Implementasi *Regularized Singular Value Decomposition* dalam Sistem Rekomendasi Buku *Collaborative Filtering*

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***Abstrak* — Pada tingkat sekolah, waktu dibatasi oleh sistem jam pelajaran. Hal ini membuat siswa harus menggunakan waktunya dengan bijak sebelum berpindah pelajaran. Namun, memilih bahan bacaan yang tepat sering kali membutuhkan lebih banyak waktu sehingga mengakibatkan jam pelajaran terbuang percuma. Pengembangan sistem rekomendasi dengan metode *Collaborative Filtering* (CF) dan *Regularized Singular Value Decomposition* (SVD) dipilih untuk mengatasi permasalahan sulitnya siswa mencari buku di perpustakaan. Data yang digunakan adalah data interaksi siswa dengan buku berupa *rating* yang dikumpulkan secara langsung dan diolah untuk memberikan rekomendasi. Hasil penerapan *Regularized Singular Value Decomposition* (SVD) dalam memprediksi *rating* dan mencari fitur laten yang sesuai untuk menggambarkan karakteristik siswa dan buku menghasilkan nilai *Mean Absolute Error* (MAE) dan *Root Mean Square Error* (RMSE) sebesar 0,478 dan 0,686. Penelitian yang dilakukan juga menunjukkan bahwa jumlah faktor atau fitur laten yang tepat dan penambahan regularisasi berpengaruh terhadap peningkatan akurasi prediksi. Nilai prediksi *rating* tersebut kemudian digunakan untuk memberikan rekomendasi buku personal dan nilai fitur laten dari buku yang ditemukan digunakan dalam perhitungan *Cosine Similarity* untuk memberikan rekomendasi buku non-personal.**

***Kata kunci*— *Collaborative Filtering*; *Cosine Similarity*; *Singular Value Decomposition*; Sistem Rekomendasi.**

Implementation of Regularized Singular Value Decomposition in Collaborative Filtering Book Recommendation System

Abstract — At the school level, time is limited by the system of lesson hours. This makes students have to use their time wisely before changing lesson. However, choosing appropriate reading material often requires more time which results in wasted class hours. The development of a recommendation system using the Collaborative Filtering (CF) and Regularized Singular Value Decomposition (SVD) methods was chosen to solve the problem of students having difficulty finding books in the library. The data used is student interaction

data with books in the form of ratings which are collected directly and processed to provide recommendations. The results of applying Regularized Singular Value Decomposition (SVD) in predicting ratings and looking for appropriate latent features to describe the characteristics of students and books produce Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values of 0.478 and 0.686. The research conducted also shows that the appropriate number of latent factors or features and the addition of regularization have an effect on increasing prediction accuracy. The predicted value of the rating is then used to provide personal book recommendations and the latent feature values of the books found are used in calculating Cosine Similarity to provide non-personal recommendations.

Keywords— Collaborative Filtering; Cosine Similarity; Recommendation System; Singular Value Decomposition.

I. INTRODUCTION

In this modern era, the amount of information that can be accessed on the internet is enormous. With so much information available online, it can be a challenge for someone when faced with a condition where the person has to choose an item from among the many choices of items provided. For example, in the world of education, during limited class hours students are usually asked to go to the library to look for reading materials. Searching for books manually or only through keywords on the school library website will result in a lot of wasted class hours and the reading sources chosen can end up not really suiting the students' interests. Apart from that, the ease of finding books in the library can increase students' interest in reading at school [1].

Recommendation system is a system that can be used to filter data by providing suggestions for items that users might like [2]. The application of a recommendation system aims to assist users in the process of searching for an item. In the problem of selecting books, the use of a recommendation system allows us to recommend books that are more appropriate to students' interests.

Based on the content presented, recommendations can be divided into two types, namely personal and non-personal recommendations [3]. Personal recommendations are recommendations that are tailored to the user's preferences, so that each user has different recommendations. Meanwhile, non-personal recommendations are general recommendations based on certain factors such as similarities between items.

The Collaborative Filtering (CF) method is one of the most widely used methods in creating recommendation systems. This method provides recommendations based on previous user interactions [4]. The CF method uses interaction data between users and items to identify patterns and similarities between users or items [5]. However, in real cases, there will be many users who have a small number of interactions with items, especially new users. If these very few interactions are processed directly, they will result in inaccurate recommendation [6].

The Singular Value Decomposition (SVD) matrix factorization technique can be used to solve the sparsity problem. In the case of little interaction data, SVD is able to provide better Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) results of 0.737 and 0.9358 compared to K-NN of 0.7732 and 0.979 [7]. The SVD algorithm is also considered better than other matrix factorization algorithms. Research conducted by Shalannanda et al. in 2022 shows that the CF method in collaboration with the SVD algorithm is able to provide the best performance compared to other matrix factorization algorithms such as CoClustering, SlopeOne, and NMF with an RMSE of 1.055586 [8]. Given these challenges and advancements, this research aims to explore two key questions:

1. How to address the difficulty students face in finding suitable books in the school library.
2. How does the implementation of Regularized Singular Value Decomposition (SVD) method in predicting ratings and generating relevant book recommendations in a collaborative filtering-based recommendation system.

By investigating these questions, this study seeks to provide insights into improving the efficiency and effectiveness of book recommendations in school libraries, ultimately enhancing students' reading experiences.

II. RESEARCH METHOD

The research utilized a methodological approach to develop recommendation system with Collaborative Filtering (CF) and Regularized Singular Value Decomposition (SVD). The method consists of several steps, including collecting student rating data, pre-processing, data splitting, training and testing the model, evaluating its performance, and implementing personal and non-personal book recommendations. Figure 1 illustrates the details of the research steps.

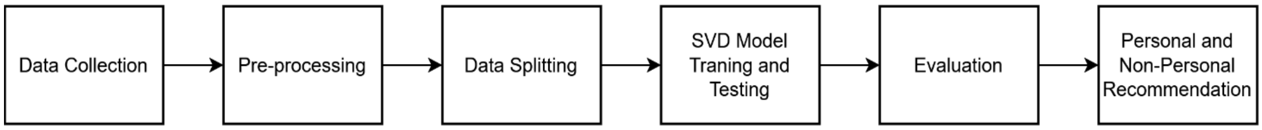

Figure 1. Research steps

A. Data Collection

The data used in this research is primary data, directly obtained from the students of SMP Negeri 3 Kediri. It is collected manually from the school's library application database, where students provide book ratings. The rating in this case describes the student's interest in reading further the title presented. It is hoped that the collection of ratings carried out will help in mapping user preferences. Users who give high ratings to the same book likely have similar interests. This can also indicate that highly rated books may have something in common.

B. Pre-processing

Pre-processing is a process of preparing data before it is used in further analysis. In this study, the pre-processing process carried out is data cleaning to eliminate irrelevant data. Books without ratings will be removed during the data cleaning process, as they do not provide useful information for the recommendation system.

C. Data Splitting

The data splitting process aims to divide the rating data into training and testing sets. The training set is used for model training, while the testing set is used to evaluate the model's performance. This research implements the holdout splitting method, using 80% of the data for training and 20% for testing.

D. Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) is a matrix factorization algorithm that is often used in CF methods and is included in the model-based CF method [9]. The CF method provides recommendations based on similarities between users or items seen from the interactions that users carry out on the system. When the number of interactions that occur is very small (sparse), the CF method can lead to the system failing to provide appropriate recommendations.

SVD maps the user-item rating matrix into a combined latent factor space with dimension f, so that the user-item matrix is represented as the result of the inner product of that space. This latent space attempts to explain ratings by describing user-items based on factors or characteristics discovered automatically through user feedback. Thus, implementing the SVD method will help in predicting unknown rating matrix values by finding bias values and latent features or hidden characteristics of each user and item [10]. The rating prediction is determined through equation 1.

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T p_u \tag{1}$$

Where,
$\hat{r}_{ui}$: Rating prediction user u for item i
μ : Average value of dataset
b_u : User bias
b_i : Item bias
q_i : Item's latent factor
p_u : User's latent factor

The latent factor or feature values found can represent a characteristic of the user and the item, namely books. However, the meaning of each latent feature value found is not an important thing to determine because it can represent any characteristic that a user or item has in the real world. The value of each parameter model is found by minimizing the regularized squared error defined in Equation 2 as the objective function.

$$\sum_{r_{ui} \in R_{train}} \left(r_{ui} - \hat{r}_{ui}\right)^2 + \lambda\left({b_i}^2 + {b_u}^2 + ||q_i||^2 + ||p_u||^2\right) \tag{2}$$

Where,
r_{ui} : Rating user u for item i

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λ : Regularization parameters

In the case of incomplete interaction data, the calculated relationship value is very small. If the training process is carried out directly, this can end in overfitting because the model does not have enough data to recognize existing patterns [11]. Overfitting is a situation where the model fits the training data too well so that it fails to predict new data. The constant λ controls the extent of regularization. The aim is to avoid cases of overfitting in the model and increase the accuracy of rating predictions.

E. Evaluation

The model evaluation process is carried out to find appropriate hyperparameter values from the SVD model. There will be several training and testing scenarios conducted to evaluate the model, consisting of different pairs of hyperparameter values. The evaluation metrics used to test the accuracy of the system or model that has been built in this research are the resulting MAE and RMSE values. Mean Absolute Error (MAE) is a metric that can be used to determine the level of accuracy of a model in making predictions. In the case of SVD, MAE can be used as a metric to see how well the model is at predicting unknown ratings and assessing the results of the decomposition carried out in finding latent features from users and items [12]. Giving recommendations will be inaccurate if the MAE value is more than or equal to 1 [13].

$$MAE = \frac{1}{n}\sum |r_{ui} - \hat{r}_{ui}| \quad (3)$$

Where,
r_{ui} : Rating user u for item i
$\hat{r}_{ui}$: Rating prediction user u for item i

Root Mean Square Error (RMSE) is another evaluation metric that can be used in addition to MAE. The RMSE value is the result of the square root of the average squared error or the difference between the actual value and the predicted value [14].

$$RMSE = \sqrt{\frac{1}{n}\sum (r_{ui} - \hat{r}_{ui})^2} \quad (4)$$

F. Personal and Non-Personal Recommendation

After training the SVD model, the stage continues to implement the model in providing personal and non-personal recommendations. The process of generating personal recommendations starts by sorting the book rating prediction results for the inputted users. A specific number of books with the highest predicted rating values will then be recommended to the user as personal recommendations. Figure 2 depicts the flowchart of providing personal recommendations.

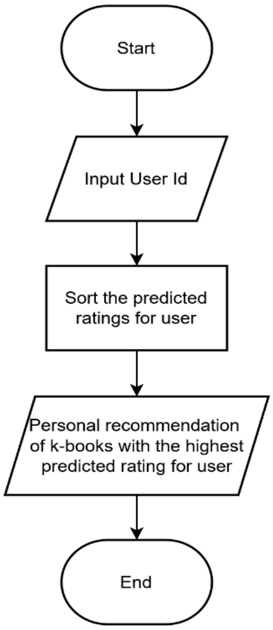

Figure 2. Personal recommendation flowchart

Non-personal recommendations are generated based on the similarity of latent features or characteristics among books. The similarity between books is determined using the cosine similarity measure. The top k books with the highest cosine similarity to a reference book are then suggested to users. The flowchart illustrating this recommendation process is shown in Figure 3.

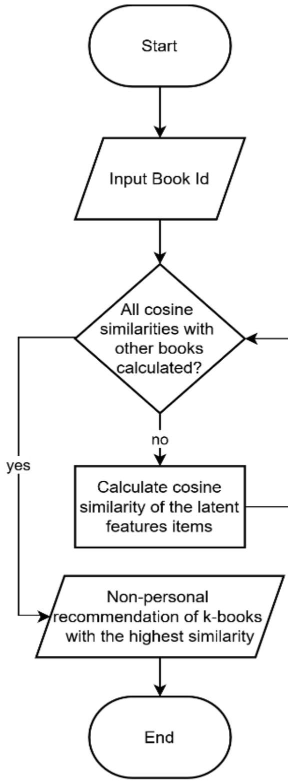

Figure 3. Non-personal recommendation flowchart

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G. Cosine Similarity

Cosine similarity is a calculation of the similarity between two n-dimensional vectors by finding the cosine of the angle between them [15]. Mathematically, the cosine similarity between two vectors x and y is defined in equation 5.

$$Similarity(x, y) = cos\ cos\ (\theta) = \frac{x.y}{||x||\ ||y||} \quad (5)$$

Where,
$x.y$: Dot product of vectors x and y, calculated by $\sum_{k=1}^{n} x_k y_k$
$||x||$: Norm or length of vector x
$||y||$: Norm or length of vector y

The value of cosine similarity between two vectors ranges from -1 to 1. A value close to 1 indicates high similarity, while a value near -1 suggests significant differences. In some cases, a cosine similarity value that is above 0.5 is considered capable of indicating that two items have a high level of similarity. In providing recommendations, cosine similarity is applied to search for items, namely books that have the closest neighbors based on the latent features found.

III. Result and Discussion

The developed book recommendation system is designed to be directly accessible to students through a web-based interface. Below are the results and discussion, covering the process from data collection to the implementation of the recommendation system in a web-based interface.

A. Data Collection

The dataset used in this research consists of primary data collected between January 22, 2024, and February 19, 2024. The dataset collected includes users, books, and ratings. The user dataset contains user information, the book dataset contains book metadata, and the rating dataset contains ratings given by users to certain books on a scale of 1-5. From this collection process, the total data obtained was 1,319 books, 332 users, and 124,841 ratings. An overview of the rating data collected can be seen in Table 1.

TABLE 1
Rating Data

user_id	book_id	rating
51e49f25-397d-43a1-a807-005933626d2e	1283	3
51e49f25-397d-43a1-a807-005933626d2e	11	3
51e49f25-397d-43a1-a807-005933626d2e	207	3
…	…	…
b06db5a6-f1ca-4f2a-ab7f-90109157e4be	664	3
b06db5a6-f1ca-4f2a-ab7f-90109157e4be	208	3
b06db5a6-f1ca-4f2a-ab7f-90109157e4be	113	3

B. Pre-processing

After collecting the data, the step continued with data pre-processing by removing books that did not have any ratings. This is important to ensure that only relevant data is used and to know the number of books that need to be considered in developing the model. The number of books was then reduced to 886. As a result, the final dataset consisted of 886 books, 332 users, and 124,841 ratings.

C. Data Splitting

The data splitting process was performed on the collected rating dataset. The data was divided into 80% for training and 20% for testing. As a result of the data splitting process, the rating dataset with a total of 124,841 records was divided into 99,872 records for training and 24,969 records testing data.

D. SVD Training and Testing

The training process of the SVD model is carried out to allow the model to predict unknown rating data. During training, the model learns underlying patterns by identifying bias values and latent features that influence ratings to make predictions. Once training is complete, the model is evaluated through testing, where its predictions are assessed using Mean Absolute

Error (MAE) and Root Mean Square Error (RMSE). Lower MAE and RMSE values indicate improved rating predictions and more accurately identified latent features.

To optimize performance, multiple training and testing scenarios were conducted with different hyperparameter combinations. The model that achieves the best performance will later be implemented in both personal and non-personal recommendation systems. Table 2 shows a detailed comparison of the results obtained from testing various hyperparameter combinations applied in training the SVD model.

TABLE 2
SVD MODEL EVALUATION RESULTS

No	Parameter		MAE	RMSE
	Latent Factor	Regularization		
1	50	0	0.517	0.741
2	50	0.02	0.505	0.731
3	50	0.05	0.482	0.689
4	100	0	0.507	0.733
5	100	0.02	0.485	0.700
6	**100**	**0.05**	**0.478**	**0.686**

The comparison of hyperparameter values in the SVD model evaluation shows that the combination of 100 latent features and a regularization value of 0.05 delivers the best performance among all tested scenarios. This result suggests that a latent feature size of 100 is more suitable for describing the characteristics of users and items based on the interactions that occur between the two. Increasing the number of latent features appears to affect the accuracy of the prediction results. Apart from that, the tests carried out also showed that the Regularized SVD model outperforms the SVD model without regularization.

Without regularization, the SVD model tends to overfit the training data, leading to poor generalization on unseen data and inaccurate rating predictions. These inaccuracies can result in unreliable recommendations and ineffective latent feature representations, reducing the overall quality of the model. Regularization plays a key role in reducing overfitting by creating a more generalized model. This improves the model's ability to predict ratings and generates better recommendations.

E. Personal Recommendation

After the model has been developed and the predicted values for ratings and latent features of the books have been found, the model is then tested to provide personal and non-personal recommendations. The SVD model development process produces predicted rating values for each user across all items or books in the dataset. All the resulting rating prediction values can be seen in Table 3, which consists of 294,152 ratings from 332 users and 886 books.

TABLE 3
RATING PREDICTION RESULTS

User ID	Rating Prediction				
	Book [0]	Book [1]	...	Book [884]	Book [885]
51e49f25-397d-43a1-a807-005933626d2e	3.382928	3.313553	...	3.192885	3.239956
25d1508a-f07f-4f5e-8fac-68baeba802de	3.171148	3.386832	...	3.174061	3.110988
77861dd0-f767-43df-b0c0-313fcc03f9f1	3.385508	3.257397	...	3.108808	3.251445
...	...	...	...	...	...
38a645ce-a9c8-4849-ac01-89c70934d5c9	3.194910	3.314743	...	3.067967	3.056371
bf47b86d-67fd-42e0-a73d-535590d495d7	3.740308	3.500559	...	3.371598	3.168756
b06db5a6-f1ca-4f2a-ab7f-90109157e4be	3.679651	3.587864	...	3.426994	3.737597

Personal recommendations are made based on the predicted results of the highest book ratings for specific users. Table 4 is an example of a personal book recommendation for a user with the last ID 'd2e' based on the predicted book ratings in descending order. This approach helps the user discover books that are both new and relevant to those they have known before.

TABLE 4
PERSONAL RECOMMENDATIONS FOR USERS WITH LAST ID 'D2E'

Book ID	Title	Rating Prediction
614	MENGENAL ALAM SEMESTA	3.691228
423	SOPAN SANTUN BERBAHASA	3.628779
546	HEWAN HEWAN LANGKA DI INDONESIA	3.624231
571	DINOSAURUS	3.608796
271	PENDIDIKAN KEWIRAUSAHAAN	3.573214
476	MENJELAJAH ALAM SEMESTA	3.571689
122	ETIKA HINDU	3.540067
346	SEJARAH INDONESIA	3.538186
536	MENJELAJAH RUANG ANGKASA	3.537602
277	ANEKA BISNIS EKONOMI KREATIF	3.531373

F. Non-Personal Recommendation

Non-personal recommendations are based on the latent feature vectors of items, namely books. Table 5 provides an overview of the latent features or factors of items (q_i) resulting from the SVD model development process.

TABLE 5
BOOK LATENT FEATURES RESULTS

Book Index	Latent Feature								
	0	1	2	3	...	96	97	98	99
0	0.190303	0.116081	-0.071519	-0.089485	...	-0.295446	0.007254	-0.150799	-0.085527
1	-0.201434	0.208697	-0.030189	0.146548	...	-0.006046	0.097541	-0.033872	0.013564
2	0.051045	-0.109489	-0.058299	0.16062	...	-0.087239	0.0657	0.156728	0.039114
3	-0.02654	0.024873	0.041809	0.006346	...	-0.007587	-0.009768	-0.077077	-0.056812
4	0.085866	0.055543	-0.130389	0.126188	...	0.030774	0.065928	0.207823	0.046057
...	...	...	...	...	...	...	...	...	...
881	-0.004269	0.03175	-0.060918	-0.012144	...	0.15323	0.065709	0.058485	-0.115789
882	-0.098071	0.168538	0.17192	-0.141234	...	-0.077324	0.051916	0.090684	-0.057098
883	0.004771	0.034305	-0.025056	0.072442	...	-0.030096	0.086369	0.043697	0.103628
884	0.160111	0.036665	-0.062488	-0.019268	...	0.048411	0.087566	-0.066152	0.047773
885	0.151642	-0.109255	-0.128585	0.055776	...	-0.076979	0.033382	0.175167	-0.057459

A comparison of the latent features of books is conducted using the cosine similarity equation to identify similar items. For example, to determine the similarity between the books indexed at 0 and 881, we calculate the cosine similarity of their respective latent feature vectors, as shown in Equation 6.

$$Similarity(q_0, q_{881}) = \frac{q_0 \cdot q_{881}}{||q_0||\,||q_{881}||} = \frac{(0.190303 \times -0.004269) + \cdots + (-0.085527 \times -0.115789)}{1.292728 \times 0.843727} = -0.286901 \quad (6)$$

Where,
q_0 : Latent factor or feature vector representing the book at index 0
q_{881} : Latent factor or feature vector representing the book at index 881

The similarity value between the books indexed at 0 and 881 is -0.286901, indicating a weak correlation. This suggests that they are not closely related.

In the non-personal recommendation implementation, when a user views the details of a book, the system calculates the cosine similarity between that book and all other books in the dataset, as done in the previous calculation. The books with the highest similarity values are then suggested as non-personal recommendations. In this research, the number of books that will be recommended is 25 books.

Several book titles were selected as an experiment to see the results of the book recommendations generated by the SVD model. Table 6 shows the non-personal recommendation for the book at index 881, titled Perkembangan Masyarakat pada Masa Kerajaan Hindu Budha.

TABLE 6
NON-PERSONAL RECOMMENDATIONS FOR BOOK TITLED PERKEMBANGAN MASYARAKAT PADA MASA KERAJAAN HINDU BUDHA

Book ID	Title	Cosine Similarity
59	KISAH RAMAYANA	0.535194
121	MENCEGAH STRESS BERSAMA HINDU	0.49809
127	AKHLAK MULIA BAHAGIA DENGAN JUJUR	0.492093
456	PANTAI DAN KEHIDUPANNYA	0.491025
634	CAHAYA BAGI KEHIDUPAN	0.490669
385	BELAJAR BAHASA INGGRIS MELALUI PERMAINAN	0.479821
776	OBAT YANG ADA DI SEKITAR KITA	0.451397
424	BERBAHASA INGGRIS YANG BAIK DAN BENAR	0.427737
272	ETIKA PENDIDIKAN KELUARGA, SEKOLAH DAN MASYARAKAT	0.421206
66	SIAPA BILANG AKU LEMAH	0.409933
85	PENEMUAN YANG MENGUBAH DUNIA	0.407383
562	MEMAHAMI SAINS DARI ALAM GUNUNG	0.405457
528	PENGENALAN DINI OBAT ALAMI	0.401195
257	KISAH PUTRI SALJU DAN 7 KURCACINYA	0.388881
332	BERPRESTASI TUJUAN HIDUPKU	0.387206
751	BELAJAR MEMASAK SIAPA TAKUT	0.369558
650	RAHASIA SEHARI-HARI	0.365083
140	BUDI PEKERTI KETIKA MAKAN	0.361087
731	MENYELAMATKAN LINGKUNGAN HIDUP DENGAN PENGOLAH...	0.347146
935	PUPULANING GENDING BALI	0.346088
180	SEJARAH HUKUM DI INDONESIA	0.34219
529	PANDUAN PENDIDIKAN ANTI KORUPSI	0.338596
159	MENGELOLA MAJALAH SEKOLAH	0.333915
796	ANEKA MAKANAN DARI TEPUNG KETAN DAN UMBI-UMBIAN	0.332505
641	MANUSIA	0.323661

Next, the book Legenda dan Dongeng Nusantara Batu Menangis was selected to also view the recommendations generated by the model. Table 7 shows the non-personal recommendations for that book.

TABLE 7
NON-PERSONAL RECOMMENDATIONS FOR BOOK TITLED LEGENDA DAN DONGENG NUSANTARA BATU MENANGIS

Book ID	Title	Cosine Similarity
306	JAKA TARUB DAN TUJUH BIDADARI	0.590054
198	ASAL MULA DANAU TOBA	0.580125
283	BAWANG MERAH BAWANG PUTIH	0.52727

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Book ID	Title	Cosine Similarity
220	LEGENDA DAN DONGENG NUSANTARA MALINKUNDANG	0.501555
305	LEGENDA DONGENG NUSANTARA TELAGA BIRU	0.496468
345	KEJAIBAN CANDI BOROBUDUR	0.486158
315	LEGENDA TIMUN MAS	0.447321
239	LEGENDA SITU BAGENDIT	0.423883
219	ASAL MULA CANDI BOROBUDUR	0.411636
722	MEMBUAT NATA DE COCO	0.388016
292	LEGENDA DAN DONGENG NUSANTAR LUTUNG KASARUNG	0.385316
485	PERCOBAAN TERHADAP AIR	0.381941
919	BERTANAM KACANG TANAH DAN MANFAATNYA	0.36046
373	PENDAKIAN JAYA WIJAYA	0.358507
415	KECIL KECIL BERANI BERKIRIM SURAT	0.343998
213	ASAL MULA CANDI RORO JONGGRANG	0.335687
214	ASAL MULA CANDI PRAMBANAN	0.32229
546	HEWAN HEWAN LANGKA DI INDONESIA	0.321611
869	SANG KESATRIA	0.311524
835	TRANSPORTASI	0.302681
45	SAAT LIBURAN YANG KUNANTI	0.301236
668	KEANEKARAGAMAN FLORA INDONESIA	0.300758
327	PERSAHABATAN MERPATI DAN SEMUT	0.297237
472	BERANEKA RAGAM HEWAN BERONGGA DAN HEWAN BERKUL...	0.288294
547	PELUANG USAHA BUDIDAYA UDANG GALAH	0.283989

Similarly, Table 8 shows the non-personal recommendations for the book English Everywhere. These results highlight further how the system identifies and suggests books with the highest cosine similarity values.

TABLE 8
NON-PERSONAL RECOMMENDATIONS FOR BOOK TITLED ENGLISH EVERYWHERE

Book ID	Title	Cosine Similarity
385	BELAJAR BAHASA INGGRIS MELALUI PERMAINAN	0.63298
378	LEST UNDERSTAND ENGLISH	0.580843
380	SINONIM DAN ANTONIM DALAM BAHASA INGGRIS	0.568173
855	PANDUAN PRAKTIS BERBUSANA	0.547544
386	ENGLISH COMPETENCY READING COMREHENSION	0.539986
424	BERBAHASA INGGRIS YANG BAIK DAN BENAR	0.539079
1136	THE FISH AND THE TORTOIS	0.491248
134	SAINS UNTUK PEMULA 4 MARI BERMAIN PESAWAT SEDE...	0.490906
808	AKUNTASI DASAR UNTUK SMU	0.489594
1	RANGKUMAN PENGETAHUAN UMUM	0.487544
44	THE GOATS SECRET AND OTHER STORIES	0.473052
562	MEMAHAMI SAINS DARI ALAM GUNUNG	0.467461
502	MEREKA YANG HAMPIR PUNAH	0.452686
194	SEJARAH INDONESIA ZAMAN ORDE LAMA 8	0.430512
413	KAMUS IDEAL	0.417691
430	ENGLISH IS FUN	0.405781
656	MENGENAL SAINS	0.401265
1075	DON’T JUDGE A MAN BY HIS FACE	0.394465
121	MENCEGAH STRESS BERSAMA HINDU	0.384521
408	PERSONALITY PLUS	0.380121

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Book ID	Title	Cosine Similarity
127	AKHLAK MULIA BAHAGIA DENGAN JUJUR	0.378946
332	BERPRESTASI TUJUAN HIDUPKU	0.37503
394	I SPEAK ENGLISH	0.359797
598	DUNIA YANG HILANG	0.352639
320	SEJARAH KABINET DI INDONESIA 7	0.345662

G. System Implementation

The SVD model that has been built then implemented into a web-based application so that students can access the recommendations. Figure 4 shows the interface of personal recommendations given to students. Personal recommendations are intended to be given to users who have registered with the system. These recommendations are provided on the home page of the application.

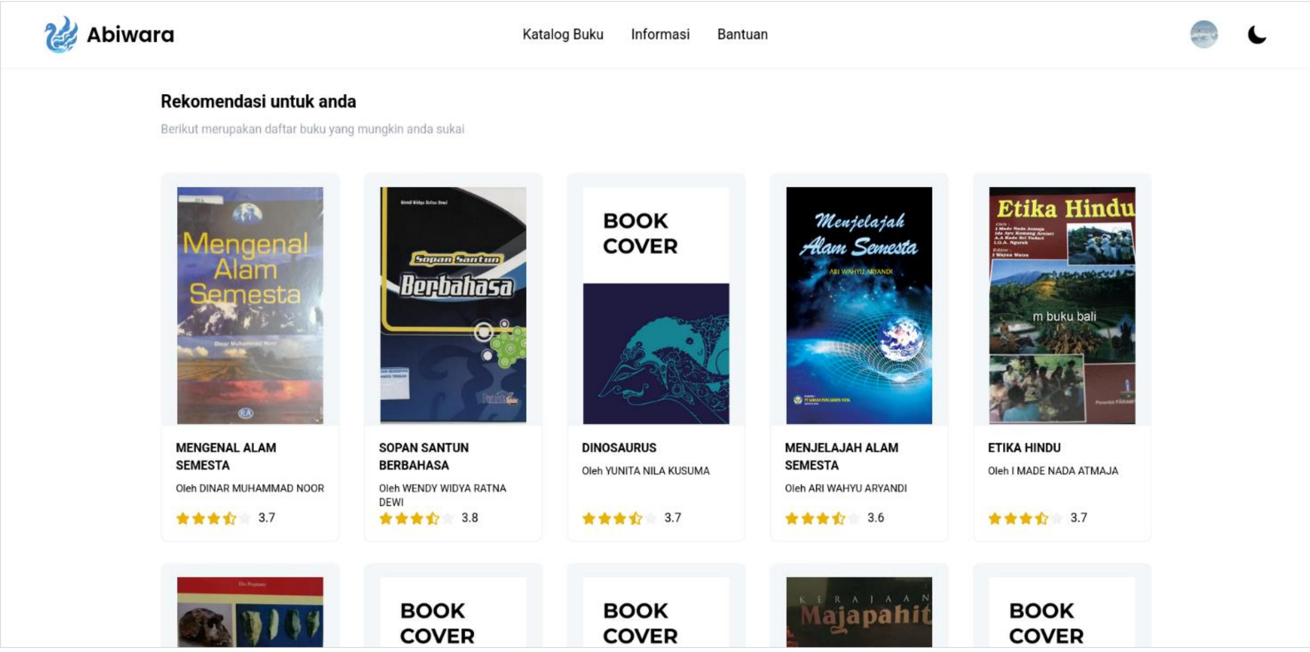

Figure 4. Personal recommendation implementation

If students choose a book title, it will continue with the appearance of a non-personal recommendation. Non-personal recommendations can be given to anyone who accesses the application, as these recommendations are general in nature. These recommendations are placed below the details of a book being viewed. This is intended to create a continuous book search experience. The information presented in the recommendation includes the title, author, and overall book rating. Figure 5 shows how non-personal recommendations are implemented when the details of a book with the title English Everywhere are being viewed.

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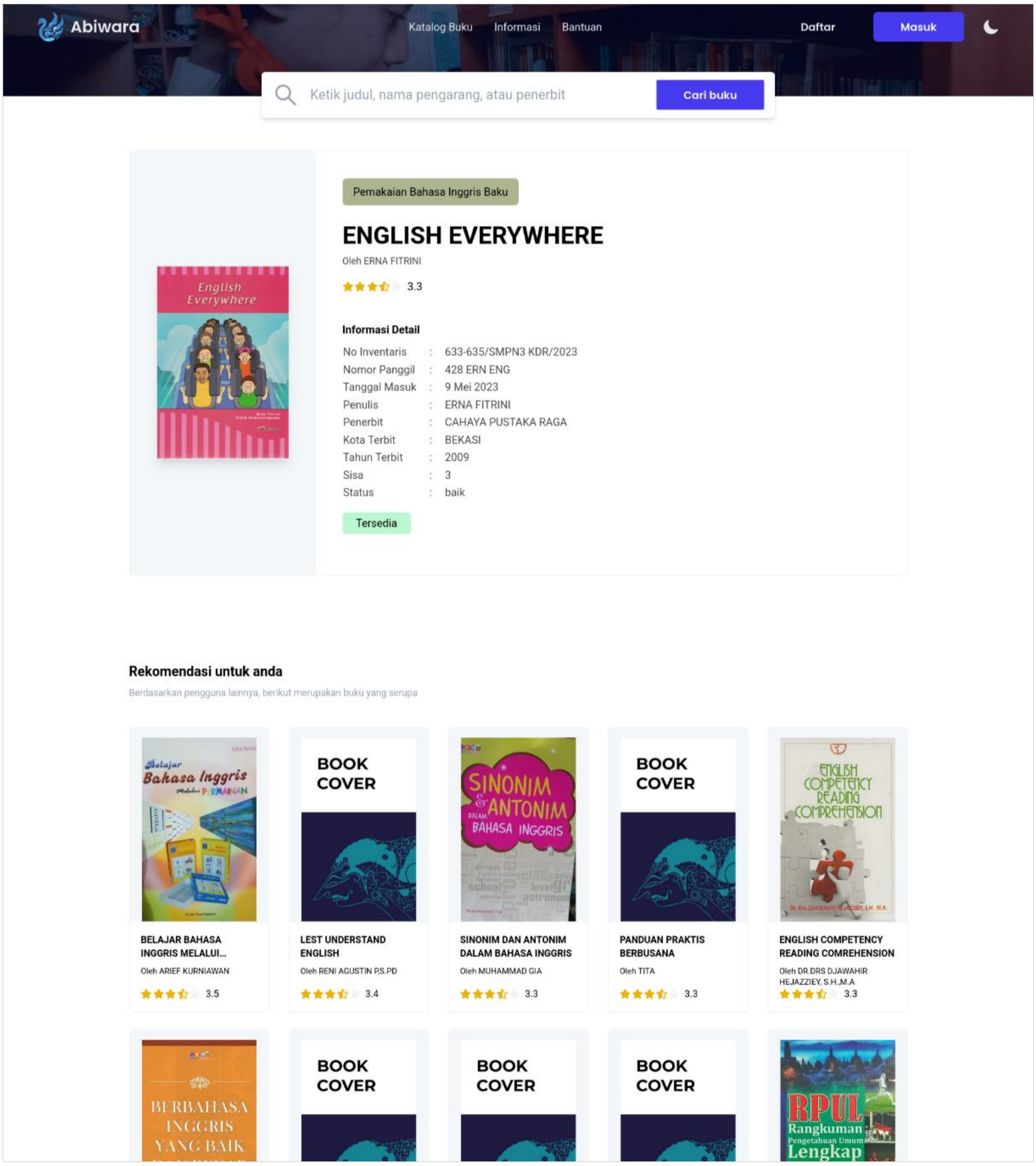

Figure 5. Non-personal recommendation implementation

IV. Conclusion

Based on the results of the analysis and testing carried out in this research, it can be concluded that the implemented Regularized Singular Value Decomposition (SVD) method is able to decompose and predict the rating matrix value and can be used in generating relevant book recommendations. The predicted ratings are used for personal recommendations, while the latent features of the book extracted help in calculating cosine similarity to suggest similar books for non-personal recommendations. The method is capable of identifying latent features to describe the characteristics of students and books based on the relationship between the two through ratings. By taking into account a total of 100 latent features, the rating prediction results have Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values of 0.478 and 0.686.

The research conducted also shows that the addition of regularization, along with selecting an appropriate number of latent features, has a significant effect on increasing rating prediction accuracy. The addition of regularization appeared to prevent the model from overfitting to the training data. Together, these factors enhance the model's ability to predict ratings, leading to more reliable book recommendations.

The development of a web-based system that implements the Regularized Singular Value Decomposition (SVD) method is a potential solution to overcome students' difficulties in finding suitable books in the school library. With the Regularized SVD method that is able to provide relevant book recommendations, this makes it easier for students to find books and get a better reading experience.

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