Recommendation System for Matching Patients and Doctors in Telemedicine Based on Hybrid Filtering

Yesi Sofia
Department of Informatics
Universitas Jenderal Achmad Yani
West Java, Cimahi, Indonesia
yessisofia18@if.unjani.ac.id

Faiza Renaldi, Irma Santikarama
Department of Information Systems
Universitas Jenderal Achmad Yani
West Java, Cimahi, Indonesia
faiza.renaldi@unjani.ac.id, irma.santikarama@lecture.unjani.ac.id

Abstract

Telemedicine is a technology that can make it easier for patients to interact with doctors through online media. The influence of the doctor on the patient in real life can occur physiologically at any time. Therefore, patients must choose a suitable doctor to communicate with to get the right and appropriate health services. Many previous studies have focused on patient-physician matching, but such technical implementations have not been carried out in much healthcare, especially the remote healthcare domain. Currently, the selection of doctors for telemedicine depends only on the available doctor information while the number of doctors there is not small, which causes patients difficulties in choosing a doctor. The recommendation system can be helpful in providing doctor recommendations. This study created software that can provide recommendations for matching doctor patients in telemedicine using a hybrid filtering method that combines two methods, namely the collaborative filtering method using rating parameters and the Content-based filtering method using the availability of content contained in the doctor's profile. The study was conducted on the get-well app. From the results of the calculation process that has been carried out, the content-based filtering method can recommend new doctors who have never treated patients and have no previous ratings, while collaborative filtering methods can recommend doctors who have a history and have had a rating from patients. After the implementation, we conducted a test of accuracy. The test was carried out using a confusion matrix with the accuracy results obtained, which was 91 %. In these results, the hybrid filtering method can help choose the right doctor according to the criteria and needs of the patient. For future research, it can use other parameters in providing recommendations, such as comments or likes and dislikes.

Keywords
Telemedicine, Recommendation Systems, Hybrid Filtering, Collaborative Filtering, Content-Based Filtering

1. Introduction

It is difficult for Indonesians to get quality health services due to the uneven distribution of health workers and facilities. On the other hand, the ever-increasing development of technology provides many benefits in various fields, especially in the fields of communication and health. One of the uses of technology in the field of communication and health is the construction of telemedicine, which is a system that allows patients to communicate with doctors through online media (Haleem et al. 2021). By using this system, patients get the correct treatment from experts without having to visit hospitals or health centers so as to save costs and energy, considering that not all diseases require medical treatment. In telemedicine, a process of interaction between the patient and the doctor occurs. The influence of the doctor on the patient in real life can occur physiologically at any time, so the interaction between the patient and the doctor is considered important in the process of consultation and treatment. Accuracy in the selection of doctors can improve the quality of care and patient satisfaction with doctors, considering that the process of curing diseases is usually quite time-consuming, which allows for a lot of interaction between patients and doctors(Ju and Zhang 2021).

It is not easy to choose the best doctor to deal with the health problems experienced by patients. Moreover, interactions are carried out online or remotely (Vigier et al. 2021). The selection of doctors in remote consultations (telemedicine) requires a lot of information, such as doctor profiles, doctor specialties, to other patient reviews of doctors. However, it is impossible for patients to find all the information themselves; moreover, the doctors on telemedicine are not small, so it is possible that patients experience confusion in choosing a specialist doctor who suits the patient's needs.

One of the efforts that can be made to deal with this is by utilizing computer technology, namely a recommendation system that is able to assist patients in choosing doctors by providing recommendation services in the form of items according to patient personalization (Han et al. 2019) (Afoudi, Lazaar, and Achhab 2021). Previous research has created a system of physician recommendations based on doctors' performance and patient preferences aimed at eliminating the problem of excess doctor information and helping patients schedule appointments with doctors. The algorithm was designed by adding patient preference characteristics to the framework of the physician performance model, which is built with the Analytic Hierarchy Process method, which results in a physician recommendation system with a 75% confidence value algorithm evaluated by patient operating records and reservation records where patients can use the recommendation system only patients who have had a previous history of the disease(A et al. 2020).

Currently, the commonly used approaches in recommendation systems are collaborative Filtering and content-based filtering methods (Isinkaye 2015). The content-based filtering method can recommend new items that do not yet have a rating. This method uses user profile descriptions or analyzes the attributes of an item to generate a recommendation. The Content-based filtering method works best when recommending documents such as web pages, publications, and news reports. However, Content-based Filtering has limitations. If there is a new user, the system cannot recommend items. Weaknesses in the Content-based filtering method give rise to Collaborative filtering methods that can fix these weaknesses. This approach leverages other users' opinions or ratings in the form of existing ratings or feedback to predict items that may be liked by users. But this method also has limitations where a rating parameter is needed so that if there is a new item that does not yet have a rating, the system does not recommend the item. To make up for the weaknesses contained in each method, you can use a hybrid filtering method that combines the two methods to produce recommendation items that suit the wishes of the user who handles the sparsity problem and improves the accuracy of the prediction value (Han et al. 2019).

Several previous studies have created an image recommendation system using the hybrid filtering method (Kobyshev, Voinov, and Nikiforov 2021) by combining content-based Filtering and collaborative filtering methods using CNN and knn algorithms based on the analysis of image metadata and user interest matrices from image metadata that users assessed previously in generating recommendations, then System book recommendations use the hybrid filtering method using the knn algorithm in producing recommendations that produce outputs in the form of appropriate classifications and do not correspond to an accuracy value of 78%. (Yang et al. 2017).

This study created a recommendation system for matching doctor patients in telemedicine using a hybrid filtering method that combines collaborative Filtering and content-based filtering methods. The parameters used in this study are patient data and doctor data that has a rating. The collaborative filtering method implements an adjusted cosine-similarity algorithm to calculate the similarity value between doctors, then the calculation of the predicted value, then the content-based filtering method implements the TF-IDF algorithm to find the availability of content contained in the doctor's profile.

2. Methods

This study was carried out with several stages in achieving the goal, as shown in figure 1. The first step is the collection of data on the object under study. The next step is pre-processing to process data which includes data cleaning and data selection. Furthermore, this research develops a recommendation system model using the hybrid filtering method by combining two methods, namely content-based Filtering and Collaborative Filtering. Next, designing and implementing soft device. Then the final stage of this study evaluates the web to ensure that the results of the item recommendations are in accordance with the model. The stages of the study can be seen in Figure 1.

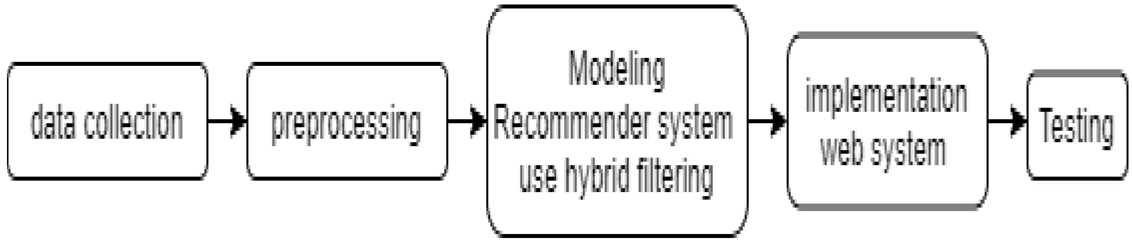

Figure 1. Research flow overview

2.1 Data Collection

Before carrying out the pre-processing and modeling stages of the recommender system using the hybrid filtering method, data collection is carried out first. The data used is patient data that contains a profile of the doctor who handles the patient and the rating of doctors at Azra hospital and getwell health startup. The doctor's data used consists of 4 doctor specialists, namely general practitioners, heart, nerve, and internal practitioners. The variables used in this study were the type of patient's name, doctor's name, doctor's specialist, patient complaint, doctor's price, medical action, and doctor's rating. The variable will be processed using a hybrid filtering method consisting of content-based Filtering and collaborative filtering methods to generate item recommendations.

2.2 Pre-Processing

At this stage, it functions to change the doctor's data that is already available data so that it is processed into data that is ready to be processed as a research object. There are several stages in this pre-processing, namely data cleaning and data selection.

2.2.1 Data Cleaning

At this stage, data cleaning is carried out for data analysis that does not have complete data, such as patient data that does not have complete data, so that they can easily find the data. In previous research on A Data Fusion and Data Cleaning System for Smart Grids, Big Data wrote that one of the data cleaning processes is to maintain data quality. The solution given in the previous study to carry out data cleaning is that it must involve finding incorrect data records, correcting data, eliminating data that does not have completeness for large amounts of data, which cannot be made estimates, and matching duplicate data (Lv et al. 2019). The solution taken from previous research for the data cleansing process is to correct the data and eliminate data that does not have completeness for large amounts of data(Pesantez-Aviles et al. 2018). This data cleansing process resulted in 1254 data from 1598 patient data.

2.2.2 Data Selection

At this stage, a selection of data that already has complete information in each attribute is carried out, and the data is selected to group attributes according to the information needed. The selection data from the attributes needed are doctor data that has attributes of doctor's name, patient name, and rating, which is then processed using Hybrid filtering techniques as stated in Table 1.

Table 1. Patient Data

No	PatientID	Patient_name	DoctorID	Doctor_name	MedicalSpecialist	Complaint	Rating
1	27333	Budi Yudantara, Tn	PD04	RIZASYAH DAUD, Dr. MSc,SpPD-KR.,FINASIM	Internal Medicine	shortness of breath	3.0
2	163220	Yusmarni, Ny	PD02	Dr. Satrio Sukmoko, SpPD	Internal Medicine	shortness of breath	5.0
3	4813	Bethesda Noverianti M, Nn	PD01	Achmad Saleh, Dr. Sp.PD	Internal Medicine	Cough up blood	4.0
..	…	…	…	…	…	…	..
..	…	…	…	…	…	…	..
1254	4825	Siti Utami, Ny	S04	Supadmadi, Dr. Sp.S	Nerve	Arm muscle pain	4.0

2.3 Modeling Recommender System use Hybrid Filtering

After carrying out the pre-processing data stage, then carry out the recommendation process using the hybrid filtering method, which combines collaborative filtering methods that calculate the value of match predictions based on doctors' raring, and the content-based filtering method that uses doctor profiles to produce recommendations. The following are the stages of collaborative Filtering and content-based filtering methods to produce doctor's recommendations:

2.3.1. Collaborative filtering Algorithm

The Collaborative filtering method works by building a database of user preferences for items (a matrix of user items). Then, match users with related interests and preferences to make recommendations by calculating similarities between user profiles (Li et al. 2019). The user Receives recommendations for items that he has never rated before but has received positive reviews from users in his environment (Yu et al. 2021). *Collaborative Filtering recommends items based on the opinions or opinions and interests of several users, which are usually given in the form of ratings* (Dai, Xia, and Gui 2018). Figure 2 shows the flow of the collaborative filtering process to generate recommendations.

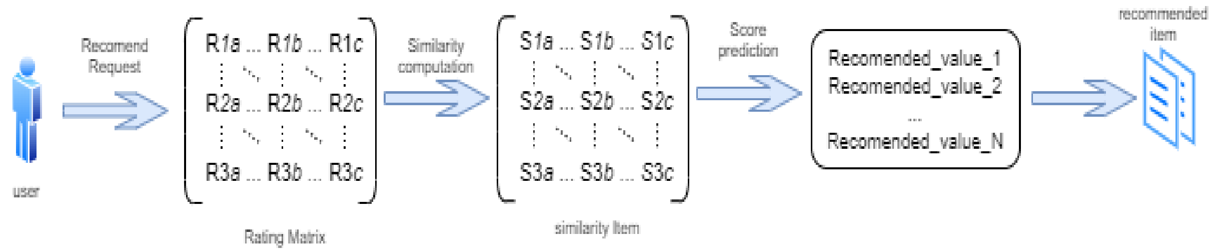

Figure 2. Collaborative Filtering Algorithm (Li et al. 2019)

The results of the recommendations on this method largely depend on the opinion or opinion of other users on an item. In this study, the recommendation process using the collaborative filtering method was divided into three steps as follows:

1) Formation of the rating data matrix

The first step to generating rating data is to change the rating data to take the form of a user-item matrix. The scale of rating by patients to doctors is 1 – 5, as shown in Table 2.

Table 2. Data Rating

Patient	Doctor	Rating
Pxx1	d1	4.0
Pxx1	d2	4.0
Pxx1	d3	0
Pxx1	d4	2.0
..	..	..
Pxx5	d2	3.0
Pxx5	d3	3.0
Pxx5	d4	5.0
Pxx5	d5	0

The rating data contained in Table 2 is changed to a matrix user item, as shown in Table 3.

Table 3. Matrix conversion results

		Doctor Name					$\bar{R}_u$
		d1	d2	d3	d4	d5	
Patient Name	Pxx1	4.0	4.0	0	2.0	0	3,3
	Pxx2	0	2.0	0	0	5.0	3.5
	Pxx3	4.0	0	5.0	0	3.0	4.0
	Pxx4	2.0	0	1.0	3.0	0	2.0
	Pxx5	0	3.0	3.0	5.0	0	3.6

2) Calculating similarity doctor

The next step is the discovery of similar items. This study used the Adjusted-cosine similarity algorithm to calculate similarities between doctors. This similarity calculation is a modification of the vector-based similarity calculation by looking at the fact that each user has a different rating scheme (Musa and Zhihong 2020). Sometimes the user gives a high rating to item a; on the other hand, the user gives a very low rating on item b. Therefore, each rating is reduced by the average rating given by the user.

As for the adjusted-cosine similarity algorithm equation, it is as follows:

$$Sim(i,j) = \frac{\sum_{u\in U}\left(R_{u,i} - \bar{R}_i\right) + (R_{u,j} - \bar{R}_u)}{\sqrt{\sum_{u\in U}(R_{u,i} - \bar{R}_i)^2} + \sqrt{\sum_{u\in U}(R_{u,j} - \bar{R}_i)^2}}$$

Information:

Sim (i,j) = The value of the similarity between item i and item j.

$u \in U$ = The set of u users that rate item i and item j.

$R_{u,i}$ = User rating u on item i.

$R_{u,j}$ = User rating u on item j.

$\bar{R}_u$ = The average value of user rating u.

Here is the calculation of the algorithm-adjusted cosine similarity; the calculation is carried out if there are two or more ratings of other patients against the two doctors; for example, we will calculate the similarity between d1 and d2.

$$Sim(d1, d2) = \frac{(4.0 - 3{,}3)(4{,}0 - 3{,}3)}{\sqrt{(4{,}0 - 3{,}3)^2 + (4{,}0 - 3{,}3)^2}} = \frac{0{,}49}{0.98} = 0{,}5$$

From the calculation process, the result of the similarity of d1 and d2 is 0,5. The calculation of similarity is calculated for all doctors so that the results are shown in Table 4.

Table 4. Similarity of Doctors

	Similarity				
	d1	d2	d3	d4	d5
d1	1,0	0,5	0	0,3	0
d2	0,5	1,0	0,42	-0,41	-1,06
d3	0	0,42	1,0	0,45	0
d4	0,3	-0,41	0,45	1,0	0
d5	0	-1,06	0	0	1,0

1) calculate prediction weight

The next stage is to calculate the patient's prediction of the doctor, and this study uses the weighted sum method to calculate the predicted value. In the previous study, it implemented implementing a weighted sum algorithm to predict proposal rankings in the recommendation system for student creativity program proposals with an accuracy of 87% (Sugianto and Gunawan 2020). The formula used for calculating predictions using the weighted sum algorithm is as follows:

$$P(u,j) = \frac{\sum_{i\in j}(R_{u,i} * S_{i,j})}{\sum_{i\in j}(R_{u,i}|S_{i,j}|}$$

Information:

$P(u,j)$ = prediction for user u on item j.

$\sum_{i\in j}$ = The set of items similar to item j.

$R_{u,i}$ = User rating u on item j.

$S_{i,j}$ = The value of the similarity between item i and item j.

For example, we will lead the weight of the prediction of Pxx1 patients against d3 as follows:

$$P(pxx1, d3) = \frac{(4*0) + (4*0{,}42) + (2*0{,}45) + (0*0)}{|0| + |0{,}42| + |0{,}45| + |0|} = \frac{2{,}58}{0{,}87} = 2.9655$$

From this calculation, the predicted weight of patient pxx1 to doctor d3 is 2.9655. Prediction calculations are carried out on each doctor so that the results are as shown in the Table 5.

Table 5. Prediction weight

		Doctor Name				
		d1	d2	d3	d4	d5
Patient name	Pxx1			2,96		4
	Pxx2	1,25		0,96	-0,61	
	Pxx3		-1,67		4,14	
	Pxx4		-0,34			0
	Pxx5	3,75				3

As shown in Table 5, the recommended doctor is the doctor who has the highest predictive weight, therefore pxx1 gets a d4 recommendation with a predictive weight rating of 4 and so on.

2.2.3 Content-based Filtering Algorithm

The *content-based* method implements a domain-dependent algorithm and puts more emphasis on analyzing item attributes to generate recommendations. In content-based techniques, recommendations are made based on user profiles using features extracted from the content of items that the user has previously evaluated. Mostly related items are recommended to users (Portugal, Alencar, and Cowan 2018). This study used the Term Frequency Inverse Document Frequency (TF/IDF) model to model the relationships between documents. TF-IDF is used to look up term values in a given document with respect to a corpus or set of documents (Sharma, Rana, and Malhotra 2021). The equation for calculating the weights of the TF-IDF is as follows:

$$IDF = (D/DF)$$
$$W = TF * (IDF + 1)$$

Information:
W: the weight of each document.
TF: the number of occurrences of a word or term in the document.
D: the sum of all documents.
DF: the number of documents containing the word (term).
IDF : inverse document frequency.IDF : inverse document frekuensi.

The steps of the content-based filtering method to produce recommendations are as follows:

1) Define a query term

The first step is to determine the query term; the variables used include the doctor's specialist, medical action, price, schedule, and location of the doctor. The speculation data are combined to form a query. Next, process the term query with the doctor data available for the example as in Table 6, looking for the term query of the three available doctors.

Table 6. Demographic data overview

Doc	Document Contents
Q	General Practitioner | General health consultation | 100000 | Monday | Jakarta
d1	General Practitioner | General health consultation, vitamin C infusion | 150000 | Friday | Bogor

d2	General Practitioner | General health consultation, Medical check-up | 100000 | Wednesday | Jakarta
d3	Nerve | Migraine Treatment, Epilepsy Treatment | 250000 | Monday | Bekasi

2) Calculate the weight of TF-IDF

The calculation of the weight of the TF-IDF is carried out on each attribute or information contained in the doctor's profile based on the query. The calculation for determining the weight of the TF- IDF can be seen in Table 7.

Table 7. Calculate of TF-IDF

Query	TF			DF	D/DF	IDF	IDF+1	W = TF * (IDF+1)		
	d1	d2	d3					d1	d2	d3
General practitioners	1	1		2	2	0.30102	1.30102	1.30102	1.30102	0
General health consultation	1	1		2	2	0.30102	1.30102	1.30102	1.30102	0
100000		1		1	4	0.60205	1.60205	0	1.60205	0
Monday			1	1	4	0.60205	1 .60205	0	0	1. 60205
Jakarta		1		1	4	0.60205	1. 60205	0	1. 60205	0
Number of Weights of Each Document								2.60204	5,80614	1. 60205

From the results of the calculations that have been done, the item that has the highest weight is the recommended item. All equations are implemented in the software for automatic calculations.

3. Results and Discussion

3.1 Calculation of Optional Course Recommendations Using Collaborative Filtering

The doctor rating scale ranges from 1 to 5 for the 1254 patients who rated. In the data set, most doctors have received less than 50 ratings, but each patient gave a rating to at least one doctor. Figure 3 shows the average number of ratings available.

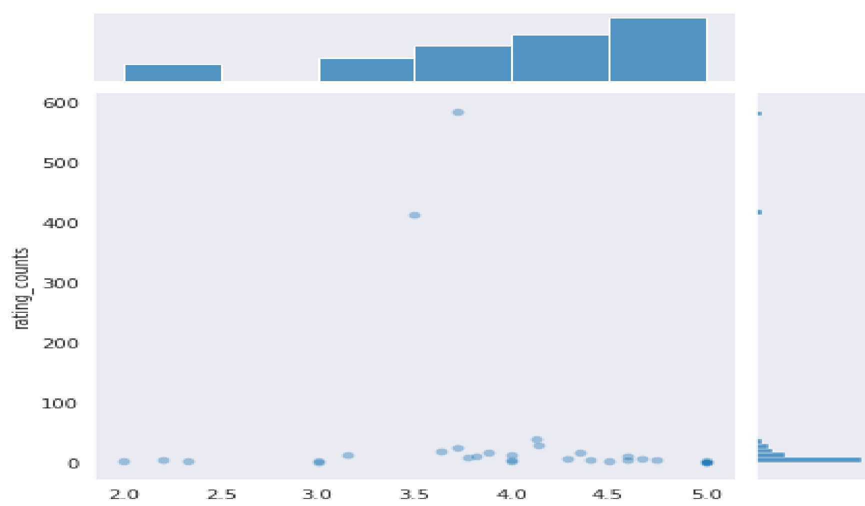

Figure 3. Average ratings against the number of ratings.

Calculations using the Adjusted-cosine similarity algorithm obtained the value of the similarity results between doctors to then predict the value of the patient's suitability to the doctor. From the calculation process carried out, the results of similarity between doctors were obtained as shown in Table 8.

Table 8. Result of Similarity Value

	similarity value						
	d1	d2	d3	..	d30	d31	d32
d1	1	-0.36	0.21	..	-0.02	-015	0.19
d2	-0.36	1	-0.25	..	-0.78	0.91	-0.28
d3	0.21	-0.25	1	..	-0.02	-0.11	0.13
…	..	..	..	..	..	..	..
d30	-0.02	-0.78	-0.02	..	1	-0.95	-0.04
d31	-0.15	-0.91	-0.11	..	-0.95	1	-0.16
d32	0.19	-0.28	0.13	..	-0.04	-0.16	1

The final stage of getting a recommendation is to calculate the predicted value after obtaining the value of similarity between doctors using the *weighted sum* algorithm. From the calculation process of the algorithm, the results of the patient's predictive weights to the doctor are obtained, as shown in Table 9.

Table 9. The recommendation of the collaborative filtering method

Patient	Doctor	Match value prediction
Pxx1	d2	4.0

3.2 Calculation of Optional Course Recommendations Using Content Based filtering

The recommendations generated using the content-based filtering method show the percentage of the TF-IDF weight calculation carried out to each attribute or information contained in the doctor's profile based on queries or patient needs data.

An example of a description of the desired doctor (query term) is as follows:

Q │ General Practitioner | General health consultation | 100000 | Monday | Bogor

The results of the TF-IDF calculation are shown in Table 10.

Table 10. Result of Content based filtering

Doctor's	Weight	Percentage
d1	0.0	0.0 %
d2	0.00661	0.66 %
d3	0.00643	0.64 %
…	…	…
d21	0.83179	83,1%
d22	0. 35361	35.3 %
…	…	…
d32	0.35361	35.3 %

The process of calculating content-based Filtering produces weight values and percentages of doctors. The doctor who has the highest percentage is the recommended doctor. As shown in table 10, d21 has a weight value of 0. 83179 and a percentage of 83.1%, so the doctor is recommended because it is in accordance with the criteria desired by the patient based on the query term.

3.3 Recommender system model in the web

Figures 4 and 5 show the application of recommendation system modeling to web systems using the flask framework. The pre-built recommendation System model is unified in a module so that flask applications can access it.

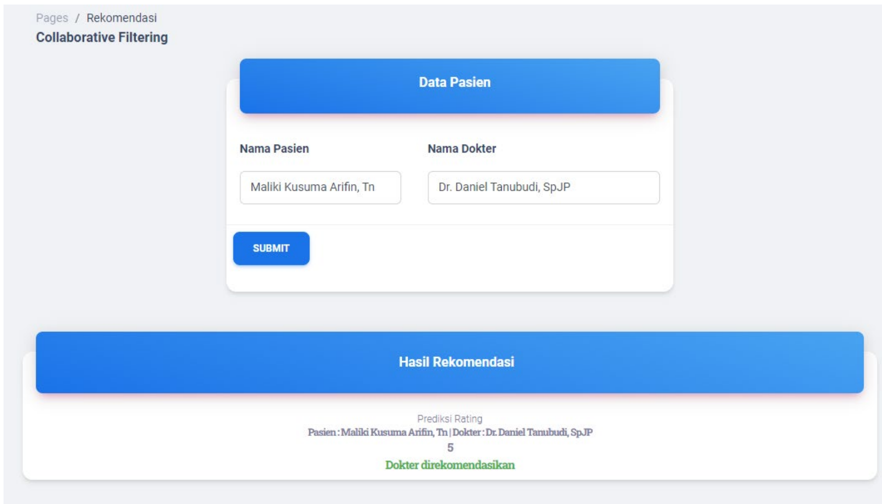

Figure 4. implementation of recommendation system using collaborative Filtering

Figure 4 shows the results of recommendations processed using the Collaborative Filtering method by entering the doctors name and the patients name and then generating predictions. Collaborative Filtering recommends doctors who have a history and have a rating and can only provide recommendations to old patients who already have medical records and have rated doctors.

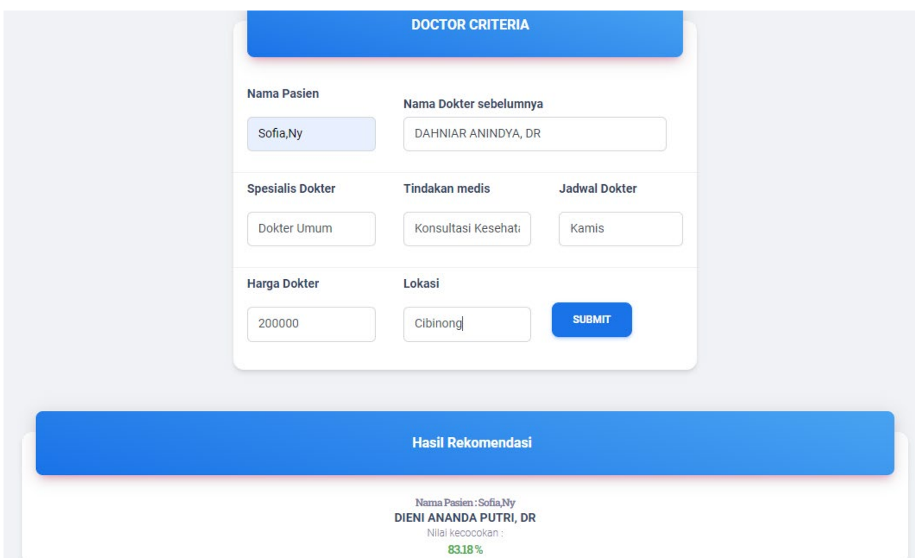

Figure 5. implementation of recommendation system using content-based Filtering

Figure 5 shows the results of the recommendations processed using the content-based filtering method, which displays the patient's name, the recommended doctor's name, and the match value. Patients can enter the query terms used to generate recommendations. After the patient inputs the required doctor's criteria, the system displays the results of the appropriate doctor's recommendation, and the match value is determined based on the query term or the occurrence of the word available in the doctor's data. Content-based filtering methods can recommend new doctors who have never treated patients and do not have a previous rating.

3.4 Confusion matrix

The next stage is testing to determine the level of accuracy in the software that has been made. Tests were carried out using the Confusion Matrix. One study entitled "A hybrid recommender system for e-learning based on context awareness and sequential pattern mining" uses a Confusion matrix to determine the level of Accuracy, Precision, and recall of the e-learning recommendation system using 1200 student data in the study. Recall, Accuracy, and Precision are rated on a scale of 1-5. E-learning rated 1-3 is considered "irrelevant," while those rated 4-5 are considered "relevant" (Tarus, Niu, and Kalui 2018). This study uses 100 test data with a ratio of 7: 3, where 70 data is recommended, and 30 data is not recommended. Calculation of Accuracy, Recall, and Precision is calculated based on the doctor's rating on a scale of 1-5. The predicted rating results given a rating of 1-3 are considered "not recommended," while those given a rating of 4-5 are considered "Recommended." Figure 6 displays the results of the test data using a confusion matrix.

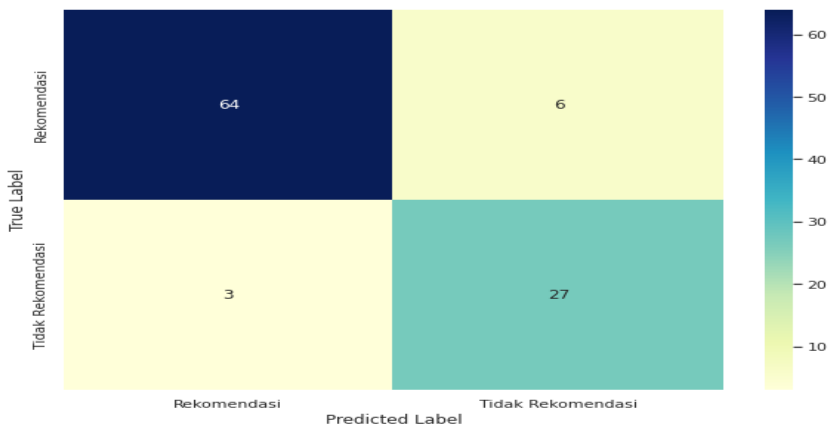

Figure 6. Results of the test data using a confusion matrix

The results of the test data are then used to calculate accuracy, Precision, and recall; the calculation results are shown in Table 11.

Table 11. Evaluation result

Recall	91,4 %
Precision	95,5 %
Accuracy	91 %

Based on the results of tests that have been carried out using the confusion matrix, it displays the results of Recall by 91.4%, Precision by 95.5%, and accuracy by 91 %, so that the recommendation system for matching patients and doctors has good results and can be implemented into a recommendation system that can help patients in finding doctors who are suitable for their needs.

4. Conclusion

Based on the results of this study, it is stated that the content-based filtering method can recommend new doctors who have never treated patients and did not have a previous rating, while the collaborative filtering method can recommend doctors who have a history and already have ratings from patients. After implementation, the next step is to test the accuracy. The test was carried out using a confusion matrix with an accuracy of 91%. In this result, the hybrid filtering method can help choose the right doctor according to the criteria and patient needs. For further research, other parameters can be used in providing recommendations, such as comments or likes and dislikes.

References

A, Safikureshi Mondal, Anwesha Basu B, Nandini Mukherjee C, and A Departemen. "Jurnal Informatika Biomedis Grafik Multilayer." 110(April). 2020.

Afoudi, Yassine, Mohamed Lazaar, and Mohammed Al Achhab. "Simulation Modelling Practice and Theory Hybrid Recommendation System Combined Content-Based Filtering and Collaborative Prediction Using Artificial Neural Network." *Simulation Modelling Practice and Theory* 113(April): 102375. 2021.https://doi.org/10.1016/j.simpat.2021.102375.

Dai, Anyu, Yangyang Xia, and Yue Gui. "A Self-Learning Collaborative Filtering Algorithm in Recommendation System." *2017 3rd IEEE International Conference on Computer and Communications, ICCC 2017* 2018-Janua: 2195–99. 2018.

Haleem, Abid, Mohd Javaid, Ravi Pratap Singh, and Rajiv Suman. "Telemedicine for Healthcare: Capabilities, Features, Barriers, and Applications." *Sensors International* 2(June): 100117. 2021.https://doi.org/10.1016/j.sintl.2021.100117.

Han, Qiwei et al. 2019. "A Hybrid Recommender System for Patient-Doctor Matchmaking in Primary Care." *Proceedings - 2018 IEEE 5th International Conference on Data Science and Advanced Analytics, DSAA 2018*: 481–90.

Isinkaye, F O. "Recommendation Systems : Principles , Methods and Evaluation.": 261–73. 2015.

Ju, Chunhua, and Shuangzhu Zhang. "Doctor Recommendation Model Based on Ontology Characteristics and Disease Text Mining Perspective." *BioMed Research International* 2021.

Kobyshev, Kirill, Nikita Voinov, and Igor Nikiforov. "Hybrid Image Recommendation Algorithm Combining Content and Collaborative Filtering Approaches." *Procedia Computer Science* 193: 200–209. 2021.https://doi.org/10.1016/j.procs.2021.10.020.

Li, Taoying, Linlin Jin, Zebin Wu, and Yan Chen. "Combined Recommendation Algorithm Based on Improved Similarity and Forgetting Curve." *Information (Switzerland)* 10(4). 2019.

Lv, Zhining et al. "A Data Fusion and Data Cleaning System for Smart Grids Big Data." *Proceedings - 2019 IEEE Intl Conf on Parallel and Distributed Processing with Applications, Big Data and Cloud Computing, Sustainable Computing and Communications, Social Computing and Networking, ISPA/BDCloud/SustainCom/SocialCom 2019*: 802–7. 2019.

Musa, Jamilu Maaruf, and Xu Zhihong. "Item Based Collaborative Filtering Approach in Movie Recommendation System Using Different Similarity Measures." *ACM International Conference Proceeding Series*: 31–34. 2020.

Pesantez-Aviles, F. et al. "A Recommender System Based on Data Mining Techniques to Support the Automatic Assignment of Courses to Teachers in Higher Education." *Proceedings - 2017 International Conference on Information Systems and Computer Science, INCISCOS 2017* 2017-Novem: 231–36. 2018.

Portugal, Ivens, Paulo Alencar, and Donald Cowan. "The Use of Machine Learning Algorithms in Recommender Systems: A Systematic Review." *Expert Systems with Applications* 97: 205–27. 2018.https://doi.org/10.1016/j.eswa.2017.12.020.

Sharma, Sunny, Vijay Rana, and Manisha Malhotra. "Automatic Recommendation System Based on Hybrid Filtering Algorithm." *Education and Information Technologies* (0123456789). 2021.https://doi.org/10.1007/s10639-021-10643-8.

Sugianto, R A, and M Gunawan. "Implementation of Simple Additive Weighting (SAW) in Decision Support Systems as a Recommendation for Student Creativity Program Proposals." *International Journal of ...* 1(1): 70–76. 2020.http://jurnal.ceredindonesia.or.id/index.php/injects/article/view/155.

Tarus, John K., Zhendong Niu, and Dorothy Kalui. "A Hybrid Recommender System for E-Learning Based on Context Awareness and Sequential Pattern Mining." *Soft Computing* 22(8): 2449–61. 2018.

Vigier, Marta et al. "Physiological Linkage during Interactions between Doctors and Cancer Patients." *Social Science and Medicine* 284(January): 114220. 2021. https://doi.org/10.1016/j.socscimed.2021.114220.

Yang, Shuo et al. "Combining Content-Based and Collaborative Filtering for Job Recommendation System: A Cost-Sensitive Statistical Relational Learning Approach." *Knowledge-Based Systems* 136: 37–45. 2017.http://dx.doi.org/10.1016/j.knosys.2017.08.017.

Yu, Jing et al. 2021. "Collaborative Filtering Recommendation with Fluctuations of User' Preference." *2021 IEEE International Conference on Information Communication and Software Engineering, ICICSE 2021*: 222–26.

Biographies

Yesi Sofia is a bachelor's degree student at the Universitas Jenderal Achmad Yani, West Java, Indonesian, and joined in informatics in 2018. His research interests are health informatics, information systems/information technology management, agile project management, and data mining.

Faiza Renaldi, M.Sc., is a lecturer in the department of informatics, Faculty of Science and Informatics, Universitas Jenderal Achmad Yani Indonesia. He received his Master of Business Informatics at Universiteit Utrecht, The Netherlands, in 2006. His research interests are related to health informatics, information systems/information technology management, e-government, agile project management, and IT entrepreneurship.

Irma Santikarama, S.Kom., M.T. received a Bachelor's degree in Information systems from Universitas Kristen Maranatha and a Master's degree in Informatics from Institut Teknologi Bandung. Now, she is a lecturer in the Information Systems Department, Faculty of Science and Informatics, Universitas Jenderal Achmad Yani. Her interest area related to information system, eGoverment, and agile project managemet.