Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16305
e-ISSN : 2541-2019
p-ISSN : 2541-044X

A Web-Based Personalized Diet Recommendation System Using Decision Tree for Food Suitability Classification

Muhammad Farhansyah[1)*], Safitri Jaya[2)]
[1,2)] Informatics, Faculty of Technology and Design, Universitas Pembangunan Jaya, Indonesia
[1)]muhammad.farhansyah2022@student.upj.ac.id, [2)] safitri.jaya@upj.ac.id

Submitted :June 1, 2026 | **Accepted** : June 10, 2026 | **Published** : July 5, 2026

Abstract: Obesity and unhealthy eating patterns have become significant health concerns due to poor dietary habits and a lack of personalized nutritional guidance. Existing food recommendation systems often provide general recommendations without considering individual calorie and nutritional requirements. Therefore, this study aims to develop a web-based diet food recommendation system that integrates nutritional requirement calculations and Decision Tree-based food suitability classification. The system utilizes user information, including age, gender, weight, height, physical activity level, and diet goals, to calculate nutritional requirements through Body Mass Index (BMI), Basal Metabolic Rate (BMR) using the Mifflin-St Jeor method, and Total Daily Energy Expenditure (TDEE). A food dataset containing Indonesian foods and beverages was preprocessed and labeled using a rule-based approach based on macronutrient similarity scores. The Decision Tree algorithm was implemented to classify foods into suitable and unsuitable categories according to users' nutritional requirements. Suitable foods were subsequently processed through a scoring mechanism and meal construction procedure to generate personalized meal plans. Experimental results showed that the Decision Tree model achieved an accuracy of 92.50%, precision of 78.26%, recall of 94.74%, and F1-score of 85.71%. System testing demonstrated that the developed features functioned properly and generated structured diet recommendations automatically. In conclusion, the proposed system can assist users in selecting foods according to their nutritional requirements and support healthier dietary planning.

Keywords: Calorie Needs; Decision Tree; Diet Food Recommendation; Nutritional Requirements; Web-Based System

INTRODUCTION

Obesity and unhealthy dietary patterns have become major public health concerns worldwide, including in Indonesia. Poor dietary habits and excessive calorie intake are key contributing factors to obesity and related chronic diseases such as diabetes and cardiovascular disorders (Sakir et al., 2024). In many cases, individuals struggle to manage daily food consumption due to the lack of personalized nutritional guidance based on their physiological conditions. Personalized nutrition has emerged as an approach that considers individual characteristics, lifestyle, and nutritional needs rather than applying a one-size-fits-all dietary strategy (Roman et al., 2024). As a result, dietary decisions are often made without proper nutritional consideration, which may lead to ineffective diet management and adverse health outcomes.

To address these issues, calorie estimation methods such as Body Mass Index (BMI), Basal Metabolic Rate (BMR), and Total Daily Energy Expenditure (TDEE) are commonly used to determine individual energy requirements. These methods provide a quantitative approach to estimate daily caloric needs based on physiological attributes such as weight, height, age, and physical activity level. Among these methods, the Mifflin-St Jeor equation is widely used due to its relatively high accuracy in estimating energy expenditure and nutritional requirements (de Hoogh et al., 2023). These calculations serve as an important foundation for personalized dietary planning.

Recent advances in artificial intelligence have enabled the development of recommendation systems in various domains, including healthcare and nutrition. Machine learning-based recommendation systems have been widely applied to generate personalized suggestions based on user characteristics and preferences (Rostami et al., 2023;

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16305
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Singh & Dwivedi, 2023). Health-aware recommendation systems further enhance this process by incorporating user health indicators and nutritional conditions (Chen et al., 2023). Recent studies have also highlighted the growing role of artificial intelligence in personalized nutrition, where recommendation systems can support individualized dietary planning based on users' nutritional requirements and health conditions (Kalpakoglou et al., 2025; Wang et al., 2025). However, several limitations remain in existing diet recommendation studies. Most previous studies focus either on calorie requirement estimation or food recommendation mechanisms separately, resulting in limited integration between nutritional analysis and recommendation generation. In addition, many recommendation systems provide limited explanation regarding the decision-making process, reducing the interpretability of generated recommendations. Furthermore, limited studies integrate nutritional assessment, food classification, and recommendation generation within a unified web-based system. These limitations reduce the effectiveness and transparency of personalized diet planning systems.

Among various machine learning techniques, the Decision Tree algorithm is widely used for classification tasks due to its interpretability, simplicity, and ability to generate clear decision rules from structured data. This algorithm enables systematic classification of food items based on nutritional characteristics and predefined criteria. Although previous studies have explored food recommendation systems and calorie requirement estimation, several research gaps remain. Existing studies generally focus on these components separately, resulting in limited integration between nutritional analysis and recommendation generation. In addition, many recommendation systems provide limited explanation regarding the decision-making process behind recommended foods. Furthermore, limited studies integrate BMI, BMR, and TDEE calculations with machine learning-based food classification and personalized meal generation within a single web-based system.

Based on these limitations, this study proposes a web-based personalized diet recommendation system that integrates BMI, BMR, and TDEE calculations with Decision Tree-based food suitability classification within a unified recommendation framework. Unlike previous studies that mainly focus on recommendation algorithms or calorie estimation separately, this study combines nutritional requirement analysis, rule-based food suitability labeling, interpretable Decision Tree classification, and meal construction procedures in a single web-based system. The main contribution of this study lies in the integration of these components to generate personalized meal recommendations while maintaining transparency in the food classification process.

LITERATURE REVIEW

Diet food recommendation systems have become increasingly important in supporting healthier dietary behavior through personalized nutritional guidance. The increasing prevalence of obesity and unhealthy eating patterns has encouraged the development of systems that assist individuals in selecting foods based on their nutritional requirements. Existing studies have explored various recommendation approaches based on nutritional intake, calorie estimation, and user preferences. For instance, Bondevik et al. (2024) discussed the development and implementation of food recommender systems that utilize user dietary preferences, nutritional profiles, and health-related requirements to recommend healthier food choices. These studies indicate that recommendation systems have the potential to improve nutritional awareness and dietary management.

Recommendation systems are generally developed based on the concept of providing personalized suggestions by matching user characteristics with available alternatives. In the healthcare domain, personalized recommendation systems play an important role in supporting decision-making processes by considering individual health conditions and nutritional requirements. According to Chen et al. (2023), health-aware recommendation systems utilize user health information to generate recommendations that are more relevant to individual needs. Therefore, personalized nutrition recommendation can be considered as a form of decision support system that assists users in selecting appropriate foods based on nutritional requirements

Determining calorie requirements is a crucial aspect of developing personalized diet recommendation systems. Body Mass Index (BMI) is commonly used to classify body condition based on weight and height and to support dietary target determination. Basal Metabolic Rate (BMR) estimates the minimum energy required by the body at rest, while the Mifflin-St Jeor equation is widely used due to its relatively high accuracy in estimating energy expenditure (de Hoogh et al., 2023). Furthermore, Total Daily Energy Expenditure (TDEE) is used to estimate total daily calorie needs based on physical activity levels. These measures are essential in personalized diet planning because nutritional requirements vary among individuals.

Machine learning techniques are increasingly applied to improve recommendation accuracy and decision-making in health-related systems. The Decision Tree algorithm is widely used in classification tasks due to its simplicity, interpretability, and ability to generate clear decision rules from structured data. Previous studies have implemented Decision Tree–based approaches in health-related systems and reported promising results in improving classification and decision-making performance (Bahalkeh et al., 2023). Likewise, Rahayu et al. (2026) demonstrated the effectiveness of Decision Tree in classifying food groups based on nutritional composition, including carbohydrates, proteins, and fats. Rahman (2023) also emphasized that Decision Tree provides more transparent classification mechanisms compared to more complex machine learning models.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16305
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Several studies have also highlighted the role of rule-based systems in improving recommendation quality in healthcare applications. Papadopoulos et al. (2022) explained that decision-support systems enhance recommendation consistency through structured decision logic. Furthermore, previous studies have explored various approaches related to food recommendation, nutritional analysis, and Decision Tree classification. A comparison of selected previous studies is presented in Table 1. Based on these studies, most existing approaches focus on calorie estimation, recommendation generation, or nutritional classification separately. Limited research integrates BMI, BMR, and TDEE calculations with Decision Tree-based food suitability classification and personalized meal plan generation within a unified web-based recommendation system.

Table 1 Comparison of Previous Studies

Author	Method	Dataset	Result	Research Gap
Pangestu et al. (2025)	Content-Based Filtering	Indonesian healthy food dataset	Healthy food recommendation	No machine learning-based food classification
Chen et al. (2023)	Health-Aware Recommendation System	Health and nutrition dataset	Personalized nutrition recommendation	Does not integrate BMI, BMR, and TDEE calculations
Bondevik et al. (2024)	Food Recommender System Review	Food and nutrition recommendation studies	Personalized food recommendation approaches	No machine learning-based food classification and calorie requirement estimation
Rahayu et al. (2026)	Decision Tree	Food nutrition dataset	Food group classification	No calorie requirement estimation and recommendation generation
Papadopoulos et al. (2022)	Rule-Based Decision Support System	Clinical decision support data	Consistent recommendation generation	Not focused on food recommendation and nutritional classification

Based on the comparison presented in Table 1, previous studies have mainly focused on food recommendation, nutritional analysis, health-aware recommendation systems, or Decision Tree classification as separate approaches. In contrast, the proposed study integrates BMI, BMR, and TDEE calculations with rule-based nutritional labeling, Decision Tree-based food suitability classification, and personalized meal plan generation within a single web-based system. Therefore, this study aims to provide a more comprehensive and interpretable framework for personalized diet recommendation.

METHOD

Data Collection and Preprocessing

The data collection stage involves gathering two main categories of data, namely user data and food nutritional datasets. User data include age, gender, body weight, height, and physical activity level, which are used to calculate users' daily energy requirements. These data are obtained through direct input into the application system. Meanwhile, the food dataset is obtained from the *Indonesian Food and Drink Nutrition Dataset* (Hanif, 2023), which is derived from the Indonesian Food Composition Table (Tabel Komposisi Pangan Indonesia/TKPI) published by the Ministry of Health of the Republic of Indonesia. The dataset contains nutritional information such as calories, proteins, fats, carbohydrates, and food names, which are utilized as the basis for food classification and recommendation processes.

After data collection, preprocessing was performed to ensure dataset quality before classification. The preprocessing stage included data cleaning to remove incomplete, duplicated, empty, or invalid records. In addition, keyword-based filtering was applied to exclude irrelevant food items such as infant formula, raw ingredients, flour-based products, and non-consumable entries, while retaining commonly consumed Indonesian foods, following the filtering approach adapted from previous nutritional dataset studies. Formatting adjustments and data standardization procedures were conducted to ensure consistency among nutritional attributes and improve data quality. The food dataset initially consisted of approximately 1,346 Indonesian food and beverage records obtained from the nutritional dataset. During preprocessing, duplicate entries and nutritionally irrelevant food items were removed according to predefined filtering criteria. As a result, the dataset size was reduced to 400 food records. No sampling or class balancing techniques were applied in this study.

The resulting dataset was subsequently used for rule-based labeling and divided into training and testing sets using an 80:20 ratio with a random state of 42 before Decision Tree model training and evaluation. The dataset includes nutritional attributes such as calories, proteins, fats, carbohydrates, and food names. Although calorie

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026 e-ISSN : 2541-2019
DOI : https://doi.org/10.33395/sinkron.v10i3.16305 p-ISSN : 2541-044X

information is available, the Decision Tree classification model uses protein, fat, and carbohydrate attributes as input features, while calorie information is used to support nutritional analysis and recommendation presentation. An example of the dataset structure is shown in Table 2.

Table 2. Sample of Food Nutrition Dataset

ID	Calories	Protein	Fat	Carbohydrates	Name
1	297	35.9	15.2	1.6	Kentucky Fried Chicken Wing
2	298	34.2	16.8	0.1	Kentucky Fried Chicken Breast
3	300	24	20.7	4.5	Fried Duck Meat
4	154	3	4.5	25.5	Fried Rice Vermicelli
5	252	19.9	19.1	0	Fried Catfish
6	265	40.6	10.1	0	Fried Squid
7	154	16.6	9.2	0	Goat Meat
8	34	4.1	0.4	5.8	Long Bean Leaves
9	31	3.7	0.6	4.8	Boiled Cassava Leaves
10	180	3	0.3	39.8	Rice
11	212	18	10.6	59.3	Shredded Beef

System Design

The diet food recommendation system is implemented as a web-based application that includes several main features such as login, registration, generate diet plan, recommendation history, and logout. The system is designed to assist users in obtaining personalized food recommendations according to calorie and macronutrient requirements. Through the web-based platform, users can easily access the system and generate meal recommendations based on their individual nutritional needs. The use case and activity diagrams were modeled using Unified Modeling Language (UML) to represent user interactions and system workflows clearly (Wayahdi & Ruziq, 2023). The main feature, namely generate diet plan, allows users to input personal information such as age, gender, body weight, height, physical activity level, and diet goals. The system then processes these data to calculate nutritional requirements and generate personalized diet recommendations.

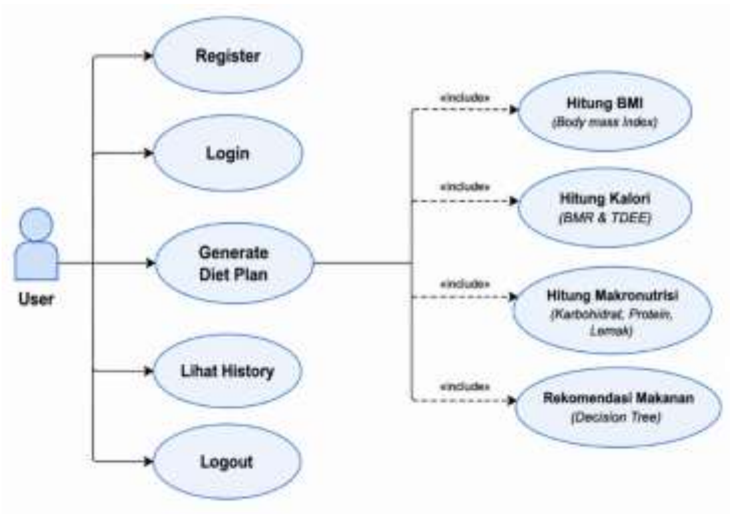

Figure 1 Use Case Diagram System

The use case diagram shown in Fig. 1 illustrates interactions between users and the recommendation system. Users can perform several activities including registration, login, generating diet plans, viewing recommendation history, and logging out. These functionalities represent the main operational flow of the system in generating personalized meal recommendations according to users' nutritional needs.

BMI, BMR, and TDEE Calculations

The next stage involves calculating calorie requirements using Body Mass Index (BMI), Basal Metabolic Rate (BMR), and Total Daily Energy Expenditure (TDEE). BMI calculations are conducted to identify users' body condition categories such as underweight, normal, or overweight. The BMI formula is shown in Equation (1).

*name of corresponding author

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

After obtaining BMI values, Basal Metabolic Rate (BMR) calculations are performed using the Mifflin-St Jeor method due to its effectiveness in estimating calorie requirements.

For male users:

$$BMR = (10 \times Weight) + (6.25 \times Height) - (5 \times Age) + 5 \quad (2)$$

For female users:

$$BMR = (10 \times Weight) + (6.25 \times Height) - (5 \times Age) - 161 \quad (3)$$

Subsequently, Total Daily Energy Expenditure (TDEE) is calculated to determine total daily calorie needs according to physical activity levels.

$$TDEE = BMR \times Activity \quad (4)$$

The obtained TDEE value is then used to determine daily macronutrient requirements consisting of proteins, fats, and carbohydrates before recommendation generation is conducted.

Data Labeling Process

Before classification, the food dataset underwent a rule-based labeling process to determine food suitability according to users' nutritional requirements. Target macronutrient values (protein, fat, and carbohydrate) were calculated from the user's daily calorie requirements obtained through BMI, BMR, and TDEE calculations. For each food item, a nutritional distance score was calculated as the sum of the absolute differences between the food's protein, fat, and carbohydrate values and the corresponding target macronutrient values. The food items were then ranked according to their distance scores. Food items belonging to the lowest 30% of distance scores were labeled as Suitable (1), while the remaining items were labeled as Unsuitable (0). These labels were subsequently used as target variables for training the Decision Tree classification model.

Classification Using Decision Tree

The classification stage utilizes the Decision Tree algorithm to learn food suitability patterns from the labels generated during the rule-based labeling process. The model uses protein, fat, and carbohydrate content as input variables, while the suitability label (Suitable/Unsuitable) obtained from the nutritional distance-based labeling process serves as the target variable. Based on these attributes, the Decision Tree model learns the relationship between nutritional characteristics and the generated suitability labels, allowing it to classify food items according to the learned patterns and generate interpretable decision rules. The Decision Tree model was implemented using the Gini impurity criterion (default setting), with a maximum depth of 5 and a random state of 42. The labeled dataset was divided into training and testing sets using an 80:20 ratio before model training and evaluation.

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16305
e-ISSN : 2541-2019
p-ISSN : 2541-044X

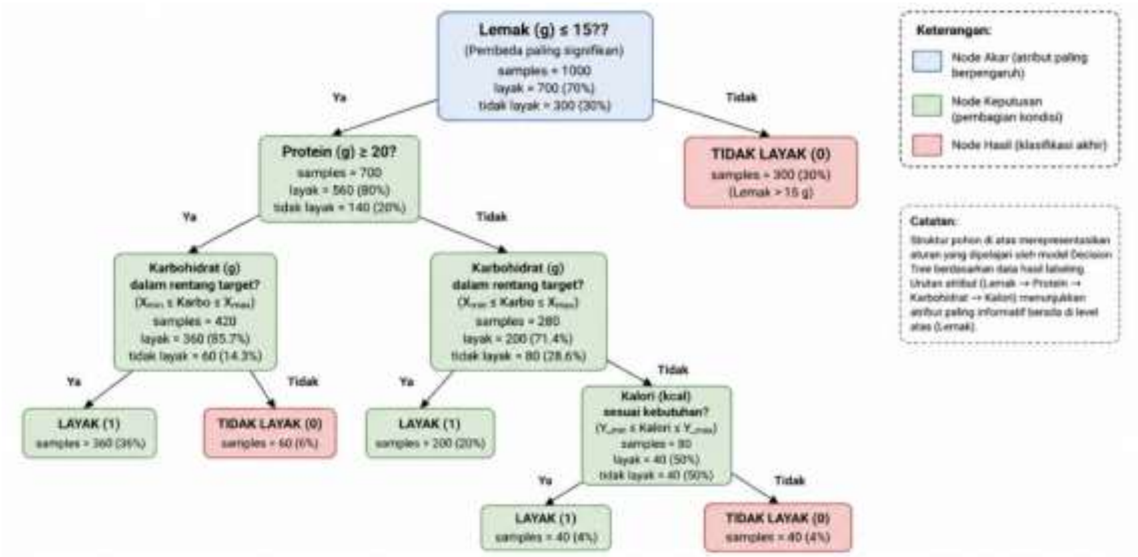

Figure 2 Decision Tree Classification Diagram

The Decision Tree classification model shown in Fig. 2 illustrates the classification process used to determine food suitability based on nutritional attributes. The model evaluates nutritional features consisting of protein, fat, and carbohydrate content and applies decision rules learned during training to classify food items as either Suitable or Unsuitable.

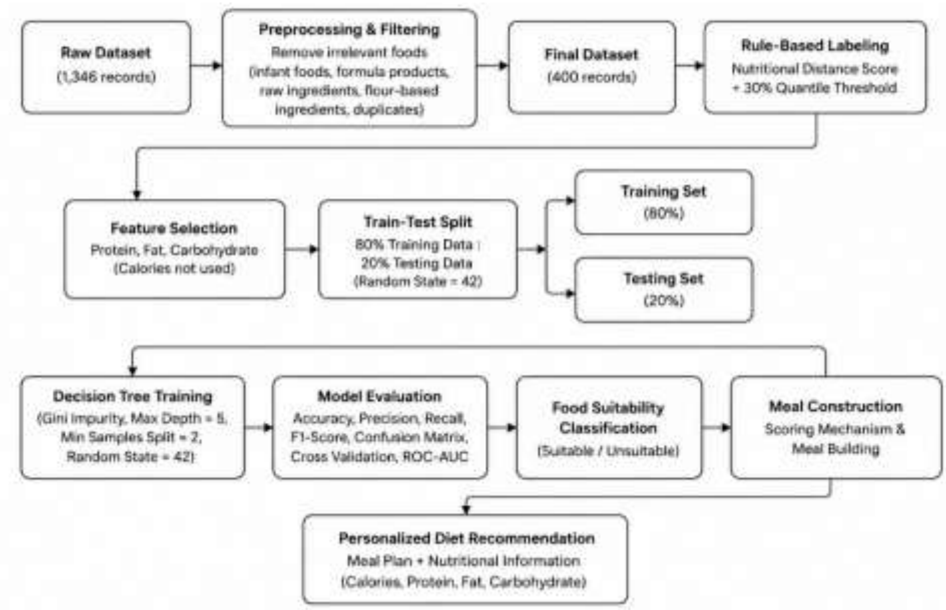

Figure 3 Machine Learning Pipeline

Figure 3 illustrates the machine learning pipeline implemented in this study. The process begins with dataset preprocessing and filtering, followed by rule-based labeling using nutritional distance scores and a 30% quantile threshold. The labeled dataset is then divided into training and testing sets before being used to train the Decision Tree model. Finally, the classification results are utilized during the meal construction stage to generate personalized diet recommendations.

System Implementation

The recommendation system is implemented through a web-based platform. During the generate diet plan process, users are required to input personal information including age, gender, body weight, height, activity level, and diet goals. After data validation, the system automatically calculates BMI, BMR, TDEE, and macronutrient

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026 e-ISSN : 2541-2019
DOI : https://doi.org/10.33395/sinkron.v10i3.16305 p-ISSN : 2541-044X

requirements before generating personalized meal recommendations. After the classification process, food items predicted as Suitable are ranked using a scoring mechanism based on the difference between their nutritional values and the user's target macronutrient requirements. The selected food items are then combined through a meal construction process to generate personalized meal plans.

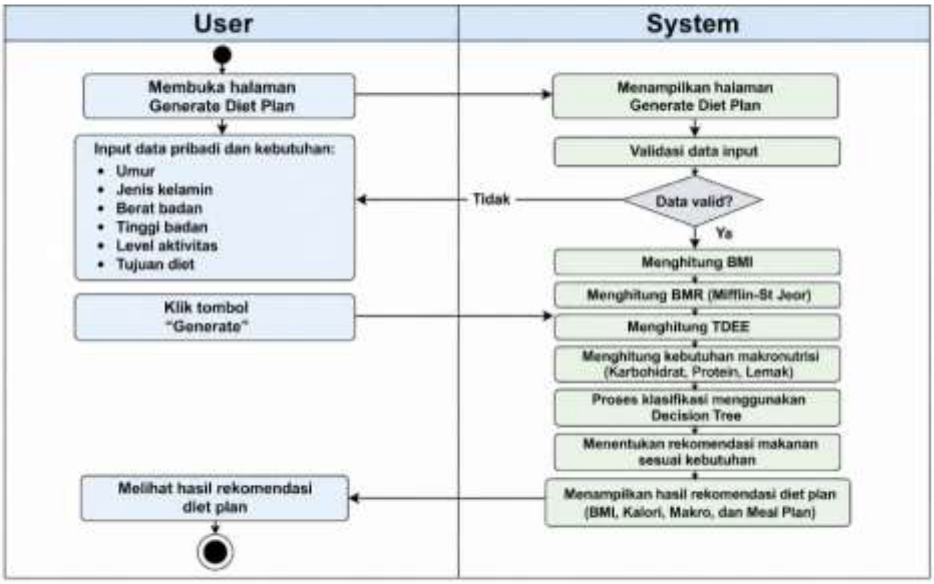

Figure 4 Activity Diagram of Generate Diet Plan

The activity diagram illustrates the recommendation process starting from user input, validation, calorie calculations, nutritional requirement estimation, classification using Decision Tree, and recommendation generation. At the final stage, the system displays users' BMI status, calorie requirements, macronutrient information, and recommended meal plans.

System Testing

System testing is conducted using Black Box Testing and White Box Testing approaches to evaluate system functionality and program logic. Software testing techniques are widely used in software engineering to validate whether a system meets its functional requirements and to ensure correctness of internal logic execution. Black Box Testing focuses on validating system inputs and outputs without considering internal implementation details, while White Box Testing analyzes internal code structure, control flow, and execution paths to ensure system correctness and reliability (Aghababaeyan et al., 2023). Testing is performed on several main features including login, registration, generate diet plan, recommendation history, and logout.

RESULT

System Implementation Results

The diet food recommendation system was successfully implemented as a web-based application using the Decision Tree algorithm. The system was developed to assist users in obtaining food recommendations based on their calorie and macronutrient requirements. Several main features were implemented, including login, registration, generate diet plan, recommendation history, and logout. In the generate diet plan feature, users are required to enter personal information such as age, gender, body weight, height, and physical activity level. The system then calculates BMI, BMR, and TDEE to determine daily calorie requirements and macronutrient targets. These values are subsequently used in the food recommendation process using the Decision Tree algorithm.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16305

e-ISSN : 2541-2019
p-ISSN : 2541-044X

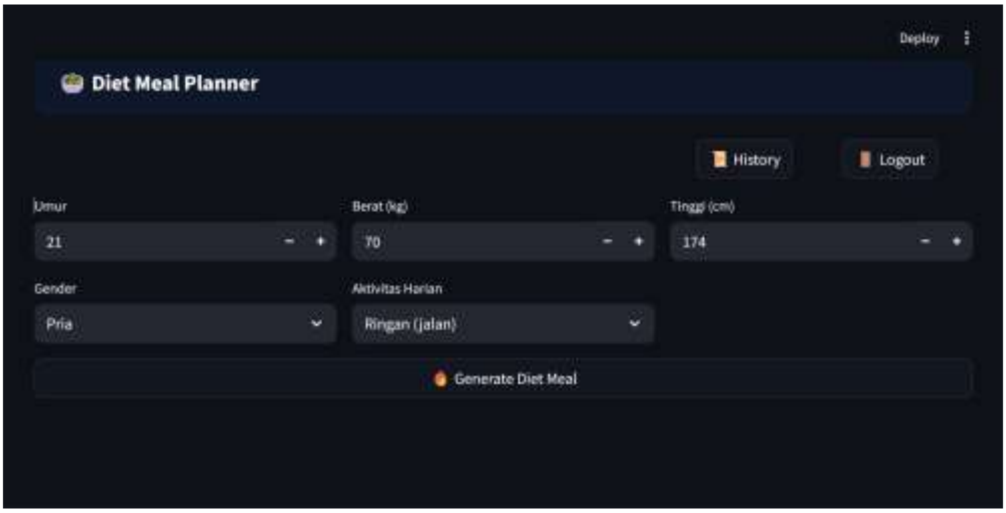

Figure 5 Generate Diet Plan Page

Based on Fig. 5, users can input personal and physical information, including age, gender, body weight, height, and activity level, before generating a diet plan. The entered data are processed by the system to calculate BMI, BMR, TDEE, and daily macronutrient requirements. These calculations are used to determine the user's nutritional needs and serve as the basis for the recommendation process.

After the calculation stage is completed, the system applies the Decision Tree algorithm to classify food data and identify suitable food alternatives. The classification process evaluates nutritional attributes, including protein, fat, and carbohydrates. Through this process, the system can filter foods that are more appropriate for the user's dietary needs and exclude less suitable alternatives.

The final output is presented in the form of a personalized meal plan along with information on calorie, protein, fat, and carbohydrate requirements. The generated recommendations are tailored according to the user's nutritional profile and activity level, allowing the system to provide more personalized diet suggestions. This feature enables users to obtain diet recommendations that are aligned with their individual nutritional needs and can support healthier dietary planning.

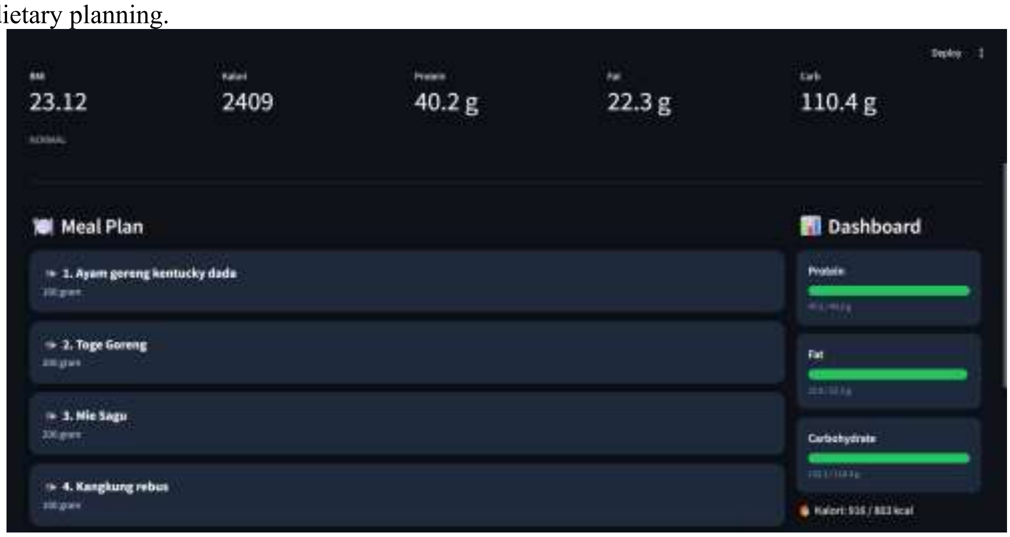

Figure 6 Meal Plan Recommendation Result

Based on Fig. 6, the system successfully displays meal plan recommendations together with calorie, protein, fat, and carbohydrate information. The generated meal plan consists of food items selected according to the user's nutritional requirements calculated in the previous stage. The recommendation process considers the user's daily calorie target and macronutrient requirements obtained from BMI, BMR, and TDEE calculations, ensuring that the suggested foods are aligned with the user's nutritional needs.

In addition, a nutrition dashboard is provided to help users compare nutritional targets with the nutritional content of the recommended foods. The dashboard presents nutritional information in a more structured and understandable manner, allowing users to evaluate whether the recommended meal plan meets their daily

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16305
e-ISSN : 2541-2019
p-ISSN : 2541-044X

nutritional needs. Users can observe the distribution of calories, protein, fat, and carbohydrates obtained from the recommended foods and compare them with the calculated nutritional targets.

The recommendation results demonstrate the integration between nutritional calculations and the Decision Tree classification process. By utilizing nutritional attributes such as protein, fat, and carbohydrates, the system is able to identify suitable food alternatives and generate personalized meal plans automatically. This feature supports users in making more informed dietary decisions and monitoring their nutritional intake more effectively. Furthermore, the presented recommendations can assist users in planning daily food consumption in a more structured and practical manner.

System Testing Results

System testing was conducted using Black Box Testing and White Box Testing methods to evaluate the functionality and reliability of the proposed diet food recommendation system. Black Box Testing was performed to verify whether each feature produced outputs according to the expected functional requirements, while White Box Testing was used to evaluate the internal logic and program flow implemented in the system.

The Black Box Testing process covered all major features, including login, registration, diet plan generation, recommendation history, and logout. The testing results indicate that all features functioned properly and produced outputs consistent with the expected system behavior. User inputs were successfully processed, and the system was able to generate personalized meal plan recommendations without functional errors. In addition, the recommendation history feature successfully stored and displayed previous recommendation results.

Table 3. Black Box Testing

No	Test Case	Process	Expected Result
1	Login	Enter a valid username and password, then click the Login button	The system successfully logs in and stores the user session
2	Access System Without Login	Open the application without an active login session	The system displays a warning message and redirects the user to the login page
3	Generate diet plan	The user enters age, weight, height, gender, and activity level, then clicks Generate	The system calculates BMI, BMR, and TDEE and displays food recommendations
4	Incomplete Data Input	The user submits the generate diet plan form with incomplete data	The system displays a validation message and rejects the process
5	View Recommendation History	The user opens the history page	The system displays the user's recommendation history along with the corresponding dates
6	Delete Single History Record	The user clicks the delete button on a specific history record	The selected record is removed from the database and no longer appears in the history page
7	Delete All History Records	The user clicks the delete all history button	All recommendation history records belonging to the user are removed from the database
8	Return to Application	The user clicks the "Back to App" button	The system redirects the user to the main application page
9	Logout	The user clicks the logout button	The user session is terminated and the system redirects the user to the login page

Meanwhile, White Box Testing was conducted to evaluate the correctness of the program logic involved in BMI, BMR, and TDEE calculations, macronutrient requirement estimation, data labeling, Decision Tree classification, and meal plan generation. The testing results show that the implemented algorithms and program flow executed according to the designed workflow. All calculation processes produced valid outputs, and the classification mechanism successfully determined food suitability based on users' nutritional requirements. Overall, the testing results demonstrate that the proposed system operates reliably and is capable of providing personalized diet food recommendations in a consistent and structured manner. The successful execution of both functional and logical testing indicates that the developed application meets the intended system requirements.

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16305
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Decision Tree Classification Performance

To evaluate the Decision Tree classification model, the labeled food dataset was divided into training and testing sets using an 80:20 ratio. Protein, fat, and carbohydrate contents were used as input features, while the rule-based suitability label served as the target variable. Calorie values were excluded because they are derived from macronutrient composition and may introduce redundant information. Suitability labels were generated using a nutritional distance score, and a 30% quantile threshold was applied, where the lowest 30% of scores were labeled as Suitable and the remaining records as Unsuitable. This threshold was selected to maintain class representation and reduce the risk of class imbalance. The resulting dataset was used to train and evaluate the Decision Tree model using Accuracy, Precision, Recall, F1-Score, cross-validation, and ROC-AUC metrics. The evaluation results are presented in Tables 4–7.

Table 4. Decision Tree Classification Performance

Metric	Value
Accuracy	92.50%
Precision	78.26%
Recall	94.74%
F1-Score	85.71%

Table 5. Classification Report

Class	Precision	Recall	F1-Score	Support
Unsuitable	0.98	0.92	0.95	61
Suitable	0.78	0.95	0.86	19
Accuracy	-	-	0.93	80
Macro Average	0.88	0.93	0.90	80
Weighted Average	0.93	0.93	0.93	80

Table 6. Confusion Matrix

Actual / Predicted	Unsuitable	Suitable
Unsuitable	56	5
Suitable	1	18

Table 7. Cross Validation Result

Fold	Accuracy
1	97.50%
2	93.75%
3	97.50%
4	92.50%
5	92.50%
Average	94.75%

The performance evaluation results presented in Tables 4–7 indicate that the proposed Decision Tree model achieved satisfactory classification performance. The dataset was divided into 320 training records and 80 testing records using an 80:20 train-test split with a random state of 42. The Decision Tree model was implemented using the Gini impurity criterion, a maximum depth of 5, a minimum samples split value of 2, and a random state of 42. Based on Table 4, the model achieved an accuracy of 92.50%, precision of 78.26%, recall of 94.74%, and an F1-score of 85.71%. The confusion matrix results show that 56 unsuitable food items and 18 suitable food items were correctly classified, while six records were misclassified. Furthermore, the classification report demonstrates strong performance across both classes. The unsuitable class achieved a precision of 0.98, recall of 0.92, and F1-score of 0.95, while the suitable class achieved a precision of 0.78, recall of 0.95, and F1-score of 0.86. The 5-fold cross-validation results produced an average accuracy of 94.75%, indicating that the model maintained stable performance across different data partitions. In addition, the ROC-AUC score of 0.9633 demonstrates a strong ability to distinguish between suitable and unsuitable food categories. These results suggest that protein, fat, and carbohydrate attributes provide sufficient information for food suitability classification and support the effectiveness of the proposed approach. The relatively high classification performance may be attributed to the consistency between the nutritional attributes and the rule-based suitability labels used during training, enabling the Decision Tree algorithm to learn clear classification patterns from the dataset.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16305
e-ISSN : 2541-2019
p-ISSN : 2541-044X

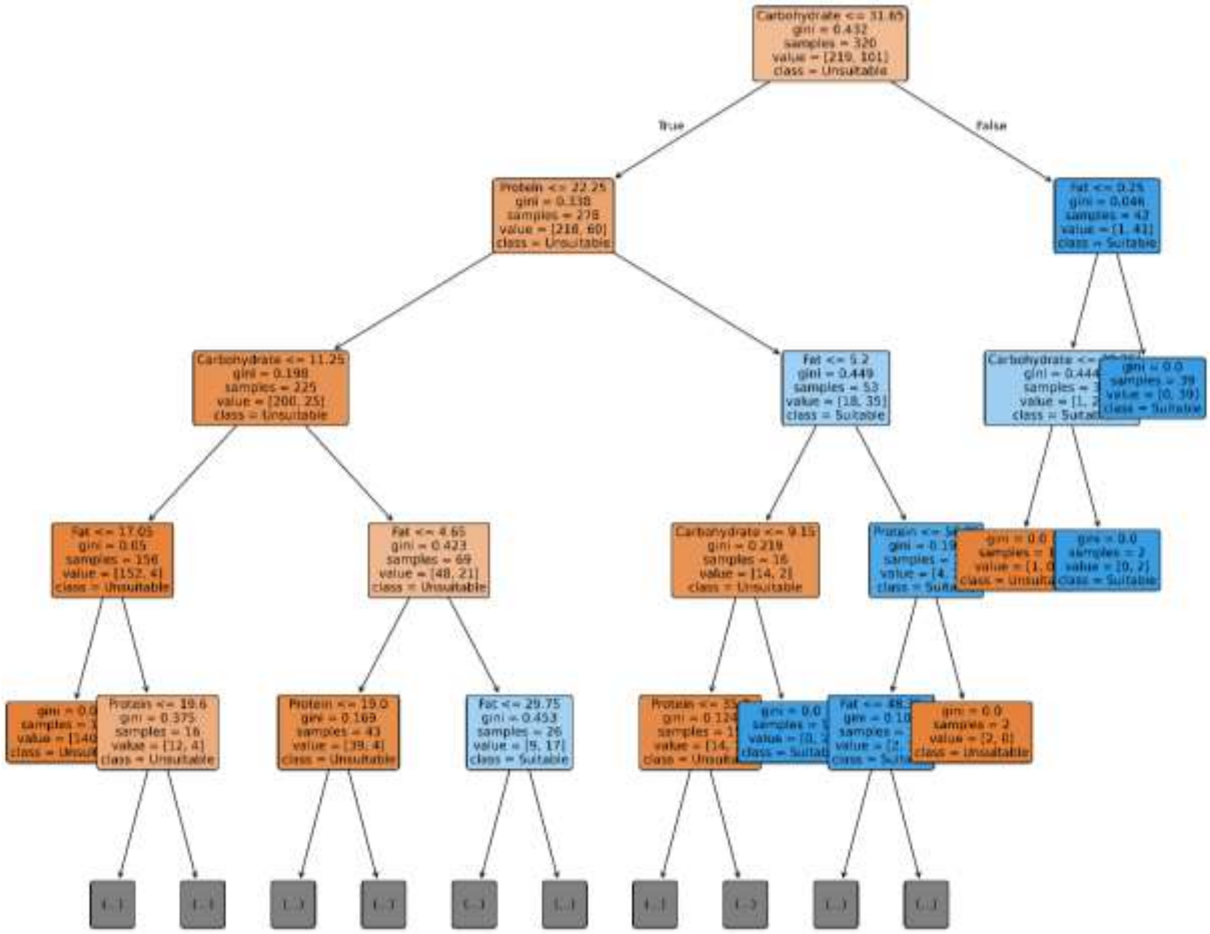

Figure 7 Decision Tree Visualization

Figure 7 presents the structure of the Decision Tree model used to classify food suitability based on protein, fat, and carbohydrate attributes. The visualization demonstrates the interpretable nature of the Decision Tree algorithm, where classification decisions are represented through hierarchical rules. This transparency facilitates understanding of the classification process and supports the explainability of the proposed model.

Feature importance analysis shows that carbohydrate content contributed the most to the classification process with an importance value of 0.4353, followed by protein (0.2926) and fat (0.2721). These results indicate that all three macronutrient attributes play important roles in determining food suitability, with carbohydrate having the greatest influence on the Decision Tree model.

The generated Decision Tree also produces explicit classification rules based on nutritional attributes. For example, food items with carbohydrate values greater than 31.65 g and fat values above 0.25 g tend to be classified as Suitable. Conversely, food items with carbohydrate values below 11.25 g, protein values below 22.25 g, and fat values below 17.05 g are generally classified as Unsuitable. These findings further demonstrate the transparency and interpretability of the Decision Tree algorithm.

DISCUSSIONS

The results demonstrate that the proposed diet food recommendation system can generate nutritionally personalized meal plans based on users' nutritional requirements. By integrating BMI, BMR, and TDEE calculations with Decision Tree-based food suitability classification, the system is able to determine calorie requirements and classify food items according to users' nutritional targets. Personalized meal plans are subsequently generated through a scoring mechanism and meal construction procedure. The implementation results indicate that the recommendation process can be performed automatically while providing structured information regarding calorie, protein, fat, and carbohydrate requirements.

Compared with previous studies that mainly focused on calorie calculation or recommendation mechanisms separately, the proposed system combines nutritional requirement calculations and food classification within a single web-based application. Studies conducted by Pangestu et al. (2025), Wang et al. (2025), and Kalpakoglou et al. (2025) utilized recommendation approaches to generate healthier food suggestions based on nutritional

*name of corresponding author

information and user preferences. However, the proposed system additionally incorporates BMI, BMR, and TDEE calculations before performing food classification using the Decision Tree algorithm. This integration enables the recommendation process to consider individual nutritional requirements more comprehensively.

In the proposed system, the Decision Tree algorithm functions primarily as a food suitability classifier rather than a direct meal plan generator. Foods classified as suitable are subsequently processed through a scoring mechanism and meal construction procedure to generate personalized meal plans that satisfy users' nutritional requirements. The use of the Decision Tree algorithm also provides advantages in terms of interpretability and transparency. Unlike more complex machine learning models, Decision Tree generates classification rules that are easier to understand and analyze (Frasca et al., 2024). This characteristic is beneficial in nutritional recommendation systems because the decision-making process can be interpreted based on nutritional attributes such as protein, fat, and carbohydrate content. The testing results indicate that the classification process and recommendation generation were successfully executed according to the designed workflow.

The proposed system has practical implications for personal diet planning, nutritional consultation, and health-support applications. By providing interpretable food classification and personalized meal recommendations, the system may assist users in making healthier dietary decisions (Papastratis et al., 2024). In addition, the transparency of the Decision Tree model allows users and practitioners to better understand the factors influencing food suitability recommendations. It is important to note that the suitability labels used in this study were generated through a rule-based nutritional distance approach before model training. Therefore, the Decision Tree model does not create new ground-truth labels independently but learns and generalizes the suitability patterns represented by the rule-based labeling process. This approach enables the model to transform predefined nutritional rules into an interpretable classification model that can be applied efficiently during recommendation generation.

The classification performance further supports the effectiveness of the proposed approach. The Decision Tree model achieved high accuracy, precision, recall, and F1-score values, indicating its ability to reliably classify food items according to nutritional suitability criteria. The cross-validation and ROC-AUC results also demonstrate consistent performance and good discriminative capability. These findings suggest that protein, fat, and carbohydrate attributes provide sufficient information for distinguishing food suitability while maintaining model transparency and interpretability. It should also be noted that the initial dataset consisted of 1,346 food records before preprocessing. Filtering procedures were applied to remove nutritionally irrelevant items, duplicate records, and foods that were not suitable for meal-planning purposes, resulting in a final dataset of 400 records. Therefore, the reduction in dataset size was caused by preprocessing and filtering procedures rather than sampling or balancing techniques.

Despite the promising results, several limitations should be acknowledged. First, the suitability labels were generated using a rule-based approach rather than manually annotated by nutrition experts. Therefore, the performance of the Decision Tree model depends on the quality and assumptions of the labeling rules used in this study. Second, the food dataset was limited to nutritional information obtained from the Indonesian Food Composition Table (TKPI), which may not represent all food variations consumed by users. Third, the recommendation process primarily considers nutritional requirements and does not incorporate additional factors such as food preferences, allergies, medical conditions, or cultural dietary habits. Finally, the evaluation focused on functional testing and classification performance metrics, while user satisfaction and recommendation effectiveness were not assessed through user-based experiments. Future studies may improve the system by expanding the food dataset, incorporating user preference features and expert validation, and exploring advanced machine learning approaches such as Random Forest and XGBoost.

CONCLUSION

This study developed a web-based diet recommendation system that integrates BMI, BMR, TDEE calculation, food suitability classification, and meal construction to generate personalized meal plans based on users' nutritional needs. The system utilizes user information, including age, gender, body weight, height, physical activity level, and diet goals, to calculate Body Mass Index (BMI), Basal Metabolic Rate (BMR), and Total Daily Energy Expenditure (TDEE). These calculations are subsequently used to determine individual calorie and macronutrient requirements as the basis for food recommendation generation. A food dataset containing Indonesian food and beverage nutritional information was preprocessed and labeled using a rule-based approach according to users' macronutrient requirements. The Decision Tree algorithm was then applied to classify food items into suitable and unsuitable categories based on protein, fat, and carbohydrate content. Foods classified as suitable were further processed through a scoring mechanism and meal construction procedure to generate personalized meal plans. The Decision Tree classification model achieved an accuracy of 92.50%, precision of 78.26%, recall of 94.74%, and F1-score of 85.71%, indicating its effectiveness in classifying food items according to nutritional suitability. Furthermore, the model obtained an average cross-validation accuracy of 94.75% and a ROC-AUC score of 0.9633, demonstrating good generalization performance and strong discriminative capability.

*name of corresponding author

From a research perspective, this study contributes an interpretable framework that combines rule-based nutritional labeling with Decision Tree classification for food suitability analysis. The findings demonstrate that protein, fat, and carbohydrate attributes provide sufficient information for distinguishing food suitability while maintaining model transparency and explainability. This approach highlights the potential of interpretable machine learning techniques in supporting personalized nutrition applications.

System testing using Black Box Testing and White Box Testing indicated that all implemented features functioned according to the specified requirements and that the recommendation process operated consistently based on the designed workflow. Therefore, the proposed system can assist users in selecting foods that meet their nutritional needs and support healthier dietary planning.

Future studies may improve recommendation quality by utilizing larger datasets and exploring more advanced machine learning algorithms, such as Random Forest and XGBoost. Additional personalization factors, including food preferences, allergies, and medical conditions, may also be incorporated to enhance recommendation quality and provide more comprehensive diet recommendations.

REFERENCES

Chen, Y., Guo, Y., Fan, Q., Zhang, Q., & Dong, Y. (2023). Health-Aware Food Recommendation Based on Knowledge Graph and Multi-Task Learning. *Foods*, *12*(10), 2079. https://doi.org/10.3390/foods12102079

Farhan maulana pangestu, Andri Pramuntadi, Dita Danianti, & Dhina Puspasari Wijaya. (2025). IMPLEMENTASI ALGORITMA CONTENT-BASED FILTERING UNTUK REKOMENDASI MAKANAN SEHAT BERDASARKAN KALORI PENGGUNA. *Jurnal Informatika Teknologi Dan Sains (Jinteks)*, *7*(4), 1669–1674. https://doi.org/10.51401/jinteks.v7i4.6566

Aghababaeyan, Z., Abdellatif, M., Briand, L., Ramesh, S., & Bagherzadeh, M. (2023). Black-Box Testing of Deep Neural Networks through Test Case Diversity. IEEE Transactions on Software Engineering, 49(5), 3182–3204. https://doi.org/10.1109/TSE.2023.3243522

Bahalkeh, E., Chiam, T. C., & Yih, Y. (2023). An interpretable clustering classification approach for assessing and adjusting hospital service lines. Healthcare Analytics, 4. https://doi.org/10.1016/j.health.2023.100255

Bondevik, J. N., Bennin, K. E., Babur, Ö., & Ersch, C. (2024). A systematic review on food recommender systems. Expert Systems with Applications, 238, 122166. https://doi.org/10.1016/j.eswa.2023.122166

Hanif Anas Fikri. (2023). Indonesian Food and Drink Nutrition Dataset. Retrieved June 1, 2026, from PANGANku / Kementerian Kesehatan RI website: https://www.kaggle.com/datasets/anasfikrihanif/indonesian-food-and-drink-nutrition-dataset

Papadopoulos, P., Soflano, M., Chaudy, Y., Adejo, W., & Connolly, T. M. (2022). A systematic review of technologies and standards used in the development of rule-based clinical decision support systems. *Health and Technology*, *12*(4), 713–727. https://doi.org/10.1007/s12553-022-00672-9

de Hoogh, I. M., Reinders, M. J., Doets, E. L., Hoevenaars, F. P. M., & Top, J. L. (2023). Design Issues in Personalized Nutrition Advice Systems. Journal of Medical Internet Research, 25, e37667. https://doi.org/10.2196/37667

Rahayu, S., Safitri, R. D., & Hermansyah, E. N. (2026). Implementasi Decision Tree dalam Mengelompokkan Makanan Berdasarkan Kandungan Gizi. *IKN: Jurnal Informatika Dan Kesehatan*, *3*(1), 22–30. https://doi.org/10.35473/ikn.v3i1.4937

Sakir, N. A. I., Hwang, S. Bin, Park, H. J., & Lee, B. H. (2024). Associations between food consumption/dietary habits and the risks of obesity, type 2 diabetes, and hypertension: a cross-sectional study in Jakarta, Indonesia. Nutrition Research and Practice, 18(1), 132–148. https://doi.org/10.4162/nrp.2024.18.1.132

Rahman, A. (2023). Klasifikasi Performa Akademik Siswa Menggunakan Metode Decision Tree dan Naive Bayes. *Jurnal SAINTEKOM*, *13*(1), 22–31. https://doi.org/10.33020/saintekom.v13i1.349

Rostami, M., Farrahi, V., Ahmadian, S., Mohammad Jafar Jalali, S., & Oussalah, M. (2023). A novel healthy and time-aware food recommender system using attributed community detection. *Expert Systems with Applications*, *221*, 119719. https://doi.org/10.1016/j.eswa.2023.119719

Singh, R., & Dwivedi, P. (2023). Food Recommendation Systems Based On Content-based and Collaborative Filtering Techniques. *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1–5. IEEE. https://doi.org/10.1109/ICCCNT56998.2023.10307080

Wayahdi, M. R., & Ruziq, F. (2023). Pemodelan Sistem Penerimaan Anggota Baru dengan Unified Modeling Language (UML) (Studi Kasus: Programmer Association of Battuta). *Jurnal Minfo Polgan*, *12*(1), 1514–1521. https://doi.org/10.33395/jmp.v12i1.12870

Kalpakoglou, K., Calderón-Pérez, L., Boqué, N., Guldas, M., Erdoğan Demir, Ç., Gymnopoulos, L. P., & Dimitropoulos, K. (2025). An AI-based nutrition recommendation system: technical validation with insights from Mediterranean cuisine. Frontiers in Nutrition, 12. https://doi.org/10.3389/fnut.2025.1546107

e-ISSN : 2541-2019
p-ISSN : 2541-044X

Wang, X., Sun, Z., Xue, H., & An, R. (2025). Artificial Intelligence Applications to Personalized Dietary Recommendations: A Systematic Review. Healthcare, 13(12), 1417. https://doi.org/10.3390/healthcare13121417

Frasca, M., La Torre, D., Pravettoni, G., & Cutica, I. (2024). Explainable and interpretable artificial intelligence in medicine: a systematic bibliometric review. Discover Artificial Intelligence, 4(1), 15. https://doi.org/10.1007/s44163-024-00114-7

Papastratis, I., Konstantinidis, D., Daras, P., & Dimitropoulos, K. (2024). AI nutrition recommendation using a deep generative model and ChatGPT. Scientific Reports, 14(1). https://doi.org/10.1038/s41598-024-65438-x

Roman, S., Campos-Medina, L., & Leal-Mercado, L. (2024). Personalized nutrition: the end of the one-diet-fits-all era. Frontiers in Nutrition, 11. https://doi.org/10.3389/fnut.2024.1370595

*name of corresponding author