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Ontology Based Personalized Diet Recommendation System for Sri Lankan

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Hectic lifestyles and health neglect are prime causes of non-communicable diseases. Healthy diets help to prevent various non-communicable diseases such as diabetics, pressure, cholesterol etc. However, due to the busy life cycle, people do not have time to consult dietitians and get their meal plans. The diet recommendation system can solve this issue by providing a fingerprint distance response. In this study, we developed ontology based Recurrent Neural Network- Long Short-Term Memory (RNN -LSTM) model for diet recommendation in Sri Lankan context. This system recommends diet plans for breakfast, lunch and dinner based on user's calorie requirements, macronutrient needs, user preference, cultural background, dietary restriction and disease information. We developed ontology, which consists of food related information including their nutrients values. Then we developed RNN–LSTM model to predict target macronutrient values based on user information such as age, BMI, BMR and diseases information. The RNN-LSTM model demonstrated high performance with an R-squared value of 0.9704, a Pearson correlation coefficient of 0.9869, a mean squared error of 0.0209, a mean absolute error of 0.1239, and a root mean squared error of 0.1703. These metrics indicate that the RNN-LSTM model provided accurate predictions with a strong positive linear relationship between the actual and predicted value. Additionally, the RNN-LSTM model was compared with the KNN model using the same dataset. The RNN-LSTM model outperformed the KNN model across all evaluation metrics. Using content-based filtering and cosine similarity between target nutrient values and food nutrient values, the system recommends food for three meals. This recommendation properly aligns with the nutrient's needs and calorie needs. Finally, we can conclude that there is greater potential for future work in the field of food recommendation using Artificial Intelligence. Future work of this study involves further development of an ontology based RNN model combined with micronutrient needs.

Keywords: Diet Recommendation, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Ontology

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1. Introduction

Food is an essential component of human survival, acting as a source of energy and sustenance as well as being vital to people's general health and well-being. It gives the body the vital nutrients that are needed for development, repair, and optimal operation. Food has cultural, social, and emotional value in addition to its biological relevance, affecting daily life and customs throughout. Every nation has their own food culture. Additionally, Sri Lanka has a rich culinary tradition. Food is a crucial factor in the context of health. The hectic life cycle of human beings and negligence of rich nutrient foods are the main causes for non-communicable diseases. According to the World Health Organization (WHO), a healthy diet can aid in the prevention of diabetes, heart disease, stroke, and cancer like Non-Communicable Diseases (NCDs) [1].

It is a challenge to figure out healthy food menus/dishes based on our preference, cultural background and disease information. However, with the busy life we do not have time to get instructions from nutritionists about healthy diets. This is the place where food recommendation systems come into play. The food recommendation system can overcome all these challenges by helping us find the right foods to eat. They provide a workable answer for people who struggle to strike a balance between a hectic schedule and the need for a balanced diet by bridging the gap between nutritional science and daily meal planning.

When it comes to Sri Lankan context, there are few food recommendation systems are available. However, they do not align with the user’s specific needs and preferences. The main goal of this study is to develop a solution that can recommend Sri Lankan diet based on user preference, health condition and cultural background. In order to recommend diets in the context of Sri Lanka, we particularly developed an ontology-based machine-learning model. Here we developed ontology, based on food and nutrient information. Furthermore, user-specific data is included into the ontology to improve the relevance and accuracy of dietary suggestions catered to user preference, health condition and cultural background. We have developed a Recurrent Neural Network (RNN) model that calculates target nutrient values by considering factors such as Body Mass Index (BMI), Basal Metabolic Rate (BMR), age, and specific health conditions.

We are able to create a customized list of food recommendations for breakfast, lunch, and dinner by applying content-based filtering to these target nutrient values along with comprehensive food information. This ensures that the user's dietary requirements and preferences are successfully satisfied.

In the following sections, I will detail the development and implementation of the ontology-based machine-learning model and present the experimental results along with their analysis. Through this research, we aim to offer valuable contributions toward improving the precision and contextual relevance of recommendation systems powered by ontology and machine learning integration.

2. Related Work

2.1 Recommendation System

Recommendation systems are an effective technological solution to address the problem of information overload. They help users by suggesting personalized content or products, generating ranked recommendation lists, and predicting the relevance or quality of items for each individual [2]. In a service environment that can store or obtain many types of data, these systems function as information-filtering systems and offer a user a personalized suggestion for an item. Recommendation systems, which make use of information filtering, only offer suggestions that are thought to be helpful to the user or that are tailored to their preferences[3]. According to Thi Ngoc Trang Tran and his research group (2024), there are different techniques of recommendation such as a knowledge based recommendation, collaborative filtering recommendation, content based filtering (CBF), recommendation, hybrid recommendation, matrix factorization and graph-based recommendation [4]. CBF is an approach that recommends items based on their content similarity to items the user has already liked or consumed. Three parts make up a recommendation system: a filtering component, a profile learner and a content analyzer. User behavior or user evaluations of recommended things serve as the basis for CBF recommendations. It recommends items liked by similar users and explores diverse possible content [5].

When individual predictions are combined into a single prediction, content information is added to the collaborative model, the weighted average of content and collaborative recommendations is calculated, or final recommendations are derived from the combined rankings, hybrid recommendation combines the best features of both approaches [6].

2.2 Ontology Development

Ontologies and the semantic web are two exciting new technologies that can be used to represent knowledge and draw conclusions for the creation of intelligent systems. Similarity concepts serve as the foundation for the semantic web. This idea of similarity is applied in several study areas. A set of ideas or classes that represent the objects or entities found in the domain make up an ontology most frequently. A number of interconnects these ideas different relationships that show how they relate to one another [7].

According to Ying Ding (2002), the topic of ontology is one that is quickly expanding and holds enormous potential for improving information management, organization, and comprehension. It is necessary for the Semantic Web, the next phase of the Web's evolution, because it enables content-based access, communications, interoperability, and the provision of significantly higher service levels. Ontology engineers are still required to build the knowledge base and ontology for a specific job or area, as well as to manage and update the ontology to keep it current and relevant. Ontologies that are manually created take a lot of time, labor, and mistakes. There are different ontology generation techniques. They can be summed up as follows: middle-out, which starts with the most crucial concepts and moves toward generalization and specialization (Eg: Enterprise and Methodology ontologies), bottom-up: from specification to generalization, top-down, which starts with generalization and ends with specification (Eg: KACTUS ontology) and bottom-up: from specification to generalization. An ontology can be created from scratch, utilizing just global or local ontologies that already exist, a corpus of data sources, or a combination of the latter two techniques. Three are three ways as fully manual, semi-automated and fully automated [8].

2.3 Major Developments in Recommendation System with Machine Learning Techniques

The evolution of recommendation systems powered by machine learning techniques has witnessed significant advances in recent years. This section aims to explore the major development of recommendation systems with machine learning techniques across various domains culminating in depth discussion of recommendation systems within the food domain.

A team of researchers led by Jingyue Gao, Xiting Wang, Yasha Wang, and Xing Xie (2021) focused on creating a recommendation system using Attentive Multi-View Learning techniques. This study suggests creating an explainable recommendation system that combines the benefits of deep learning-based models and currently used explainable techniques to close the gap between accuracy and explainability. They provide a careful multi-view learning approach to ensure precise rating prediction. They managed sparse and noisy data by the framework's co-regularization of several feature levels and thorough combining of forecasts. Personalized explanation generation is described as a constrained tree node selection problem and a dynamic programming technique is proposed to solve it, allowing for the mining of legible explanations from the hierarchy. According to experimental results, their model performs better than previous recommendation systems in terms of explainability and accuracy when compared to state-of-the-art techniques [9].

Dexon Mckensy-Sambola and his research team (2022) intended to create nutritional recommender system using ontology technology. They created the Ontology of Dietary Recommendations (ODR) with the goal of aiding those who suffer from obesity. A set of diets, recipes, and ingredients are represented by axioms.An algorithm for making recommendations that can determine a user's level of overweight and obesity and offer food plans to help reduce it. There are 2111 records with 17 attributes used for this research study. An actual group of people who have been anonymized is used by the suggested system to validate. A group of consultants assessed every single record and recommended the best diets for the individuals in the ontology. The mean accuracy of the proposed system is 87% [10].

A team of researchers led by Maiyaporn Phanich, Phathrajarin Pholkul, Suphakant Phimoltares (2010) focused on creating a recommendation system based on K-Mean Clustering technique and SOM (Self Organizing Map).

They created this recommendation system for diabetic patients by substituting foods according to nutrition and food parameters. Eighteen (18) nutrient values are considered initially. Then based on nutritionist marks and rank, eight (8) nutrients were selected as most important nutrients for diabetics. The SOM is built and trained first, and then it is clustered using the K-mean method. The food clusters that show which foods in the same category contain roughly the same quantity of each of the eight nutrients are the end result. Nutritionists have assessed the suggested approach, and they find it to be very effective and beneficial for the field of nutrition [11].

Future developments in ontology-based recommendation systems using machine learning are expected to include enhanced data integration, hybrid recommendation techniques, contextual and explainable recommendations, and cross-domain personalization. Advanced ML models such as deep neural networks, CNNs, RNNs, and reinforcement learning can improve the interpretation of complex user behavior and multimedia data. Techniques like sentiment analysis and NLP may be used to refine user profiles by extracting dietary preferences from reviews or social content. Cross-domain recommendation (E.g. integrating fitness and dietary data) can enable comprehensive lifestyle guidance, supported by multi-task learning and complex ontologies. Context-aware systems that consider factors like location, weather, or health status can further improve recommendation relevance. Matrix Factorization, particularly Explainable Matrix Factorization (EMF), is also gaining attention for generating top-n explainable recommendations when limited side data is available, using metrics like Mean Explainability Precision and Recall [12].

3. Methodology

This study proposes an ontology-based personalized diet recommendation system tailored to Sri Lankan individuals, considering cultural food habits, medical conditions, and nutritional needs. The methodology encompasses user data collection, ontology development, and implementation of a machine learning engine for personalized diet recommendations. And the overall architecture of the ontology-based personalized diet recommendation system is illustrated in Figure 1. It outlines the key components of the system and the flow of data from user input to personalized diet recommendations. The architecture integrates a user profile management module, an ontology knowledge base, and a machine learning engine that works in conjunction with the reasoning module to generate customized dietary suggestions.

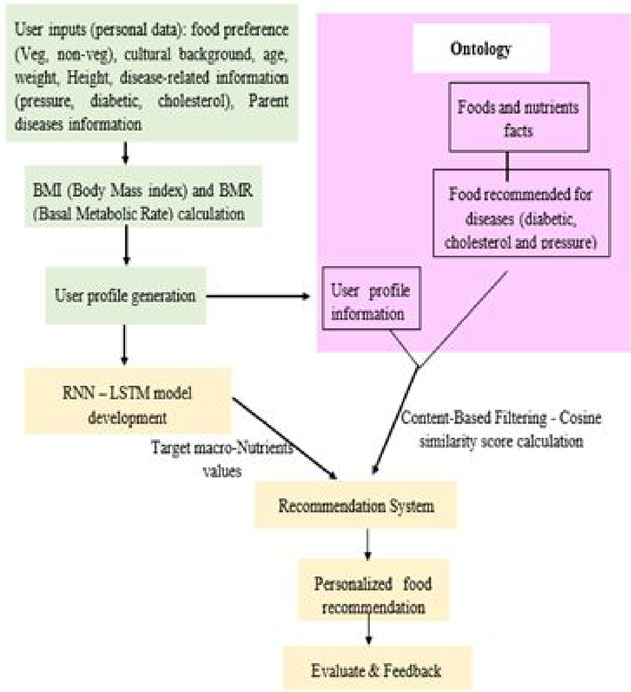

Figure 1: Proposed System Architecture

3.1 Data Collection

Data collection involves gathering various data that is essential for creating personalized diet recommendations. There are two types of data set available in this study. User information dataset and food related dataset. User information dataset includes food preference, cultural background, age, weight (kg), height (cm) and disease-related information of different individuals. There are two values considered with food preference: Vegetarian and Non-Vegetarian. In addition, we considered individual health condition by considering the availability of blood pressure, diabetes and cholesterol. An initial set of 500 user responses was collected using a structured questionnaire. This survey was conducted anonymously, and participants provided informed consent before responding. No personally identifiable information was collected. To increase the dataset size for more robust analysis and machine learning training, the original 500 user dataset was expanded to 1,000 entries using Generative AI techniques.

The second dataset comprises information about various foods along with their nutritional values and dietary guidelines tailored for individuals with specific diseases information such as high blood pressure, cholesterol issues, obesity, and diabetes. This data set is collected from nutritionists through interviews and gathered some data from public database and Sri Lanka food websites.

3.2 Data Preprocessing

Data preprocessing is a key step which cleans and transforms the input data to ensure its suitability for further analysis. We used one hot encoding technique (e.g. gender, food preference) and multi hot encoding (e.g. user health condition) to convert categorical variables as numerical values. Additionally, we performed missing value analysis to increase the accuracy of the dataset. Missing values were handled by replacing them with appropriate statistical measures such as the mean for numerical attributes

3.3 Model Selection and Development

An assessment of machine learning techniques for personalized diet recommendation required the selection of robust regression model capable of predicting individual nutrient requirements based on user health profiles. Here we have chosen Recurrent Neural Network (RNN) enhanced with LSTM. As a first step by using age, sex, height and weight values in dataset, we have calculated the BMI and BMR values. Then by getting the help of nutritionists, target nutrient values calculated for each user by considering their BMI and health status. After that, we performed feature extraction. Several important health indicators are included in our dataset throughout the feature extraction stage. We used programs to extract features from our data, including age, blood pressure, diabetes status, cholesterol levels, body mass index, and basal metabolic rate. These characteristics were combined into a multidimensional array called X, where each row and one of the previously described health indicators represent a user by each column. We simultaneously created the goal variables, which represent the estimated nutritional demands and contain the protein, fat, and carbohydrate targets. To make sure that each nutritional objective corresponds with the associated user data in X, these targets were arranged into another array, Y. In addition to guaranteeing accurate alignment between the input (x) and output (y) data, this organized approach to data preparation makes it easier to train the LSTM model effectively. Before training the models, we normalized the input and target data and split the input and target data into training and testing sets. We set the test size to 20% of the whole dataset and then shuffled the data to ensure stable model training.

3.4 Ontology Model Development

The ontology model consists of information related to food. In addition, to develop this ontology, we use food based dietary guidelines published by the Ministry of Health and World Health Organization (WHO) nutrient recommendations. Collected information is categorized into five types of food groups such as fruits, protein foods (fish and meat), vegetables, grains and dairy products. Here we consider the food name, portion size, calorie available in the food, macro nutrient contents (carbohydrate content, protein content and fat content), micronutrients (sodium content, fiber content, calcium content, potassium content, vitamins), suitable meal type and suitability for diabetics, cholesterol and pressure under food information. This information is mapped into classes, data properties and object properties within the ontology. Ontology is implemented using tools Protégé and stored in a format Web Ontology Language (OWL). There are seventy-five food information available in the ontology. Ontology consists with seven main classes such as Dietary category, Diet plans, Diseases, Food Items, Meal Type, Nutrients and User profiles. Diseases class is divided into four sub classes such as cholesterol, diabetes, obesity and pressure. Food Items class has five subclasses as vegetable, fruits, grains, meat fish and dairy products. Nutrient class consists of two subclasses such as macronutrients and micronutrients. User profile class has three subclasses such as BMI profile, BMR profile and Cultural background class. Figure 2shows the classes hierarchy of ontology.

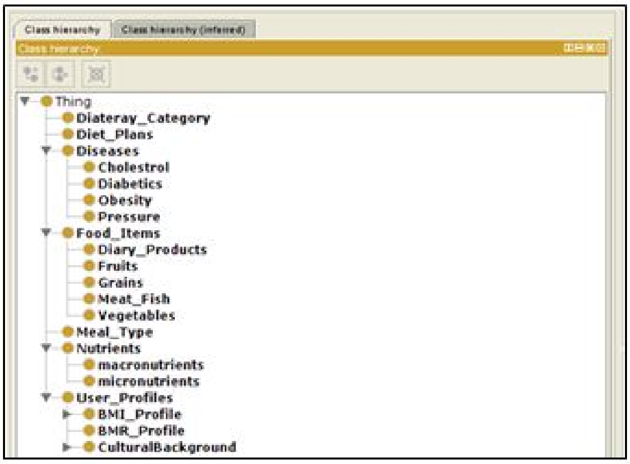

Figure 2: Classes hierarchy of the ontology

Object properties in an ontology define relationships between two instances of classes. Data properties assign data values to individual instances. There are few data properties and object properties available in our ontology. Domain and the range are the two main concepts associated with object properties and data properties. The following table represents the object properties available in the ontology with their domain and range.

Table 1: Object properties in the ontology

Object Properties	Domain	Range
belongsToMealType	Food_Items	Meal_Type
foodPreference	User_Profile	Dietary_Category
hasBMIValue	User_Profile	BMI_profile
hasCulturalBackground	User_Profile	Cultural_Background
hasDiateoryCategory	Food_Items	Dietary_Category
hasDiseases	User_Profile	Diseases
hasNutrients	Food_Items	Nutients
hasSuitableforCholestrol	Food_Items	Cholesterol
hasSuitableforDiabetics	Food_Items	Diabetes
hasSuitableforObesity	Food_Items	Obesity
hasSuitableforPressure	Food_Items	Pressure

Moreover, the ontology includes a variety of other data properties that are crucial for constructing comprehensive user profiles. These properties encompass age, Basal Metabolic Rate (BMR) values, BMI class, cultural background, gender, and specific disease-related information. Each of these data properties plays a vital role in the recommendation system by ensuring that all user-specific factors are considered when generating diet plans. Figure 3 shows the data properties available in the ontology.

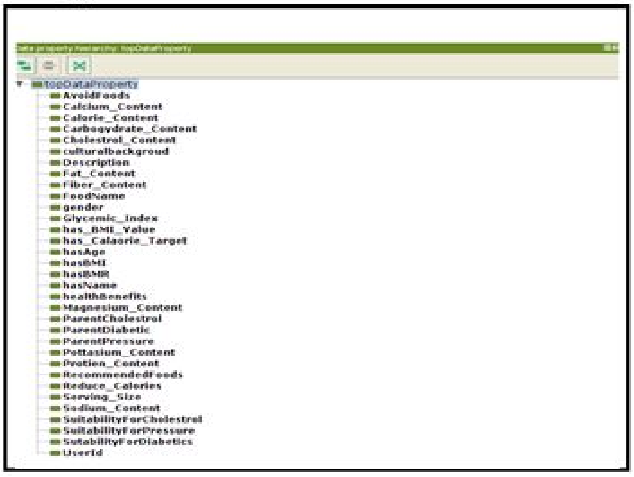

Figure 3: Data properties available in the ontology

Finally, Food items are represented using individual concepts available in ontology. For instance. Figure 4 shows the ontology graph.

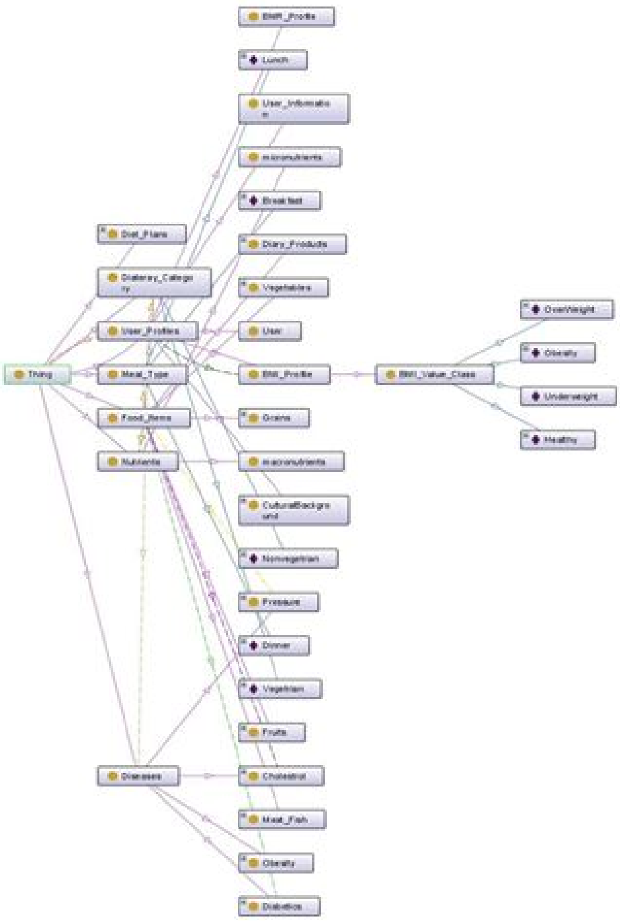

Figure 4: Ontology Grap

3.5 Recommendation Engine Implementation

A key component of this study is the implementation of a personalized diet recommendation system based on content-based filtering.

The system considers predicted protein, fat, and carbohydrate targets from the RNN model, along with user preferences, disease history, and cultural background. Diets are recommended for breakfast, lunch, and dinner. The process begins with user profile generation, which is then integrated into the ontology. Nutritional and food data are retrieved from the ontology using SPARQL queries, after loading it into the Jupiter environment. To generate recommendations, cosine similarity is computed between the predicted nutrient targets and the nutrient content of foods in the ontology. These similarity scores are then refined using user preferences, cultural context, and disease information to provide a personalized list of suitable foods.

4. Result and Evaluation

4.1 Results of Recurrent Neural Network

Several evaluation metrics are used to evaluate the performance of the RNN LSTM model. Raksha Pawar and his research team (2001) suggested the K-Nearest neighbors (KNN) algorithm to find the necessary nutrients based on user needs [13]. To evaluate the performance of the RNN-LSTM algorithm suggested by this study, we developed a KNN model using the same dataset for comparison. By implementing both models on identical data, we aim to rigorously compare their predictive accuracies and overall performance. The following table presents a comprehensive comparison between the performance metrics of the RNN-LSTM and KNN models.

Table 2: RNN- LSTM and KNN model Comparison

Metric	RNN- LSTM model	KNN model
Mean Squared Error (MSE)	0. 0209	0.0915
Mean Absolute Error (MAE)	0.1239	0.2181
Root Mean Squared Error (RMSE)	0.1703	0.3025
R-squared value (R^2)	0.9704	0.8067
Pearson correlation coefficient	0.9869	0.9054

The RNN-LSTM model has a significantly lower MSE compared to the KNN model, indicating that the RNN-LSTM model's predictions are closer to the actual values on average. In addition, the lower RMSE of the RNN-LSTM model further confirms its higher prediction accuracy, as RMSE penalizes larger errors more significantly. The RNN-LSTM model explains 97.04% ofthe variance in the target variable, compared to 80.67% explained by the KNN model, indicating a much better fit to the data.

While both models show strong positive correlations between predicted and actual values, the RNN-LSTM model has a higher correlation coefficient, indicating a better linear relationship with the actual data. Overall, the RNN-LSTM model demonstrates good performance compared to the existing KNN model across all evaluated metrics. By capturing complex patterns and relationships within the data, the RNN-LSTM model delivers more accurate and reliable predictions.

The scatter plot of actual versus predicted values was generated to evaluate the model's performance graphically, as shown in Figure 5. Ideally, if the model performs well, the data points should lie close to the diagonal line, indicating strong agreement between actual and predicted values. In our RNN model, the majority of points are tightly clustered around the diagonal, suggesting a strong linear relationship and high prediction accuracy. Although a few points deviate from the line, the overall distribution reflects robust model performance with minimal error.

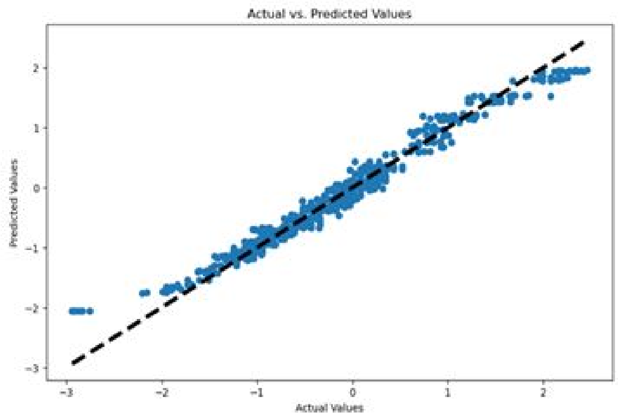

Figure 5: Scatter Plot of Predicted vs Actual Value

Finally, a graph was plotted to compare the first 20 predicted values with the corresponding actual values. Figure 6 illustrates the nutrient target predictions (carbohydrate, proteins, and fats) along with their actual values for visual evaluation of the model's performances.

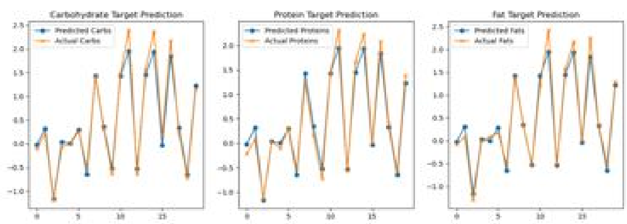

Figure 6: Scatter Plot of Predicted vs Actual Values

4.2 Results of Recommendation System

Recommendation is the most valuable part of this study. Content based filtering and cosine similarity functions are used for recommendation. The implemented recommendation system was tested by using different test scenarios simulating different user profiles. Below are two representative test cases demonstrating the system's ability to generate personalized dietary recommendations based on user preferences and health conditions.

Test Scenario 1:

Case Description:

User preference: Non-Vegetarian
Cultural Background: Sinhala
Dietary Restriction: No
Pressure: False
Diabetes: False
Cholesterol: False
Parent Pressure condition: False
Parent Diabetic condition: False
Parent Cholesterol condition: False

Recommendation Output:

Figure 7: Recommendation interface for Test Scenario 1

Test Scenario 1:

Case Description:

User preference: Vegetarian
Cultural Background: Sinhala
Dietary Restriction: No
Pressure: False
Diabetes: False
Cholesterol: False
Parent Pressure condition: False
Parent Diabetic condition: False
Parent Cholesterol condition: False

Recommendation Output:

Figure 8: Recommendation interface for Test Scenario 2

Figure 7 and Figure 8 display the output of the recommendation system for the two test cases presented above.

5. Conclusion

This study presents an ontology-based diet recommendation system tailored for the Sri Lankan population, integrating RNN-LSTM models, content-based filtering, and a domain-specific food ontology. The system successfully recommends personalized diets by considering user preferences, health conditions, and cultural factors. Evaluation results showed that the RNN-LSTM model outperformed the KNN model across all metrics, achieving higher accuracy and a better fit to the data. In future work, we aim to enhance the model's performance by increasing the user dataset size and expanding the food ontology to include a wider variety of items. Additionally, future research could focus on incorporating micronutrient analysis into the recommendation process. Overall, there is great potential for further work in this area, and continued research and development could lead to significant advancements in the field of food recommendation systems.

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