Performance of Known Ratings-Based Multi-Criteria Recommender System for Housing Selection

Yunifa Miftachul Arif
Department of Informatics Engineering
Universitas Islam Negeri Maulana Malik Ibrahim
Malang, Indonesia
yunif4@ti.uin-malang.ac.id

Muhammad Farid Muhtarom
Department of Informatics Engineering
Universitas Islam Negeri Maulana Malik Ibrahim
Malang, Indonesia
18650072@student.uin-malang.ac.id

Hani Nurhayati
Department of Informatics Engineering
Universitas Islam Negeri Maulana Malik Ibrahim
Malang, Indonesia
hani@ti.uin-malang.ac.id

***Abstract*— Housing developments are increasingly massive, and the lack of available information makes prospective customers experience difficulties in choosing a housing. These conditions resulted in the need for a recommendation system to assist consumers in choosing a place to live. In this study, we propose using the Multi-Criteria Recommender System (MCRS) to produce the most recommended housing selection recommendations in a case study of five housing complexes in Malang Raya. The system generates recommendations based on known user rating of 14 criteria and an overall rating (R0) stored in the database. In the experimental stage, the MCRS system in this study used four different methods: cosine, adjust cosine, Pearson correlation, and spearman rank-order correlation coefficient. The test results show that the recommendation system with each similarity method can produce housing recommendations by displaying the three most relevant housing recommendations to the user. Next, we use a confusion matrix to analyze the accuracy of the recommendations generated by the four similarity methods. The results of the confusion matrix calculation show that the average accuracy value for cosine-based similarity is 63.8%, the adjusted-cosine similarity is 70.4%, the Pearson correlation is 88.7%, and the Spearman rank-order correlation coefficient is 75.57%.**

Keywords—Recommendation, housing selection, known rating, MCRS, similarity.

I. Introduction

Housing is one of the most essential and primary needs in human life. One type of residence is a house, a building as a shelter and a place to rest for its inhabitants. Meanwhile, housing is ideal for someone to build or buy a house. Housing is a material object that can be produced, consumed, felt, experienced, bought and sold [1]. Over time, the human population is increasing, thus triggering the rapid development of housing, especially in urban areas. The increasingly massive development of housing and the need for more information make it difficult for potential consumers to choose housing according to their desired criteria. In choosing to house, consumers should have several considerations and criteria that become their reference.

Currently, many consumers still choose and determine housing by distributing brochures or visiting housing websites one by one. This process is inefficient because it takes much time and few consumers know what criteria must be considered when choosing housing. An inappropriate selection process can result in selection errors, so there is the potential for regret because it does not meet consumer expectations. Therefore, we need a recommendation system that is used to recommend housing. The system is expected to be implemented in a web-based application. The reason is that the internet and modern web services have improved, and everyone can easily access all information [2].

Recommender Systems (RS) is a system that has been extensively studied in the last decade and has proven to be suitable for many selection scenarios. Along with the development of the internet and the era of electronic commerce, companies choose to have RS to boost sales [3]. RS provides predictions to users of items that might interest them to buy. Most of the algorithms in the recommendation system focus on providing item recommendations according to user preferences [4].

Recommendation systems certainly require the support of methods or algorithms in recommending items. Several references state that a multi-criteria-based method produces recommendations with a better level of performance than the single-criteria approach [5]. Therefore, we propose using the Multi-Criteria Recommender System (MCRS) method in this study. To get more accurate results, we compare several similarity methods in MCRS, including cosine-based similarity, adjusted-cosine similarity, Pearson's correlation, and Spearman rank-order correlation coefficient. In this study, MCRS is used to assist users in selecting housing items by providing recommendations when users have rated the item at least once. MCRS use different rating criteria to describe an item's quality [6].

II. Related Work

Ifada et al. in their research, described various item-based multi-criteria recommendation approaches. The approaches used to predict user ratings per criterion are Content-Based (CB), Collaborative Filtering (CF), and Hybrid approaches. The results from this study indicate that on cold-start problems, the Collaborative Filtering (CF) method gets better results than other methods recommended in its application. Of the three methods used, researchers suggest using the Collaborative Filtering (CF) method [3].

Arif et al., in their research, discussed the application of one of the Multi-Criteria Recommender System algorithms, namely cosine-based similarity, to recommend halal tourism in Batu. The results of testing the algorithm from the research that has been done get an accuracy value of 72%, which means that the method has a fairly good level of accuracy [4]. In another study, Arif et al. explained that reducing costs in determining the place requires a system that can recommend tourist attractions. The research is carried out on a blockchain-based basis that can handle the wide circulation of multi-criteria ranking data nodes needed by MCRS as a reference in producing tourist destination recommendations for tourists. The fastest time for transmitting node data based on various criteria from the user to the server is 15.4 ms[7].

Furthermore, Arif et al. also explained the use and application of one of the Multi-Criteria Recommender System algorithms, namely ¬cosine-based similarity, to determine the choice of subject matter. In the research, the MCRS-based LMS produced the highest accuracy of 92% for two to three input items and the lowest 90% for four input items [8]. Nadhifah et al., in their research, explained the performance and application of one of the Multi-Criteria Recommender System algorithms, namely ¬cosine-based similarity, to recommend tours. The results of testing the algorithm from the research that has been done get an accuracy value of 77.95%, which means that the method has a relatively good level of accuracy [6].

A. Housing

Housing is an area or environment where residential units allow for social interaction between house residents. According to the Law of the Republic of Indonesia Number 1 of 2011 Article 1 Regarding Housing and Settlements, housing is a collection of houses as part of urban and rural settlements equipped with infrastructure, facilities and public facilities. Utilities as a result of efforts to fulfil livable housing. Generally, housing has facilities, infrastructure, and services that are part of the housing. Usually, there is a system of values, habits and rules that the occupants must obey in housing.

B. Multi-Criteria Recommender System

A recommendation system or Recommender System (RS) is a decision support system that suggests items to users that may be relevant to their choices [6]. According to Paul Resnick et al., a recommendation system is a software tool to assist in the social process of showing or receiving indications about what options are more suitable in exceptional cases for specific individuals [6]. The Recommendation System is designed to recommend things to users based on many different factors. Recommendation systems have been used in many practical applications in various fields, such as education, social media, financial services, agriculture, health, and so on [9]. The Multi-Criteria Recommendation System (MCRS) extends the traditional approach by increasing the ratings to cover various item attributes and combining the ratings to improve prediction accuracy [10].

The Multi-Criteria Recommendation System (MCRS) extends the traditional approach by increasing the ratings to cover various item attributes and combining the ratings to improve prediction accuracy [11]. The approach from MCRS that is often used is the Collaborative filtering approach. Collaborative filtering is an approach that carries out the process of filtering items based on other people's opinions. This system focuses on algorithms for matching people based on their preferences and considering the interests of people with similarities to produce recommendations for information seekers [12]. Collaborative filtering is also one of the most successful technologies for recommender systems that have been developed and improved over the last decade to the point where various kinds of algorithms exist to generate recommendations [14, 15]. Collaborative filtering has two forms of rating models, namely:

- User-based collaborative filtering
  User-based collaborative filtering predicts testing user interest in test items based on rating information from similar user profiles. Each user profile (line vector) is sorted by how it differs from the test user profile. Ratings by more like users contribute more to predicting test item ratings. In the top-N case, a set of top-N users similar to the test users can be generated [15].
- Item-based Collaborative Filtering
  The item-based approach implements the same idea but uses commonalities between items, not users. The unknown rating of a test item by a test user can be predicted by the average of the ratings of other similar items rated by these test users. Again, each item (column vector) is sorted and re-indexed according to its difference from the test item in the user-item matrix. The ranking of other similar items is more substantial [16].

III. Research Method

A. Research Data

The recommendation process certainly requires many data according to needs. In this study, researchers used primary data from community questionnaires relevant to the item. The amount of data that has been obtained from the results of the questionnaire is 50 data. The 50 data were divided into two kinds of data, namely 45 data as reference data and five as test data. Primary data will then be calculated using the MCRS method.

B. Research Data

The research begins with a literature study, namely collecting library data, reading and taking notes relating to the research objectives. Identification of the problem defines the problem that has been obtained from the study of the literature. After the research problem is determined, a system design is carried out to provide an overview of the system to be created. The system that has been designed is then implemented using a method that can answer problems in problem identification. After the implementation is tested to find out whether the method used to answer the problem is correct or not. The last step is to analyze the results and draw conclusions from the results of the research that has been done. System design using the MCRS method in this study is used as a description of the flow of a system to be made, as shown in Figure 1.

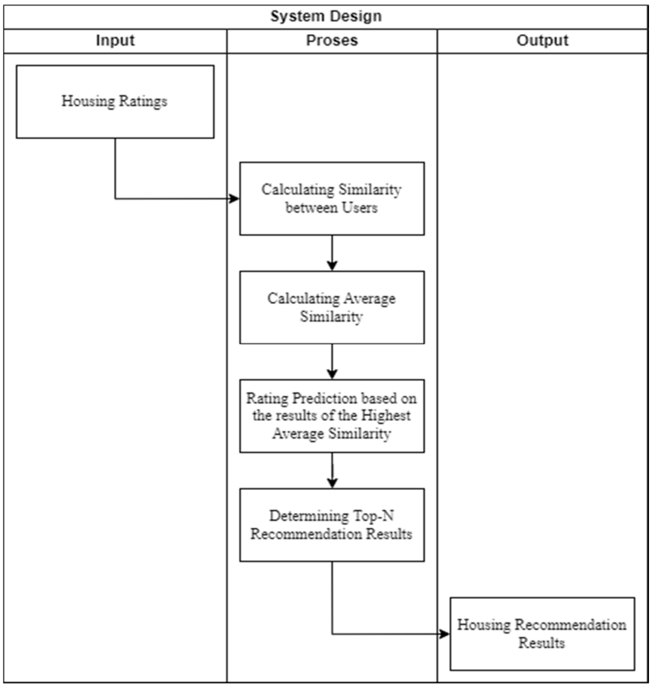

Fig. 1. System Design

The user then gives the existing criteria a rating based on the user's experience, who knows the housing that has been determined. Table 1 shows some of the criteria that used in this study. The assessment of each housing criterion can be assessed on a scale of 0 to 5. Housing that does not yet have an assessment will be given a value of 0. After the rating on the item is obtained, R0 is determined. R0 is obtained from the average rating on the criteria for each item which will later be used to determine the top-N of an item.

TABLE I HOUSING CRITERIA

Criteria Code	*Criteria*
C1	Accessibility to main roads
C2	Accessibility to school
C3	Accessibility to hospital
C4	Accessibility to shopping centres
C5	The width of the road
C6	Excess Land
C7	Public facilities
C8	Price
C9	Electric network
C10	Security
C11	Convenience
C12	Surface area
C13	House Type
C14	Not a flood area

User-assigned ratings for five housing items. This research data measures the system's accuracy in recommending housing to users. The housing items used in this study include New City Malang housing, City view, De villa, Tanjung Banjar Arum Indah, and Grand hill.

Calculating similarity is the stage of looking for similarities between users. Each user-rated item will be compared to those who have never rated an item. The results will be obtained by calculating the similarity, namely the similarity between one user and another. There are algorithms for calculating similarity, including:

- Cosine-based similarity
  The cosine-based similarity is used to determine how similar two users are in a memory-based collaborative filtering algorithm [17].

$$\mathrm{Sim}(\mathrm{u},\mathrm{u}') = \frac{(\sum i\in I(u,u')R(u,i)R(u',i))}{(\sqrt{\sum i\in I(u,u')R(u,i)^2}\ \sqrt{\sum i\in I(u,u')R(u',i)^2})} \quad (1)$$

- Adjusted-cosine similarity
  The adjusted-cosine similarity is used to calculate the similarity value between users. The similarity between products or items is calculated using the cosine angle value of the position between the two variables or vectors [18].

$$\mathrm{Sim} = \frac{(\sum i\in I(u,u')(R(u,i)-\overline{O(n)})(R(u',i)-\overline{O(n)'}))}{(\sqrt{\sum i\in I(u,u')(R(u,i)-\overline{O(n)})}\sqrt{\sum i\in I(u,u')(R(u,i)-\overline{O(n)'}})} \quad (2)$$

- Pearson's correlation-based similarity
  Pearson's correlation-based similarity is a statistical measure of the linear correlation between two variables [19].

$$\mathrm{Sim} = \frac{(\sum i\in I(u,u')(R(u,i)-\overline{R(u)})(R(u',i)-\overline{R(u')}))}{(\sqrt{\sum i\in I(u,u')(R(u,i)-\overline{R(u)})^2}\ \sqrt{\sum i\in I(u,u')(R(u',i)-\overline{R(u')})^2})} \quad (3)$$

- Spearman rank-order correlation coefficient
  Spearman's rank-order correlation is similar to Pearson's correlation-based similarity but has differences in the expressions that examine rankings on X and Y [20].

$$\mathrm{Sim} = \frac{(6\sum i\in I(u,u')(Rank(R(u,i))-(Rank(R(u',i)))}{n(n^2-1)} \quad (4)$$

The results of determining recommendations in a collaborative filtering recommendation system are not only limited to that method. After finding the similarity value between users, calculate the similarity value between individuals k + i using the average similarity [21]. The average similarity is used to see the level of similarity between users so that it can be seen that users have higher similarities than other users. The average similarity formula is as follows:

$$\mathrm{Sim}(\mathrm{u},\mathrm{u}') = \frac{1}{k+1}\sum_{c=0}^{k} Sim_c(u,u') \quad (5)$$

This research will be tested using the Confusion Matrix formula. According to Fonts et al., Matrices are often used in machine learning to evaluate classification performance on data sets [22]. The test will produce an evaluation matrix: Accuracy, Precision, Recall, and F1-Score. The values that can be generated in the confusion matrix table are true positive values (TP), false positive values (FP), false negative values (FN), and true negative values (TN). To classify, the confusion matrix is used in research with the following formula equation [23].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

IV. RESULT

Bagian ini menjelaskan pengembangan sistem dan hasil pengujian dalam dua sub-bagian: hasil sistem rekomendasi dan hasil implementasi pada website.

A. Recommender System Result

The testing phase of the recommender system in this study aims to analyze the accuracy and precision of the recommendations produced by the MCRS algorithm, namely Cosine-based similarity, Adjusted-cosine similarity, Pearson's correlation-based similarity, and Spearman rank-order correlation coefficient. Tests were carried out using the confusion matrix method to produce accuracy, precision, recall and F1 scores based on differences in True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values.

- Cosine-based similarity
  The data values of confusion matrix calculations and Cosine-based similarity result are shown in the Table 2 and Table 3.

TABLE II
MATRIX OF COSINE BASED SIMILARITY ALGORITHM TESTING RESULTS

	1	*2*	*3*
TP	3	5	10
FP	2	5	5
FN	1	2	5
TN	5	5	5

TABLE III
ACCURACY OF COSINE BASED SIMILARITY ALGORITHM TESTING RESULTS

Top-N	*Accuracy*	*Precision*	*Recall*	*F1-Score*
1	0,727	0,6	0,75	0,6
2	0,588	0,5	0,71	0,6
3	0,6	0,66	0,58	0,6

- Adjusted-cosine similarity
  The data values of the confusion matrix calculations and Adjusted-cosine similarity result are shown in the Table 4 and Table 5.

TABLE IV
MATRIX OF ADJUSTED-COSINE SIMILARITY ALGORITHM TESTING RESULTS

	1	*2*	*3*
TP	2	6	11
FP	3	4	4
FN	0	1	4
TN	6	6	6

TABLE V
ACCURACY OF ADJUSTED-COSINE SIMILARITY ALGORITHM TESTING RESULTS

Top-N	*Accuracy*	*Precision*	*Recall*	*F1-Score*
1	0,727	0,4	1	0,57
2	0,70	0,6	0,85	0,70
3	0,68	0,73	0,73	0,73

- Pearson’s correlation-based similarity
  The data values of the confusion matrix calculations and Pearson’s correlation-based similarity result are shown in the Table 6 and Table 7.

TABLE VI
MATRIX OF PEARSON’S CORRELATION-BASED SIMILARITY ALGORITHM TESTING RESULTS

	1	*2*	*3*
TP	5	9	13
FP	0	1	2
FN	1	1	2
TN	8	8	8

TABLE VII
ACCURACY OF PEARSON’S CORRELATION-BASED SIMILARITY ALGORITHM TESTING RESULTS

Top-N	*Accuracy*	*Precision*	*Recall*	*F1-Score*
1	0,928	1	0,83	0,9
2	0,894	0,9	0,9	0,9
3	0,84	0,86	0,86	0,86

- Spearman rank-order correlation coefficient
  The data values of the confusion matrix calculations and Spearman rank-order correlation coefficient are shown in the Table 8 and Table 9.

TABLE VIII
MATRIX OF SPEARMAN RANK-ORDER CORRELATION COEFFICIENT ALGORITHM TESTING RESULTS

	1	*2*	*3*
TP	4	8	11
FP	1	2	4
FN	2	2	4
TN	6	6	6

TABLE IX
ACCURACY OF SPEARMAN RANK-ORDER CORRELATION COEFFICIENT ALGORITHM TESTING RESULTS

Top-N	*Accuracy*	*Precision*	*Recall*	*F1-Score*
1	0,76	0,8	0,66	0,72
2	0,77	0,8	0,8	0,8
3	0,68	0,73	0,73	0,73

The results of the accuracy comparison of the Cosine-based similarity, Adjusted-cosine similarity, Pearson's correlation-based similarity algorithms, and Spearman's rank-order correlation coefficient have been calculated using the confusion matrix. Table 10 shows the results of comparing the accuracy of each algorithms, and Figure 2 shows them in graphical form.

TABLE X
ACCURACY COMPARISON OF EACH SIMILARITY ALGORITHM

Top-N	*Cosine-based similarity*	*Adjusted-cosine similarity*	*Pearson's correlation-based similarity*	*Spearman rank-order correlation coefficient*
1	72,7%	72,7%	92,8%	76,9%
2	58,8%	70,5%	89,4%	77,7%
3	60%	68%	84%	68%

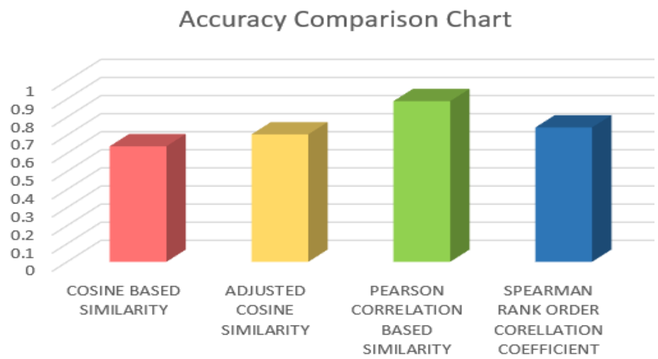

Fig 2. Accuracy Comparison Chart

B. *Implementation Results On the Website*

System implementation is a process of implementing the results of the system design that has been made. In the implementation phase, system development will be carried out by implementing the manual formula into a program to meet the uses and needs that have been determined. In this section, we want to show the implementation and visualization of the results of the housing recommendation system so that it is easier for users to interact with the system.

- The User Log-In page is asked to enter an email address and password registered on the system as shown in Figure 3. If the user does not have a registered account, the user can register first.

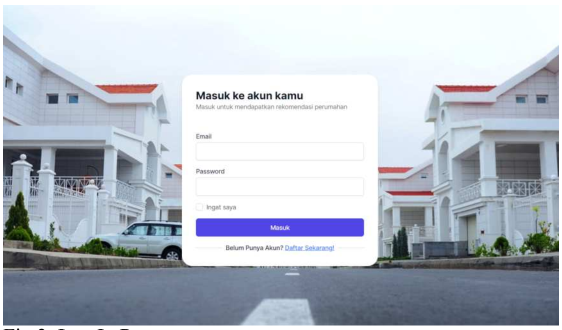

Fig 3. Log In Page

- Displays a list of housing that the user can see, but the housing list still needs to be calculated by the recommendation system. A rating button directs the user to the rating form view. Figure 4 shows an example of the housing options offered in the experiment.

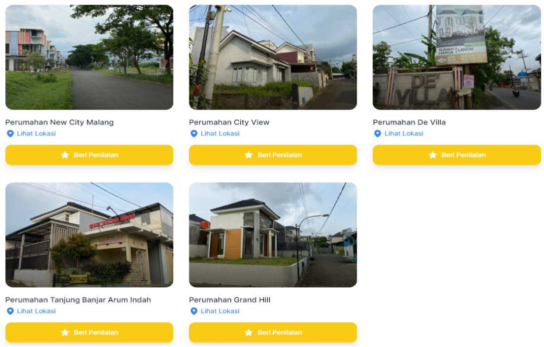

Fig 4. Housing options

- Rating Form displays a form that the user can fill in as shown in Figure 5. The rating form displays attributes, including housing names, several housing criteria, and their definitions. Each criterion has a rating option from 1 to 5. Then there is a get recommendation button to get housing recommendation results.

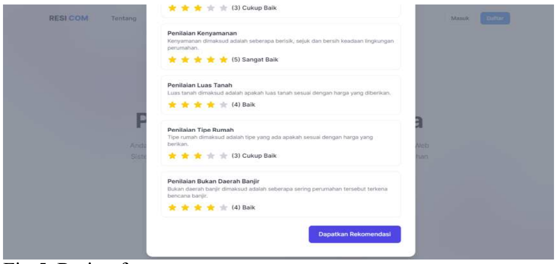

Fig 5. Rating form.

- The recommendation results displays the results of housing recommendations resulting from the computing process in the system as shown in Figure 6. The recommendation results consist of three housing processed by the system with the implementation using Pearson's correlation-based similarity algorithm. Pearson's correlation-based similarity algorithm was chosen because it has the highest average accuracy compared to the other three algorithms in the previous chapter.

x

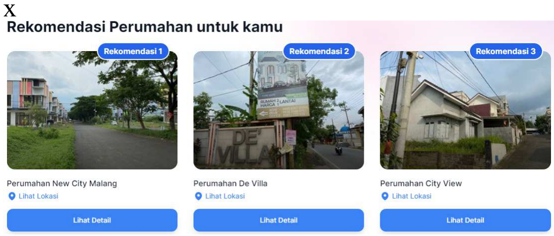

Fig 6. Example of recommendation results

V. CONCLUSION

The housing selection recommendation system is carried out in 5 housing estates in the Greater Malang area. The research was conducted using the Multi-Criteria Recommender System (MCRS) involving four algorithms: Cosine-based similarity, Adjusted-cosine similarity, Pearson's correlation-based similarity, and Spearman rank-order correlation coefficient. The test results using the Confusion matrix show that Pearson's correlation-based similarity algorithm has the highest average accuracy rate of 75.57%, compared to Cosine-based similarity of 63.8%, Adjusted-cosine similarity of 70, 4%, and Spearman rank-order correlation coefficient of 70.4%.

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