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Food Menu Recommendations using Content-based Filtering Method

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Abstract

A nutritionally imbalanced body poses significant health risks. Achieving nutritional balance and maintaining a healthy diet are therefore essential. One of the major challenges in this regard arises when a user's dietary preferences conflict with their health conditions. To address this issue, it is necessary to develop a system that not only identifies nutritional needs and assesses their adequacy but also takes into account users' medical histories. This study aims to develop a food menu recommender system that integrates nutritional requirements, user preferences, and disease history. Content-based filtering was employed to measure the similarity between user profiles and the available dataset. A weighting model was incorporated to accommodate food restrictions associated with specific health conditions. The dataset used in this study was obtained from the Center for Nutrition Research and Development and Food, Ministry of Health of the Republic of Indonesia. The research process includes data collection, pre-processing, user profile identification, and the generation of food recommendations. Additionally, this study explores the integration of user preferences and disease records using a binary vector to improve recommendation accuracy. The findings indicate that the developed system successfully provides food recommendations that are not only calorically adequate and nutritionally balanced, but also consistent with the recommended macronutrient distribution for protein, fat, and carbohydrates.

Keywords:
Content-based Filtering, Disease constraint, Food recommender, User preferences

1. Introduction

Nowadays, malnutrition is a challenge for society. An imbalanced nutritional state is a dangerous condition. When someone experiences malnutrition, their body does not get enough nutrients, which can cause wasting (low weight-for-height), stunting (low height-for-age), and underweight (low weight-for-age)[1], [2]. However, both nutritional balance and consuming a healthy food menu are important. Another challenge is that we must consider not only nutritional adequacy and balance but also user preferences. Furthermore, this consideration is not limited to needs and preferences; we also need to take medical records into account. This is necessary because the food consumed is closely related to the user's health. Therefore, it is important to create a system that identifies not only nutritional needs and adequacy but also incorporates the user's disease records.

Until now, many studies on the development of food menu recommendation systems have been conducted. Here are some examples: Research [3] explains that content-based

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filtering is used to find suitable beverages based on taste preferences, such as soda, fruit, coffee, and others. By providing like and dislike vectors, the algorithm searches for the highest matching score. Other studies, such as [4], [5], [6], [7], also demonstrate how simple these algorithms are while still providing recommendations that align with user characteristics. In [8], a comparison is made between user-based and item-based approaches for recommending recipes based on user preferences. The study shows that user preference is a crucial factor in generating relevant recommendations. Furthermore, both collaborative filtering and content-based filtering have their own advantages in providing recommendations[9], [10]. Study [11] states that content-based filtering is superior in delivering independent recommendations. This approach has also been effectively applied in various cases [12], [13], [14], [15]. Subsequent studies [16], [17], [18] have also emphasized that menu recommendations based on user preferences are very important. In addition to user preferences, information about the food itself is also a critical component. As a result, many studies utilize user preferences and food information to recommend meal plans [19]. However, no research has been found that combines user preferences with disease records. One related study [20] does exist, but it is limited to individuals with diabetes, thus focusing solely on dietary menus. In reality, many other diseases require food restrictions to prevent the condition from worsening. This is important because menu recommendations must be adjusted to both health and nutritional needs, and these two aspects cannot be separated. Therefore, when disease records are taken into consideration, content-based filtering is a more suitable approach.

This research aims to develop a food menu recommender system based on nutritional needs, user preferences, and disease records. Content-based filtering is chosen as the method to determine the similarity between the user profile and the dataset and also considering disease records. To assess the nutritional value of each food menu, a complete and valid dataset is required. In this study, the dataset is obtained from the Ministry of Health, which is responsible for food and nutrition guidelines. According to Regulation PMK No. 28 of 2019, the Ministry of Health has established the recommended nutritional adequacy rate for the Indonesian population. The dataset includes values of substances contained in food, which consist of eight main elements: energy, protein, fat, carbohydrates, fiber, water, vitamins, and minerals.

2. Proposed Research Method

The research begins with data collection, followed by data preprocessing, user profile identification, implementation of content-based filtering, and development of the food menu recommendation system. The dataset is obtained from the Ministry of Health, which is responsible for food and nutrition guidelines. The data is subsequently preprocessed in collaboration with a nutritionist to ensure it is properly prepared and results in a finalized dataset. To determine daily calorie requirements, users must input their gender, age, and weight, which will be used to calculate their Basal Metabolic Rate (BMR). To identify user preferences, users are also required to provide information about their favorite food menus. In addition, the user’s disease records must be included to account for any dietary restrictions. Based on the provided data, the content-based filtering algorithm will then generate food menu recommendations that align with the user's taste preferences while complying with dietary restrictions related to their disease conditions. Therefore, the research design is illustrated in Figure 1.

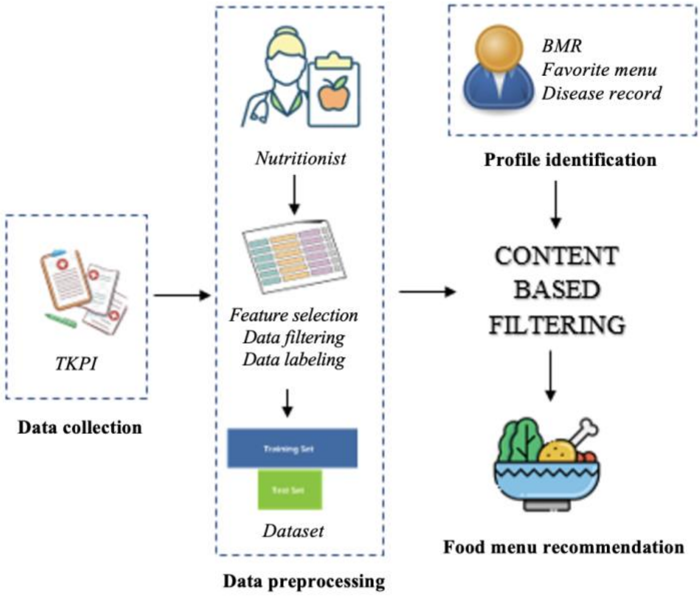


Fig. 1. Research design

2.1 Data Collection

To determine the nutritional value of a food menu, a complete and valid dataset is required. Therefore, the dataset is obtained from the Ministry of Health, which is responsible for food and nutrition. The Indonesian Food Composition Table, known as Tabel Komposisi Pangan Indonesia (TKPI), is a compilation of data on the nutritional composition of foods in Indonesia. It originates from reports and research studies conducted by the Center for Nutrition and Food Research and Development, Indonesian Ministry of Health [21]. According to nutrition experts, identifying nutritional adequacy and balance only requires macronutrients. Macronutrients are the primary components of food that build the body, provide energy, and are needed in large quantities, typically measured in grams (g). These include carbohydrates, fats, and proteins.

2.2 Data Pre-processing

Data preprocessing consists of feature selection, data filtering, and data labeling. First, the nutritional features obtained from the TKPI are selected. In the original data, the nutritional components include Water, Energy, Protein, Fat, Carbohydrates, Fiber, Ash, Calcium (Ca), Phosphorus (P), Iron (Fe), Sodium (Na), Potassium (K), Copper (Cu), Zinc (Zn), Retinol (Vitamin A), β-carotene, Total Carotene, Thiamin (Vitamin B1), Riboflavin (Vitamin B2), Niacin, and Vitamin C [21]. This step is carried out in collaboration with experts, resulting in the decision to use Protein, Fat, and Carbohydrates for calculating nutritional adequacy and balance. Next, data filtering is performed to remove food items that are not directly consumable by the general public. This step is also validated by experts, taking into account the cooking process and type of food. After filtering, the process continues with data labeling. The data labeling stage categorizes food menus from the TKPI into specific categories. These are divided into five main groups: staple foods, side dishes, vegetables, fruits, and snacks. Staple foods are further categorized based on their primary ingredients: beans, noodles, corn, tubers, and sticky rice. Side dishes are categorized into meat, fish, eggs, and legumes. Vegetables are grouped into those served with soup and those without soup. Meanwhile, fruits are classified as either sweet or non-sweet. From this process, a vectorized dataset is generated. Each element of the vector is assigned a value of 1 if it matches the criteria, and -1 otherwise, which will be used for content-based filtering. The illustration of how to create a vector is as follows:

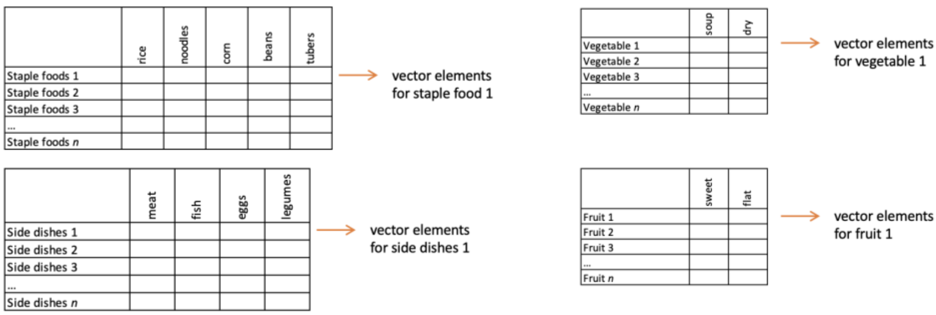


Fig. 2. Create a vector from the food menu

2.3 Profile Identification

The user profile stored in this system consists of age, gender, height, and weight. Based on this information, the Basal Metabolic Rate (BMR) is calculated. BMR represents the number of calories the body needs to perform basic physiological functions. An individual's BMR depends on their age, gender, weight, and height [22]. By calculating the BMR, the minimum caloric requirement can be determined. It is called Total Daily Energy Expenditure (TDEE). This allows for a reduction in calorie intake without compromising bodily functions or overall health. To determine TDEE, the BMR is multiplied by an activity level factor, which includes: sedentary, lightly active, moderately active, very active, and extra active [23]. If *a* represents age, *w* represents weight, *h* represents height, and *act* represents activity level, the BMR and TDEE can be calculated using formulas (1), (2), and (3):

$$BMR_{\ Male} = 66.5 + 13.7 * w + 5 * h - 6.8 * a \tag{1}$$

$$BMR_{Female} = 655 + 9.6 * w + 1.8 * h - 4.7 * a \tag{2}$$

$$TDEE = BMR * act \tag{3}$$

Furthermore, personal data also includes user preferences, which are represented by scores indicating likes or dislikes for various staple food items, vegetables, side dishes, or fruits. From this data, a user identity vector is obtained, consisting of information on staple foods, side dishes, fruits, and vegetables, as mentioned in Subchapter 2.2. Therefore, a vector with a size of 1×13 will be formed. In the food dataset, the value represents the presence of certain ingredients, whereas in the test data, a value of 1 indicates that the user likes the ingredient, and -1 indicates that the user does not. For example, if a user likes rice, noodles, corn, meat, eggs, all vegetables, and sweet fruits, the resulting vector will be as follows:

$$\text{user} = [1,1,1,-1,-1,1,-1,1,-1,1,1,1,-1]$$

To impose dietary restrictions for specific diseases, each user will be assigned a new weight based on their medical condition. Additionally, each user will have a reduction vector associated with their disease, accompanied by a confidence score. This system considers common health conditions experienced by Indonesians. Therefore, the possible disease options include asthma, anemia, diabetes, hypertension, GERD, cancer, tuberculosis (TB), liver disease, and others. If the user has any of the aforementioned conditions, the favorability value for certain ingredients will be reduced (on a scale from 0 to 1). This adjustment aims to increase the dissimilarity score when content-based filtering is applied. For example, if the user has a history of diabetes, it is not recommended to consume large amounts of rice, noodles, or sweet fruits. The user assigned a high confidence score (0.8) to the avoidance of potentially harmful foods. As a result, the previously generated vector will be adjusted as follows:

$$\begin{aligned}\mathrm{user}_{\mathrm{new}} &= \mathrm{user} - \mathrm{diabetes} \\ &= [1,1,1,-1,-1,1,-1,1,-1,1,1,1,-1] - [0.8,0.8,0,0,0,0,0,0,0,0,0,0.8,0] \\ &= [0.2,0.2,1,-1,-1,1,-1,1,-1,1,1,0.2,-1]\end{aligned}$$

2.4 Content-based Filtering

Content-based filtering is used to provide recommendations by predicting what users may like based on their profiles. The content-based filtering algorithm works as follows: first, it analyzes the content descriptions in the dataset; second, it analyzes user preferences; and finally, it calculates the similarity between the user's profile and the dataset using several constraints [11]. For example, suppose staple foods are categorized into those made from rice, noodles, corn, tubers, and sticky rice. The user then provides data about their preferred foods. This preference data—indicating likes or dislikes—is stored and used as the basis for generating further recommendations. In one case, a user likes foods made from rice but dislikes foods made from sticky rice. As a result, the system will not recommend foods made from sticky rice. In this context, content-based filtering works by calculating the similarity between the dataset and the user profile. The similarity is computed using the Euclidean distance approach, which provides an effective representation for various recommendation scenarios [24], [25], [26]. If a represents the user's personal data vector and b represents the food dataset vector, the Euclidean distance value can be calculated using the following formula:

$$\mathrm{dist} = \sqrt[2]{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \cdots + (a_{13} - b_{13})^2} \quad (4)$$

2.5 Food Recommender System Design

Once the data and algorithms have been prepared, the entire process is implemented within a food recommendation system. Figure 3 presents an activity diagram that illustrates the workflow of the system under development. As depicted in the diagram, the user initiates the process by entering their profile information, user preferences, and disease records. Upon successful submission of this data, the user may proceed to the daily menu. Subsequently, the system calculates the Basal Metabolic Rate (BMR), followed by a series of processes including nutrient identification, vector identification, the application of content-based filtering with disease constraint, and ultimately, the generation of food recommendations. Figure 3 illustrates the workflow of the system:

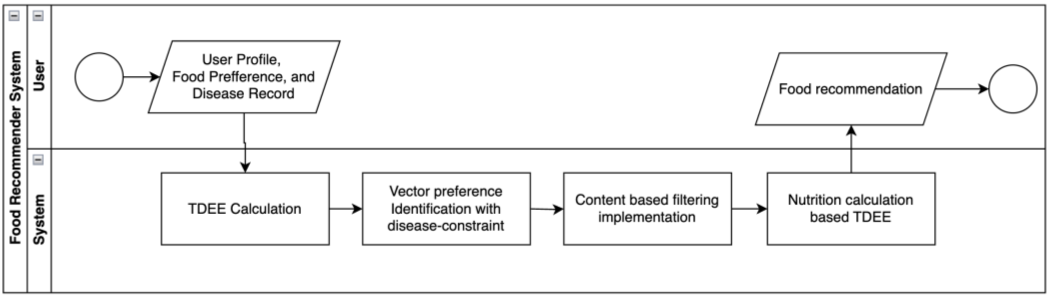


Fig. 3. Workflow system

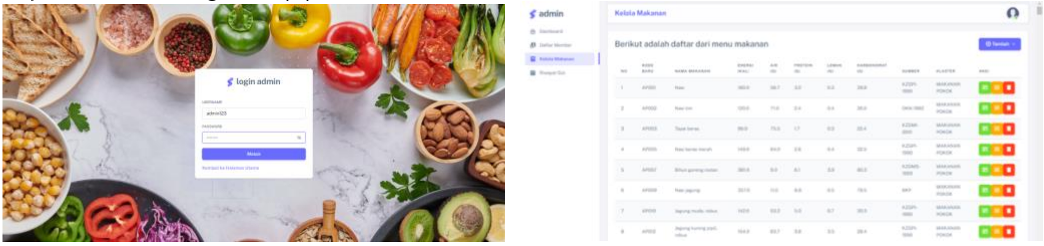
The diagram above illustrates the nutritional calculation step based on Total Daily Energy Expenditure (TDEE). This step involves determining the macronutrient composition required by the body and subsequently calculating the appropriate weight of food intake needed to meet these requirements. The nutritional recommendations are composed of 10–15% protein, 10–25% fat, and 60–75% carbohydrates. For instance, a 32-year-old woman weighing 54 kg and measuring 150 cm in height, with minimal physical activity, has an estimated daily caloric requirement of approximately 1,777.88 kilocalories. Accordingly, her recommended intake would range from 177.79 to 266.68 kilocalories from protein, 177.79 to 444.47 kilocalories from fat, and 1,066.72 to 1,333.41 kilocalories from carbohydrates.

3. Results and Discussion

This study aims to develop a food recommender system based on content-based filtering, taking into consideration patients' disease records. The following section presents the research findings:

3.1. Food Recommender System Results

Following the system design phase, the food recommender system was implemented into user interfaces, which include registration and login pages, personal information pages, home pages, preference form pages, and food menu recommendation pages. The following section presents the outcomes of the system development. To begin with, all data within the system must be manageable by an administrator. Accordingly, the system provides an administrator login page, as depicted in Figure 4(a). The system administrator is granted access to manage the food database, which includes the food name, nutritional content, and the ingredient composition vector. This functionality represents the implementation of the concept outlined in Subsection 2.2. The page for managing food data is presented in Figure 4(b).

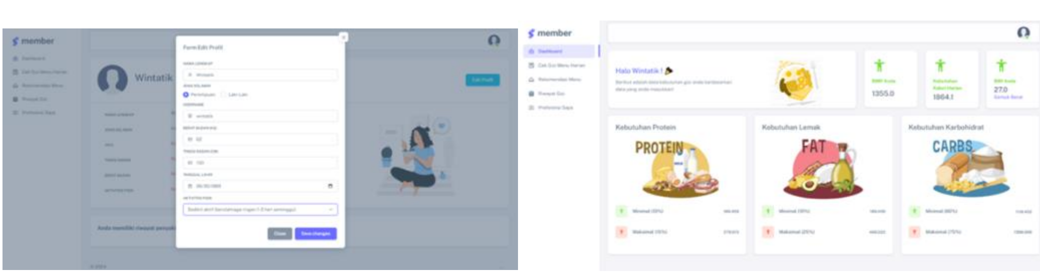


(a) (b)

Fig. 4. Registration and login page

Subsequently, once the administrator has prepared the dataset—consisting of food items, nutritional content, and the corresponding composition vectors—the user will be able to begin utilizing the system. The registration page is designed for new users, allowing them to create an account by entering a username and password. Upon successful registration, users can proceed to log in through the login interface to utilize the features of the food recommendation system. After successfully logging into the system, users are required to complete their personal profile. In cases where the profile is incomplete. Users must provide personal data that will be utilized to calculate the Basal Metabolic Rate (BMR) and Total Daily Energy Expenditure (TDEE). The required inputs include age, gender, height, weight, and activity level factor, as illustrated in the form in Figure 5(a). The input data are processed using Equation (1) for male users and Equation (2) for female users, with the result subsequently applied in Equation (3). Additionally, within the same interface, users are prompted to indicate any existing medical conditions. The system provides a selection of predefined disease categories. Once all personal information is completed, users may save their data and proceed to the dashboard, as shown in Figure 5(b). The dashboard presents the calculated BMR and TDEE values in kilocalories. It also displays the recommended macronutrient distribution, comprising protein, fat, and carbohydrates. These recommendations are in accordance with standard dietary guidelines: 10–15% protein, 10–25% fat, and 60–75% carbohydrates.

After the user has completed their profile information, they may proceed to the My Preferences menu. On this page, the user is prompted to indicate their preferences—whether they like or dislike each food ingredient. The input form is illustrated in Figure 6. The recorded preference data is then processed into a preference vector. This process serves as the implementation of the concept described in Subsection 2.3, where a preference vector is constructed. Once the system has a complete and ready-to-use dataset, and users have provided their personal information, medical history, and individual preferences, the food recommendation menu can be executed. This menu implements the content-based filtering algorithm described previously. The algorithm identifies food items whose ingredients best match the user's preference vector—calculated as the difference between the user's preference vector and their medical history vector. The algorithm selects the top three most suitable menus (and in the case of multiple candidates with equal scores, the system randomly selects among them). These three menus are assigned to breakfast, lunch, and dinner, respectively. Within each session, the system distributes the menus into categories: staple foods, protein sources, vegetables, fruits, and snacks. The quantity of intake is adjusted according to the user's Total Daily Energy Expenditure (TDEE), divided by three. The output of the system's recommendation can be seen in Figure 7.



(a) (b)

Fig. 5. User profile menu

Fig. 6. Preferences menu

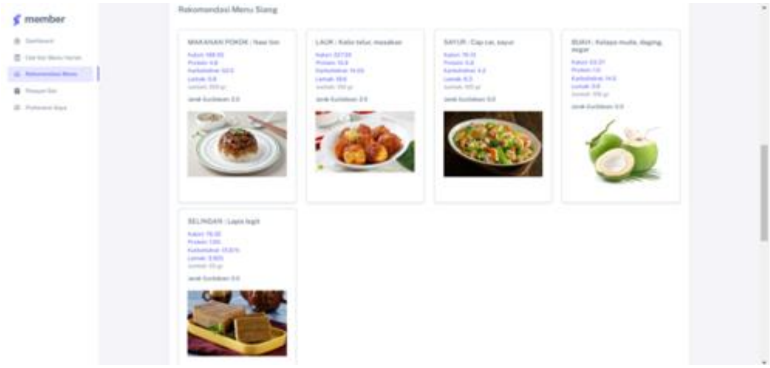


Fig. 7. Recommendation result

3.2. Discussion

The recommendation system has been tested on several user cases. The results provided by the system were then evaluated and assessed for relevance by experts. This testing was conducted by varying the system parameters, including profile, preferences, disease history, and the confidence level of each disease. The following are the test results:

Case: "The user has food preferences that include corn, sticky rice, chicken, fish, and nuts. However, the user has gerd and cancer, so the system avoids recommending foods made from sticky rice, sweet fruits, noodles, and rice, in accordance with the selected confidence level. The following are the recommendations generated by the system. He is a 30-year-old male weighing 60 kg and standing 170 cm tall, with a moderately active physical activity level."

Subsequently, the recommendations generated are based on the calculated energy requirements of a 30-year-old male weighing 60 kg and measuring 170 cm in height, with a moderate level of physical activity. As a basis for meeting nutritional needs, the system computes the daily caloric requirement using formulas (1) and (3) as described in Subsection 2.3. In order to ensure nutritional balance, the system applies macronutrient distribution guidelines of 10–15% protein, 10–25% fat, and 60–75% carbohydrates. Table 1 presents the results of the nutritional needs assessment for the specified user profile:

Table 1. System-generated recommendations

Daily calorie requirement (kal)	Calorie requirement per meal (kal)	Nutrient requirement					
		Protein (kal)		Fat (kal)		Carbo (kal)	
		min	max	min	max	min	max
2377,7	729,566	237,77	356,65	237,77	594,42	1426,62	1783,27

Finally, considering the previously specified preferences and constraints, the system delivered the following results for menu recommendation as Table 2 below. These results also represent a test using confidence levels of 0, 0.6, and 1 to observe the extent to which the severity level of medical history influences the system's recommendation outcomes.

Table 2. System-generated recommendations

Confident level	Daily meal menu	Quantity (gr)	Energy (kal)	Nutrient content		
				Protein (gr)	Fat (gr)	Carbo (gr)
0	**Breakfast**					
	Chicken noodles	194,2565	198,142	12,04391	7,576005	20,39694
	Soto bandung	471,7659	198,142	18,39887	8,02002	13,20944
	Boiled spinach	861,4855	198,142	10,33783	5,168913	31,87496
	Lampung chips	40,85395	198,142	0,694517	9,069577	28,4752
	Boiled corn kernels	127,0139	198,142	3,429375	1,651181	42,29563
	Sub total		**990,708**	**44,90449**	**31,4857**	**136,2522**
	Lunch					
	Boiled canna tuber	198,1417	198,142	1,585133	0,396283	47,15772
	Soto madura	330,2361	198,142	11,55826	14,86063	4,293069
	Gnetum skin	178,506	198,142	8,03277	1,963566	36,95074
	Bengal mango	314,5106	198,142	7,548254	1,258042	38,99931
	stuffed pancake	129,5044	198,142	5,827696	5,439183	31,46956
	Sub total		**990,708333**	**34,55212**	**23,9177**	**158,8704**
	Dinner					
	Ketoprak	129,5043573	198,142	10,23084423	9,971835512	16,83556645
	Fried punai bird meat	88,45610119	198,142	23,17549851	9,995539435	3,892068452
	Botok lamtoro	106,5277778	198,142	12,46375	10,33319444	13,84861111
	Gedong mango	450,3219697	198,142	3,152253788	0,900643939	50,43606061
	Bakwan	70,76488095	198,142	5,802720238	7,218017857	27,59830357
	Sub total		**990,708333**	**54,82507**	**38,41923**	**112,6106**
	Total		**2972,13**	**134,4**	**93,82**	**407,7**
0,6	Breakfast					
	Rice	110,0787037	198,142	3,302361111	0,330236111	43,81132407
	Egg kalio	102,664076	198,142	10,88239206	12,73034542	9,958415371
	Tondano- spinach	460,7945736	198,142	8,294302326	0,921589147	38,70674419
	Lampung chips	40,85395189	198,142	0,694517182	9,06957732	28,47520447
	Cassava chips	41,45223152	198,142	0,373070084	8,580611925	29,84560669
	Sub total		990,708	23,54664	31,63236	150,7973
	Lunch					
	Steamed savory rice	165,1180556	198,142	3,962833333	0,660472222	42,93069444
	Chicken egg omelet	78,94090305	198,142	12,8673672	15,31453519	1,105172643
	Asinan Bogor	202,1853741	198,142	7,885229592	5,256819728	29,92343537
	Fresh Gapi banana	156,0170604	198,142	3,276358268	0,468051181	48,52130577
	Kacang goyang	38,3995478	198,142	5,644733527	11,94225937	17,04939922
	Sub total		990,708	33,63652	33,64214	139,53
	Dinner					
	Steamed potato	198,1416667	198,142	1,386991667	0,594425	47,15771667
	Duck egg omelet	65,82779623	198,142	13,16555925	15,60118771	0
	Seaweed	483,2723577	198,142	6,765813008	1,449817073	39,14506098
	Sale kesemek	66,93975225	198,142	0,736337275	0,401638514	47,79498311
	Cassava stick	43,07427536	198,142	0,344594203	8,054889493	7,408775362
	Sub total		990,708	22,3993	26,10196	141,5065
	Total		**2972**	**79,58**	**91,38**	**431,8**
1	Breakfast					
	Steamed savory rice	165,1180556	198,142	3,962833333	0,660472222	42,93069444
	Fresh broiler egg	128,6634199	198,142	15,95426407	13,89564935	0,900643939
	Steamed long beans	508,0555556	198,142	15,24166667	3,048333333	38,61222222
	Fresh young mango	335,8333333	198,142	1,679166667	1,343333333	50,71083333
	Rempeyek kacang	43,9338507	198,142	4,920591279	8,874637842	26,22850887
	Sub total		**990,708**	**41,75852**	**27,82243**	**159,3829**

	Lunch					
	Ketupat kandangan	181,7813	198,142	3,99919	9,45263	24,3587
	Chicken egg omelet	78,9409	198,142	12,86737	15,31454	1,105173
	Blanched sprouts	707,6488	198,142	21,22946	5,66119	28,30595
	Melon cucumber	1238,385	198,142	16,09901	0	26,00609
	Kacang goyang	38,39955	198,142	5,644734	11,94226	17,0494
	Sub total		**990,708**	**59,83977**	**42,37062**	**96,82532**
	Dinner					
	Oily rice	95,72061	198,142	3,350221	4,786031	35,51235
	Fresh chicken egg	113,8745	198,142	12,29845	15,94243	1,366494
	Boiled katuk leaves	373,8522	198,142	19,81417	3,36467	34,02055
	Dried wild coconut	31,80444	198,142	0,636089	16,57011	11,60862
	Peanut cracker	38,62411	198,142	6,759219	12,55283	17,11048
	Sub total		**990,708**	**42,85814**	**53,21608**	**99,61849**
Total			**2972**	**144,5**	**123,4**	**355,8**

The results presented above indicate that the system successfully provides food recommendations that are both adequate in calories and nutritionally balanced. The recommendations are based on the caloric requirements of a 30-year-old male weighing 60 kg and standing 170 cm tall, with a moderately active physical activity level. This profile requires 2,377.7 kcal per day, or approximately 792.5 kcal per meal session. The system also adheres to the recommended macronutrient distribution for protein, fat, and carbohydrates, as outlined in Table 1. Furthermore, upon closer examination, it can be observed that the higher the severity level of the medical condition, the fewer the variety of recommended food items. This indicates that the system is functioning as intended to restrict food intake in accordance with health constraints.

4. Conclusion

This research aims to develop a food menu recommender system based on nutritional requirements, user preferences, and medical history. The research begins with data collection, followed by data pre-processing, user profile identification, implementation of content-based filtering, and the development of the food menu recommendation system. The novelty of this research lies in the system’s ability to simultaneously consider user preferences and health conditions. Since the data collection considers 13 nutritional components, a vector of size 1×13 is formed. In the food dataset, each value in the vector represents the presence of a specific ingredient. In the test data, a value of 1 indicates that the user likes the ingredient, while a value of -1 indicates that the user dislikes it. Content-based filtering is used to provide recommendations by predicting what users may prefer based on their profiles. Similarity is calculated using the Euclidean distance approach. The food recommender system is implemented through a user interface that includes registration and login pages, personal information pages, a homepage, a preference form page, and a food recommendation page. The results indicate that the system successfully provides food recommendations that are both calorically adequate and nutritionally balanced. It also adheres to the recommended macronutrient distribution for protein, fat, and carbohydrates. Furthermore, upon closer examination, it can be observed that the more severe a user's medical condition, the fewer the variety of recommended food items. This demonstrates that the system functions as intended in restricting food intake in accordance with health constraints.

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