study researched by Mckensy-Sambola, they used ontology in prescribing recommendations, ingredients, and diet classification for obese patients taking into account height, weight, and BMI. The results of the ontology-based diet recommendation system compared to the advice given by nutritionists produce an average accuracy value of 87% (Mckensy-Sambola et al., 2021). Research conducted by Aditya, uses ontologies and SWRL to preserve knowledge in ontologies, subsequently proceed using SWRL food recommendations based on the preferences of users who suffer from obesity. The outcome values are 92%, create an accurate healthy food recommendation system to help users take a diet depend on the nutritional needs within the required budget (Aditya et al., 2023).

Fadhil conducted research to recommend nutrition using a chatbot (Fadhil, 2018). This issue was raised because poor nutrition causes decreased immunity, susceptibility to disease, impaired physical and mental development, and reduced productivity. In making this chatbot, things that must be considered are the theory of the domain and the limitations of the chatbot. The result obtained by the chatbot can be used to recommend nutrition for users.

METHOD

Ontology is used to model knowledge about user context, knowledge about items, and domain knowledge (Yu et al., 2007). In this study, we used ontology as a knowledge base for nutritional intake according to the preferences of stunting patients, and to describe the relationship between rules, used Semantic Web Rule Language. Semantic Web Rule Language can be considered a combination of rules and ontology. When writing rules, the relations and terms contained in the ontology can be directly utilized. Initially, the relationship between classes will have additional rules that need to be explained, but the descriptions in the ontology can be used directly in the Semantic Web Rule Language (Mabotuwana & Warren, 2009). Ontology has increased with the development of the Semantic Web in recent years. The information groupings within the ontology are intended to aid machines in comprehending information and facilitating the accessibility of information (Noy & McGuinness, 2001).

The body mass index (BMI) serves as a straightforward measuring tool to track the nutritional condition of adults based on their body weight (Yhuwono, 2018). BMI classified nutritional status as underweight, normal, overweight, or obese. BMI only measure adult nutritional because usually the children measurement are not accurate. Calculation of BMI Formula 1 can be done to person above 18 years. BMI appear as an indicator of a person's normal body weight. Age, gender, and muscle mass are factors in calculating BMI. Table 1 shows the different values of BMI categories adapted to the characters of people in each country, based on WHO. BMI interpretation (Table 1) is used to determine the user's weight status.

Table 1. Body Mass Index

BMI	Weight Status
<18.5	Underweight
18.5 – 22.9	Normal
23-24.9	Overweight
>=25	Obesity

BMI body fat figure based on the calculation of body weight adjusted for height. Below are the BMI formulation methods.

$$BMI = \frac{Weight(kg)}{Height(m^2)} \quad (1)$$

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The Basal Metabolic Rate (BMR) increases in direct correlation with lean body mass; as a person possesses more lean body mass, their BMR also rises (Munawaroh & Fatimah, 2021). Basal Metabolic Rate can be stands for BMR are the minimal number of calories your body requires to carry out essential processes, including breathing, blood circulation, and digestion. Age, gender, weight, and muscle mass are factors that affect BMR. These tools estimate the amount of calories to consume. The Harris-Benedict formula is used to calculate BMR. The BMR calculations below are for man and woman.

$$BMR(man) = (13,7 \times Weight(kg)) + (5,0 \times Height(cm)) - (6,8 \times Age) + 66 \quad (2)$$

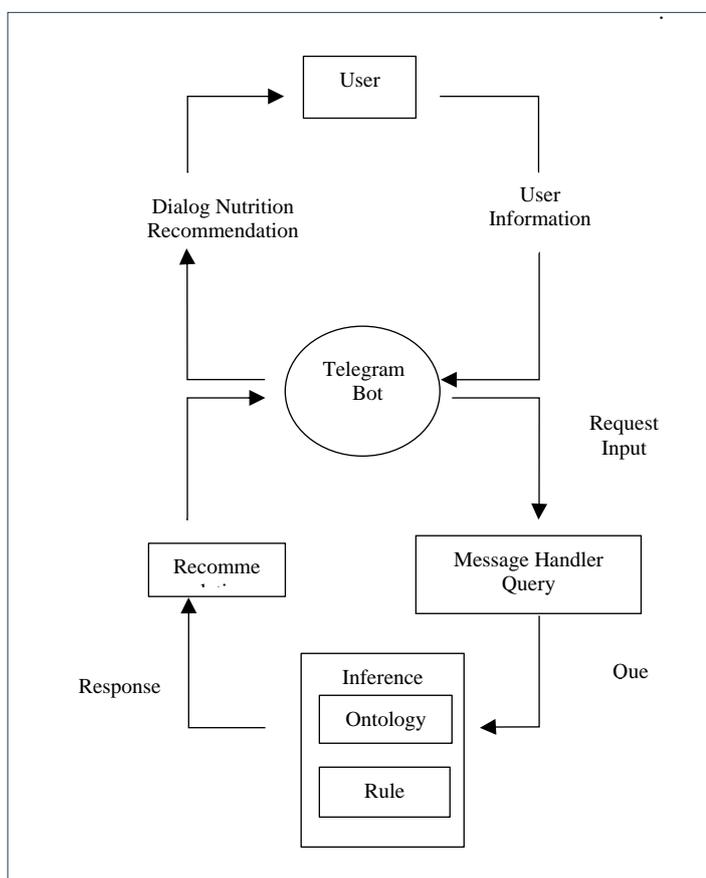
$$BMR(woman) = (9,6 \times Weight) + (1,8 \times Height(cm)) - (4,7 \times Age) + 665 \quad (3)$$

As we can see above, the BMR formula is calculated by combination of weight, height and age. W represent the weight, H represent the height, and A represent the age. The BMR can be seen by multiple exercise or physical activity factor, the results obtained by the total daily calorie requirement that matches (Utama et al., 2019). The recommended formula for daily calorie needs is in formula (4).

$$Daily\ Calories = BMR \times Activity\ Factor \quad (4)$$

System Flow

This study uses chatbots on the Telegram platform. The system will receive input from the patient: name, age, gender, height, weight, and activity level. The system will process the information obtained into a query, and SWRL will carry out reasoning to provide recommendations. The recommendation results are sent to users via chatbot. This flow is shown below in the Figure 1.



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Figure 1. Chatbot System Flow

There are three main classes listed in the ontology. The BMI class has four subclasses: underweight, normal, overweight, and obesity. The ontology structure shown in Figure 2.

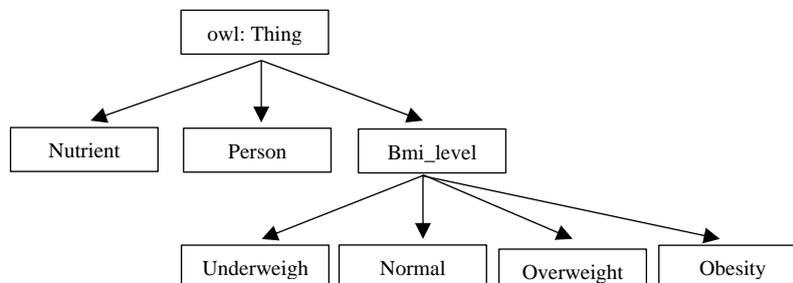


Figure 2. Ontology Classes Design

Implementation Ontology and SWRL

This study uses protégé version 5.6.1 in compiling ontology and uses a top-down (tree) technique defined by forming classes, continuing to sub-classes, and ending with instances. All classes have *data properties* that store information from each class, and object properties are also defined to link between instances of each type. *Object properties* and *data properties* are shown in Table 2 and Table 3.

Table 2. Data Properties in Ontology

Properties	Domain	Range
hasBMR	Person	Decimal
hasBMI	Person	Decimal
hasAge	Person	Integer
hasWeight	Person	Decimal
hasHeight	Person	Decimal
hasGender	Person	String
hasCalciumIntake	Nutrient	Decimal
hasCaloriesIntake	Nutrient	Decimal
hasCarbohydrateIntake	Nutrient	Decimal
hasProteinIntake	Nutrient	Decimal
hasFatIntake	Nutrient	Decimal
hasIronIntake	Nutrient	Decimal
hasFiberIntake	Nutrient	Decimal

Table 3. Object Properties in Ontology

Properties	Domain
hasCalories	Nutrient
hasCalcium	Nutrient
hasCarbohydrate	Nutrient
hasFat	Nutrient
hasProtein	Nutrient
hasFiber	Nutrient

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hasIron	Nutrient
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Class *person* has data properties:

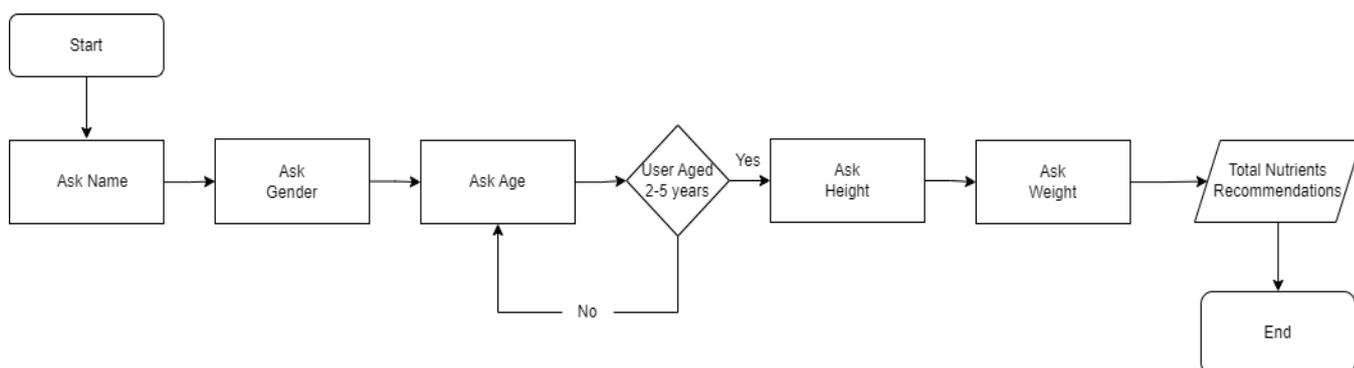
- **hasBMI** : this property used to store BMI calculation results.
 $person(?patient) , hasWeight(?patient, ?berat) , hasHeight(?patient, ?tinggi) , swrlb:multiply(?wh, ?berat, 10000) \wedge swrlb:multiply(?heightm, ?tinggi, ?tinggi) , swrlb:divide(?imt, ?weighth, ?heightm) \rightarrow hasBMI(?patient, ?imt)$
 For example, if the patient has a BMI above 27 then the calculation formula is:
 $person(?patient) , hasBMI(?patient, ?imt) , swrlb:greaterThanOrEqual(27.1, ?imt) \rightarrow obesity(?patient)$
- **hasBMR**: this property used to store BMR calculation results.
 For woman:
 $person(?patient) , hasWeight(?patient, ?berat) , hasHeight(?patient, ?tinggi) , hasAge(?patient, ?age) , hasGender(?patient, "Perempuan"^^rdf:PlainLiteral) , swrlb:multiply(?kw, ?berat, 9.563) , swrlb:multiply(?lh, ?tinggi, 1.850) \wedge swrlb:multiply(?m, ?a, 4.676) , swrlb:add(?h1, ?kw, 655.1) , swrlb:add(?h2, ?h1, ?l) \wedge swrlb:subtract(?bmr, ?h2, ?m) \rightarrow hasBMR(?patient, ?bmr)$
 For man:
 $person(?p) , hasWeight(?patient, ?w) , hasHeight(?patient, ?h) , hasAge(?patient, ?age) , hasGender(?patient, "Laki-Laki"^^rdf:PlainLiteral) , swrlb:multiply(?kw, ?berat, 13.75) , swrlb:multiply(?lh, ?height, 5.003) , swrlb:multiply(?m, ?age, 6.755) , swrlb:add(?h1, ?kw, 66.47) , swrlb:add(?h2, ?h1, ?l) , swrlb:subtract(?bmr, ?h2, ?m) \rightarrow hasBMR(?patient, ?bmr)$

Class *nutrient* has data properties:

- hasCaloriesIntake : stores the daily caloric value for the patient.
- hasCarbohydrateIntake: stores the daily carbohydrate value for the patient.
- hasProteinIntake: stores the daily protein value for the patient.
- hasFatIntake : stores daily fat values for patients.
- hasFiberIntake : stores daily fiber values for patients.
- hasIronIntake : stores daily iron values for patients.
- hasCalciumIntake : stores the daily calcium value for the patient.

Nutrient Recommendation for Stunted bot Prototype

Nutrient Recommendation for Stunted is the chatbot we used in this study. This chatbot provides nutritional recommendations according to user information. Chatbot development is carried out using the Python language and to connect the program to Telegram using the Telegram API that has been provided. The system accepts input of name, age, gender, height, weight, and activity level, also only used with Bahasa. With this information, the system recommends the daily amount of nutrients the patient must have.



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Figure 3. Chatbot Prototype

Bot Testing

Simulation involves attempting to provide input in the form of user information. This concept can be illustrated by evaluating BMI result accuracy, which relies on the user information provided. If the testing system is appropriate, the researcher continues to enter the final stage, namely, testing the results of recommendations to nutritionists.

RESULT

The process of testing the results of this bot recommendation involves a nutritionist. Nutritionists validate the amount of nutrients from the results of the recommendations in the chatbot. The validation results are used to get true positive, false positive, and false negative values. The data used for the validation process were obtained from stunting patients aged 2-5 years. The number of samples used was 28 and there was 1 nutrient that was not in accordance with a nutritionist. Precision and recall calculations are found in formulas (5) and (6).

Samples from the recommendation system are shown in Tables 4 . The inputs requested by the system are gender, age, height, weight, activity level, BMI, and BMR. From this input, the system recommends daily nutrition needed by stunting sufferers. The nutrients produced by the system are the amount of calories, protein, fat, carbohydrates, fiber, calcium, and iron. Figure 4 is a display of the recommendation system we created.

Table 4. User Samples

User	User Input	
Agung Alit	Kategori	Nilai
	Gender	Laki-laki
	Age	3 Tahun
	Height	77 cm
	Weight	8 kg
	Activity Level	Ringan
	BMI	13.49
	BMR	541.44
	Output	
	Kalori	744.47 kkal
	Protein	27.92 gram
	Lemak	16.54 gram
	Karbohidrat	120.98 gram
	Serat	16 gram
	Kalsium	650 mg
Zat Besi	8 mg	

User	User Input	
Maryam	Category	Value
	Gender	Girl
	Age	3 Years
	Height	89 cm
	Weight	11 kg
	Activity_Level	Active
	BMI	13.89

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	BMR	910.91
	Output	
	Calorie	1571.33 kkal
	Protein	58.92 gram
	Fat	34.92 gram
	Carbohydrate	255.34 gram
	Fiber	16 gram
	Calcium	650 mg
	Iron	8 mg



Figure 4. Chatbot Display

$$Precision = \frac{TP}{TP+FP} = \frac{7}{7+1} = 0,875$$

(5)

$$Recall = \frac{TP}{TP+FN} = \frac{7}{7+0} = 1$$

(6)

Table 3. Information Of Matrix

Information	
TP (True Positive)	The count of nutritional recommendations align with the nutritionist advice
FP (False Positive)	The count of nutrition recommended by the system, inconvenient by nutritionist
FN (False Negatives)	The outcomes of nutrition that are not recommended

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	by the system or nutritionists.
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Precisions and Recalls are used to calculate the F-Score, representing the mean of precision and recall. This numerical value can be derived using the subsequent formula (7):

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{0,875 \times 1}{0,875 + 1} = 0,933 \times 100\% = 93,3\%$$

(7)

F1-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%.

DISCUSSIONS

This research was developed by designing an ontology using the protégé platform version 5.6.1 and create SWRL rules used in the ontology in SWRLTab. We built a Telegram chatbot using the Python language to interact with users. We asked nutritionists to ensure our chatbot runs according to its function. The validation results from nutritionists helped us improve the ontology, SWRL rules, chatbot implementation properly, and we were able to calculate our system's accuracy value of 93,3%, where the value is close to 100%, meaning our system can provide nutritional recommendations for stunting patients who have aged 2-5 years. The limitation of this study is we use stunting patients' data in Mataram, West Nusa Tenggara, and nutrition recommendations are given only to children aged 2-5 years.

CONCLUSION

In this study, the recommendation system that has been devised succeeded in providing recommendations for stunted children's daily caloric needs based on age, height, and weight. Of the 7 data, one is considered inappropriate based on a nutritionist. So that the precision value is 0.875, the F1-score is 93.3, and the recall is 1.

In this study, there are seven nutrients used for the validation process. It is hoped that there will be additional nutrients for further research. In addition, in providing recommendations for the daily caloric needs of stunting patients, this study has not considered BMI (body mass index), so it is hoped that this feature will be added for further research.

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