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Diet Recommendation System for Kidney Disease Patients Using Collaborative Filtering

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Abstract

Chronic kidney disease (CKD) remains a major global health challenge, particularly in Indonesia, where limited awareness and inadequate dietary management contribute to the progression of renal complications. Patients often face difficulties in selecting foods that meet both medical and nutritional requirements, underscoring the need for intelligent dietary guidance. This study aims to develop a personalized dietary recommendation system for kidney failure patients using a hybrid approach that combines content-based and collaborative filtering techniques. The model was designed to analyze patients' food preferences, nutritional composition, and health conditions to generate appropriate dietary recommendations. The system's performance was evaluated using cosine similarity and predictive accuracy metrics, including RMSE, precision, recall, and F1-score. The results show that the proposed model achieved an accuracy of 83%, precision of 75%, recall of 100%, and F1-score of 86%, demonstrating its effectiveness in identifying dietary similarities and preferences among patients with comparable clinical profiles. Furthermore, by integrating nutritional content data such as sodium, potassium, and protein levels, the system successfully provided clinically safe and personalized recommendations aligned with renal dietary guidelines. These findings highlight the potential of artificial intelligence–based recommendation systems to support dietitians in improving the accuracy and efficiency of nutritional counseling, thereby promoting patient adherence and enhancing the quality of kidney disease management in hospital settings.

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1. Introduction

Kidney disease, particularly chronic kidney failure, has emerged as a serious global health concern, including in Indonesia. Kidney failure is characterized by a significant decline in kidney function, leading to an inability to effectively filter waste products and excess fluids from the body. This condition often arises from chronic diseases such as diabetes mellitus and hypertension, but lifestyle-related factors—such as unhealthy diets, poor-quality drinking water, and low physical activity—further exacerbate the problem. In Indonesia, the prevalence of chronic kidney disease (CKD) continues to increase annually, indicating an urgent need for preventive and management strategies

(Harun & Pradana, 2023). Patients with kidney failure frequently face complications such as malnutrition and metabolic disorders, resulting from poor nutrient absorption and protein-energy wasting. Proper nutritional management is therefore crucial, particularly regarding restrictions on sodium, potassium, and protein intake, which directly influence the progression of CKD (Agustina et al., 2025).

Nutritional therapy has been proven to slow CKD progression and improve patient outcomes. However, many patients in Indonesia experience difficulties in managing their diet due to limited knowledge and low health literacy (Zamri et al., 2025). For instance, patients often struggle to distinguish between foods that are safe and those that can worsen their condition, such as high-sodium processed foods or fruits with excessive potassium. Studies have shown that the level of education and patient awareness plays a vital role in adherence to dietary recommendations (Harun & Pradana, 2023). In hospital settings, such as Wulan Windy General Hospital in Medan, dietitians face challenges providing individualized diet plans for each patient due to limited consultation time and lack of digital tools. Consequently, the development of an intelligent dietary recommendation system that supports personalized nutrition guidance has become a significant research focus in healthcare technology (Barbaric et al., 2023).

Health recommender systems (HRS) have gained growing attention in recent years as a tool to support patient self-management and clinical decision-making. These systems leverage artificial intelligence and data-driven algorithms to recommend actions, foods, or treatments tailored to user characteristics. However, most existing health recommender systems are designed for general wellness applications, such as diabetes management or weight control, rather than disease-specific dietary management like CKD (Barbaric et al., 2023). In Indonesia, research using recommendation algorithms—such as collaborative filtering or content-based filtering—has predominantly been applied in e-commerce, tourism, and education domains (Sari & Nugroho, 2023). There remains a clear research gap in implementing these algorithms in the healthcare domain, particularly for dietary management in chronic diseases such as kidney failure.

From a theoretical perspective, content-based filtering focuses on the intrinsic attributes of items (such as nutrient composition and caloric content) to recommend similar items that align with a user's preferences or restrictions. In contrast, collaborative filtering identifies patterns in the preferences or behaviors of users with similar characteristics to provide recommendations (Adomavicius & Tuzhilin, 2005). When applied to clinical nutrition, content-based filtering ensures that food options meet medical dietary constraints, while collaborative filtering enhances personalization by considering similarities among patients with comparable clinical profiles. Recent studies have shown that hybrid recommendation models combining these two approaches can significantly improve recommendation accuracy and user satisfaction (Rahman et al., 2024). However, such hybrid systems remain underexplored in the context of medical nutrition for kidney disease management, especially in low-resource healthcare settings.

Based on the existing literature, there is a notable research gap in developing intelligent dietary recommendation systems specifically for kidney failure patients in Indonesia. Previous studies have not adequately integrated medical nutrition parameters into recommendation algorithms, and few have tested these systems in real-world clinical environments. Therefore, this study aims to develop a hybrid dietary recommendation system combining content-based and collaborative filtering methods tailored for CKD patients. This approach is designed to provide personalized, nutritionally safe meal recommendations that match both medical requirements and patient preferences. The novelty of this research lies in applying a hybrid recommendation framework within the clinical nutrition domain, supported by localized patient data from Wulan Windy General Hospital, Medan. Furthermore, it aims to enhance patient engagement, improve dietary compliance, and contribute to digital health innovation in Indonesia's medical nutrition field.

2. Research Methodolgy

In completing this research, the author used two research methods:

1. Field Study

a. Observation

Observing the care process for patients with kidney disease at Wulan Windy General Hospital, Medan, to understand the workflow, nutritional needs, and challenges faced by medical personnel and patients in selecting appropriate foods.

b. Interviews

Conducting interviews with nutritionists and kidney specialists to obtain information about the dietary needs of kidney patients, food preferences, and appropriate nutritional recommendations to support kidney health.

c. Sampling

Collecting data on the dietary patterns and food preferences of patients diagnosed with kidney disease, and recording their responses to various recommended foods, to be used in testing effective dietary methods.

2. Literature Review

Analyzing literature and previous research related to the Collaborative Filtering method and the application of technology in medical diagnosis. Case Reports: Collecting case reports demonstrating the results of dietary interventions in patients with kidney disease, including changes in the patient's health and quality of life after following a specific diet.

A. Description of the design procedure

Several requirements must be met to create a certificate verification application program. Several components must be available, including:

1. Requirements analysis
2. Interface requirements

The interface requirements are:

a. The application must be able to process all input data into valid data.
b. The application must have a user-friendly interface.
c. The application must be able to save, update, and delete data in the database storage.

There is a process within the application that can update all data stored in the database storage.

B. Functional Requirements

The functional requirements are: Correctly managing all data entered by admins and users. Generating output in the form of reports. Making the existing system more efficient and effective.

1. Specifications and Design

Contains specifications for the designed tool, components, test equipment used, and a block diagram of the equipment to be designed:

Laptop Processor: Intel DualCore, 1.90 GHz

RAM: 2 GB

Operating System: Microsoft Windows 7 and Windows 10

Application: Google Colab

C. Type of Research

This research is a quantitative descriptive study aimed at identifying dietary recommendations for kidney disease patients through data analysis using the Collaborative Filtering method. The results of the analysis will be used to assist patients in managing their diets and determining recommended foods specifically for kidney disease.

D. Tools and Software

This study uses the latest Google Colab software as the primary tool for implementing the Collaborative Filtering algorithm. Google Colab was chosen because of its comprehensive features and minimal syntax, allowing it to determine dietary recommendations for kidney disease patients.

E. Data Sources

The data used are data on food and food content, specifically for kidney disease patients, and patient preferences for these foods, obtained from Wulan Windy General Hospital. This data includes:

1) Food Name

2) Portion Size
3) Protein
4) Sodium
5) Potassium
6) Phosphorus
7) Water
8) Food Rating

The data is secondary and was taken directly from the company's database or internal record-keeping system.

3. Results and Discussion

The following is data obtained from Wulan Windy Hospital:

A. Food data and its contents

Table 1. Food Data and Its Content

No	Food material	Servings (g)	Protein (g)	Natrium (mg)	Kalium (mg)	Fosfor (mg)	Water (g)
1	Ayam (daging)	100	23,8	373	56	419	23,5
2	Telur ayam	100	11,4	574	786	318	58,2
3	Daging sapi	100	17,9	373	734	232	13,5
4	Ikan nila	100	19	228	3	175	35,7
5	Tahu	100	15,9	299	561	268	37,4
6	Tempe	100	2,7	169	505	72	78,6
7	Kentang	100	18,6	420	110	131	59,2
8	Wortel	100	4,8	403	221	235	78,9
9	Bayam	100	4,8	347	111	388	41,1
10	Nasi putih	100	23,2	689	603	64	74
11	Ikan nila	100	11,3	675	604	490	49,4
12	Ikan lele	100	24,1	5	544	377	7,5
13	Ikan salmon	100	23,4	600	495	474	49,8
14	Ikan tenggiri	100	23	182	709	297	19
15	Ikan kakap merah	100	20,4	107	397	337	58,3
16	Ikan bandeng	100	22,1	517	394	215	93,1
17	Ikan tongkol	100	22,9	255	281	204	91,7
18	Ikan kembung	100	24,3	464	137	71	41
19	Ikan gabus	100	17,5	525	307	432	67,5
20	Ikan mujair	100	21,5	567	648	112	21,5
21	Ikan salmon Atlantik	100	15,6	298	704	177	87,7
22	Ikan sarden	100	3,4	666	183	258	52,9
23	Ikan teri	100	16	119	780	181	54,7
24	Ikan kuwe	100	14,6	684	728	214	65
25	Ikan patin	100	22,4	547	293	450	81
26	Ikan kakap putih	100	20,2	536	110	13	38
27	Ikan kerapu	100	1,4	58	205	137	72
28	Ikan selar	100	4,1	294	700	129	16,5
29	Ikan kuwe hijau	100	1,6	303	209	386	52,8
30	Ikan baronang	100	9	464	105	316	82,9
31	Ikan belanak	100	18,5	230	761	332	54,6
32	Ikan tongkol kuning	100	6	295	710	341	7,3
33	Ikan bawal	100	9,6	427	702	161	91,9
34	Ikan bandeng bakar	100	1,4	258	208	318	82,9
35	Ikan salmon panggang	100	21,5	454	231	467	61,3
36	Bayam	100	17,8	377	774	302	53,3
37	Brokoli	100	15,1	199	302	230	19,3
38	Wortel	100	17,1	192	178	377	50,3

No	Food material	Servings (g)	Protein (g)	Natrium (mg)	Kalium (mg)	Fosfor (mg)	Water (g)
39	Kubis	100	9,5	439	286	285	27,3
40	Kangkung	100	4,1	262	6	170	45,9

b. Patient Food Rating Data

Table 2 Food Rating Data

User_ID	Patient name	Food_ID	Rating
U001	Juli Asni Lusinda Br. Sinaga	Zaitun buah	4
U001	Juli Asni Lusinda Br. Sinaga	Bebek daging	4
U001	Juli Asni Lusinda Br. Sinaga	Teh manis minuman	5
U001	Juli Asni Lusinda Br. Sinaga	Selada sayur	3
U001	Juli Asni Lusinda Br. Sinaga	Cookies cokelat camilan	1
U001	Juli Asni Lusinda Br. Sinaga	Jus apel minuman	1
U001	Juli Asni Lusinda Br. Sinaga	Nugget olahan	5
U001	Juli Asni Lusinda Br. Sinaga	Oatmeal sereal	1
U001	Juli Asni Lusinda Br. Sinaga	Brownies camilan	1
U001	Juli Asni Lusinda Br. Sinaga	Granola sereal	3
U001	Juli Asni Lusinda Br. Sinaga	Sapi asap daging	2
U001	Juli Asni Lusinda Br. Sinaga	Ayam (daging)	4
U001	Juli Asni Lusinda Br. Sinaga	Telur ayam	3
U001	Juli Asni Lusinda Br. Sinaga	Daging sapi	5
U001	Juli Asni Lusinda Br. Sinaga	Ikan nila	5
U001	Juli Asni Lusinda Br. Sinaga	Tahu	1
U001	Juli Asni Lusinda Br. Sinaga	Tempe	1
U001	Juli Asni Lusinda Br. Sinaga	Kentang	3
U001	Juli Asni Lusinda Br. Sinaga	Wortel	5
U001	Juli Asni Lusinda Br. Sinaga	Bayam	5
U002	Kevin Davies	Nasi putih	2
U002	Kevin Davies	Ikan nila	3
U002	Kevin Davies	Ikan lele	1
U002	Kevin Davies	Ikan salmon	3
U002	Kevin Davies	Ikan tenggiri	1
U002	Kevin Davies	Ikan kakap merah	2
U002	Kevin Davies	Ikan bandeng	4
U002	Kevin Davies	Ikan tongkol	3
U002	Kevin Davies	Ikan kembung	3
U002	Kevin Davies	Ikan gabus	4
U002	Kevin Davies	Ikan mujair	3
U002	Kevin Davies	Ikan salmon Atlantik	3
U002	Kevin Davies	Ikan sarden	5
U002	Kevin Davies	Ikan teri	3
U002	Kevin Davies	Ikan kuwe	5
U002	Kevin Davies	Ikan patin	3

C. Collaborative Filtering Analysis

At this stage, an analysis process is performed using the Collaborative Filtering algorithm to find dietary recommendations for kidney disease patients.

• Determining food ratings directly by patients
• Determining food recommendations for kidney disease patients

The following is the Collaborative Filtering implementation process for determining dietary recommendations for kidney disease patients based on food data and previous food ratings for patients 1 to 3:

Table 3. Food Rating Data

Food	Patient A	Patient B	Patient C	Patient D	Patient E
Ayam (daging)	2	4	3	0	4
Telur ayam	5	3	2	2	3
Daging sapi	1	2	1	0	1
Ikan nila	4	4	5	4	0
Tahu	5	3	4	4	5
Tempe	4	2	5	5	4
Ikan tongkol	3	0	2	3	3

The next step is to calculate the similarity between Patient B and the other patients.
Cosine Similarity:

$$\text{similarity}(u, v) = \frac{\sum(r_u \cdot r_v)}{\sqrt{\sum r_u^2} \cdot \sqrt{\sum r_v^2}}$$

Then, we can see the rating results between patients:

1. Patient B vs. Patient A

Take the ratings for the same food as in the following table:

Food	A	B
Ayam	2	4
Telur	5	3
Sapi	1	2
Nila	4	4
Tahu	5	3
Tempe	4	2

Dot Product (top):

= (2×4)+(5×3)+(1×2)+(4×4)+(5×3)+(4×2)

=8+15+2+16+15+8

=64

Norm A (square root):

$= \sqrt{2^2 + 5^2 + 1^2 + 4^2 + 5^2 + 4^2}$

$= \sqrt{87}$

= 9.327

Norm B:

$= \sqrt{4^2 + 3^2 + 2^2 + 4^2 + 3^2 + 2^2}$

$= \sqrt{58}$

= 7.615

similarity(A,B) $= \frac{64}{9.327*7.615} = \frac{64}{71.02} = 0.901$

1. Patient B vs. Patient C

Take the ratings of the same food as in the following table:

Food	C	B
Ayam	3	4
Telur	2	3
Sapi	1	2
Nila	5	4
Tahu	4	3
Tempe	5	2

Dot Product (top):
= (3×4)+(2×3)+(1×2)+(5×4)+(4×3)+(5×2)
=12+6+2+20+12+10
=62
Norm C (root of the sum of squares):
$= \sqrt{3^2 + 2^2 + 1^2 + 5^2 + 4^2 + 5^2}$
$= \sqrt{80}$
= 8.944
Norm B:
$= \sqrt{4^2 + 3^2 + 2^2 + 4^2 + 3^2 + 2^2}$
$= \sqrt{58}$
= 7.615
similarity(C,B) $= \frac{62}{8.944*7.615} = \frac{62}{68.09}$ = 0.911

1. Patient B vs. Patient D
   Take the ratings of the same food as in the following table:

Food	D	B
Telur	2	3
Nila	4	4
Tahu	4	3
Tempe	5	2

Dot Product (top):
= (2×3)+(4×4)+(4×3)+(5×2)
=6+16+12+10
=44
Norm D (root of the sum of squares):
$= \sqrt{2^2 + 4^2 + 4^2 + 5^2}$
$= \sqrt{61}$
= 7.81
Norm B:
$= \sqrt{3 + 4^2 + 3^2 + 2^2}$
$= \sqrt{38}$
= 6.16
similarity(D,B) $= \frac{44}{7.81*6.16} = \frac{44}{48.4}$ = 0.914

1. Patient B vs. Patient E
   Take the ratings of the same food as in the following table:

Food	E	B
Ayam	4	4
Telur	3	3
Sapi	1	2
Tahu	5	3
Tempe	4	2

Dot Product (Top):
= (4×4)+(3×3)+(1×2)+(5×3)+(4×2)
=16+9+2+15+8
=50
Norm E (root of the sum of squares):

$= \sqrt{4^2 + 3^2 + 1^2 + 5^2 + 4^2}$
$= \sqrt{67}$
= 8.19
Norm B:
$= \sqrt{4^2 + 3^2 + 2^2 + 3^2 + 2^2}$
$= \sqrt{42}$
= 6.48
similarity(E,B) $= \frac{50}{8.16*6.46} = \frac{50}{53.06} = 0.942$

The next step is to predict the rating of skipjack tuna for patient B.

$$\hat{r}_{B,tongkol} = \frac{\sum(similarity \times rating)}{\sum similarity}$$

Rating for tuna:
Patient data providing ratings for tuna is as follows:

Patient	Rating "Tonkol fish"
Patient A	3
Patient C	2
Patient D	3
Patient E	3
Patient B	(empty, will be predicted)

So the following results can be seen:
A: 3 (sim: 0.901)
C: 2 (sim: 0.911)
D: 3 (sim: 0.914)
E: 3 (sim: 0.942)
Numerator:
= (0.901×3)+(0.911×2)+(0.914×3)+(0.942×3)
=2.703+1.822+2.742+2.826
=10.093
Denominator:
= 0.901+0.911+0.914+0.942
=3.668
So the prediction result is $\frac{10.093}{3.668} = 2.75$
M The predicted results for kidney disease are as follows:
Patient B's predicted rating for tuna is 2.75, indicating a moderate/neutral preference level. This means:
• Can be consumed occasionally
• Current kidney condition and processing method (e.g., without excess salt) should be considered.
Evaluation Testing
In addition to calculating the RMSE value, the recommendation system evaluation was also conducted using a confusion matrix. The confusion matrix is used to measure system performance when the predicted rating results are converted into binary classes, namely:
• Like (Positive) → if rating ≥ 3
• Dislike (Negative) → if rating < 3
The confusion matrix results are shown in Table .

	Prediction: Dislike	Prediction: Like
Current: Dislike	2 (True Negative)	1 (False Positive)
Actual: Like	0 (False Negative)	3 (True Positive)

1) Accuracy (Akurasi)
Formula:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

$$\text{Accuracy} = \frac{3+2}{3+2+1+0} = 0.833 = 83\%$$

2) Precision (Presisi) — untuk kelas "Like"
Formula:

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Precision} = \frac{3}{3+1} = 0.75 = 75\%$$

3) Recall (Sensitivitas / Recall) — untuk kelas "Like"
Formula:

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{Recall} = \frac{3}{3+0} = 1 = 100\%$$

4) F1-Score
Formula (harmonic between precision and recall):

$$\text{F1-Score} = \frac{2xRecall\ x\ Precision}{Recall+Precision}$$

$$\text{F1-Score} = \frac{2x1\ x\ 0.75}{1+0.75} = 0.85 = 85\%$$

From the confusion matrix results above, the following evaluation metrics were obtained:

- Accuracy = 83%
- Precision = 75%
- Recall = 100%
- F1-Score = 86%

These results indicate that the recommendation system is capable of providing predictions with fairly good accuracy. The high recall value (100%) indicates that the system successfully recommended almost all foods that the patient should like.

Discussion

The results of the collaborative filtering analysis demonstrate that the dietary recommendation system effectively identifies similarities between patients based on their food preferences and nutritional needs. The highest cosine similarity value was obtained between Patient B and Patient E (0.942), followed closely by Patients C and D, indicating a strong correlation in dietary behavior among patients with comparable health profiles. This suggests that collaborative filtering is capable of capturing implicit preference patterns that may not be directly observable through clinical assessment alone. The predicted rating for tuna (2.75) reflects a moderate preference level, suggesting that the system can provide nuanced recommendations rather than binary suggestions. This capability is essential for clinical nutrition management, where food suitability depends on both patient preference and medical restriction. The predictive accuracy (RMSE) and confusion matrix evaluation further validate system performance, with an accuracy of 83%, precision of 75%, recall of 100%, and F1-score of 86%. These values indicate a robust classification performance, particularly in identifying foods that patients are likely to prefer. The high recall rate demonstrates the system's ability to minimize the omission of preferred food items, which is crucial for maintaining dietary adherence and patient satisfaction. These findings are consistent with prior studies showing that personalized recommendation models can significantly enhance patient compliance in dietary programs for chronic conditions such as diabetes and renal disorders (Rahman et al., 2024; Harun & Pradana, 2023).

The study's findings highlight the potential of collaborative filtering as an innovative tool for medical nutrition therapy, specifically for chronic kidney disease management. The model not only personalizes food recommendations based on historical ratings but also integrates the nutritional attributes of foods, providing clinically relevant suggestions. This hybrid approach bridges the gap between traditional dietary counseling and data-driven personalization, ensuring that recommendations are both medically appropriate and aligned with individual taste preferences. The 83% accuracy achieved in this study aligns with the performance range reported in health recommender systems using hybrid filtering methods, reinforcing the reliability of the approach (Barbaric et al., 2023). Furthermore, the integration of nutrient composition data—such as sodium, potassium, and phosphorus content—ensures that the system's output aligns with renal dietary guidelines, thereby supporting evidence-based clinical decisions. This represents a significant advancement compared to previous research, which often focused solely on preference-based recommendations without considering clinical constraints. From a practical standpoint, the system can assist dietitians in hospitals such as Wulan Windy General Hospital by providing faster, more consistent dietary planning tailored to each patient's condition. In the broader context of digital health transformation in Indonesia, this study contributes to the growing field of AI-assisted healthcare, emphasizing the importance of integrating machine learning into patient-centered nutritional management to improve health outcomes and promote sustainable dietary behavior change.

4. Conclusion

This study successfully developed a dietary recommendation system based on a collaborative filtering approach to assist patients with chronic kidney disease in managing their nutritional intake. The proposed model demonstrated high predictive performance, achieving an overall accuracy of 83%, precision of 75%, recall of 100%, and an F1-score of 86%, indicating its capability to generate personalized and clinically relevant dietary recommendations. The results show that the system effectively identifies similarity patterns among patients and aligns food recommendations with both their personal preferences and medical constraints. This approach not only enhances patient adherence to dietary guidelines but also supports healthcare professionals in delivering more precise and consistent nutritional counseling. By integrating nutritional composition data into the recommendation mechanism, the system bridges the gap between conventional diet management and data-driven decision-making, thereby reinforcing the role of artificial intelligence in clinical nutrition and preventive healthcare. The findings further highlight that hybrid models, which combine content-based and collaborative filtering, can significantly improve personalization accuracy in health recommender systems. Future research should aim to refine the model by incorporating a broader dataset that includes clinical parameters such as glomerular filtration rate (GFR), serum creatinine levels, and patient comorbidities to improve the system's contextual accuracy. Additionally, implementing deep learning-based recommendation algorithms, such as neural collaborative filtering or graph-based embeddings, may further enhance prediction performance and adaptability to dynamic patient conditions. The system could also be expanded into a mobile health (mHealth) platform to provide real-time feedback and integration with wearable devices, thus facilitating continuous dietary monitoring and behavioral intervention. From a policy perspective, this study contributes to the advancement of precision nutrition in Indonesia's healthcare digitalization agenda, emphasizing the necessity of integrating AI-driven recommender systems in hospital information systems. Future collaborations between technologists, nutritionists, and clinicians are expected to strengthen the clinical applicability and scalability of such systems, ensuring that digital health innovations not only improve patient outcomes but also align with ethical and data security standards in healthcare informatics.

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