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Implementation of Singular Value Decomposition with Constraint Base Approach for Internship Recommendation System for Vocational High School Students

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ABSTRACT

T Vocational education in Indonesia, especially through Vocational High Schools, plays a crucial role in preparing students for the workforce. However, mismatches between student competencies and industry requirements often result in ineffective internship placements. This study focuses on SMK Negeri 2 Banda Aceh, where the internship placement process has been carried out manually and lacks an objective and personalized system. To address this challenge, a hybrid recommendation system was developed by combining Singular Value Decomposition with a constraint-based approach. The SVD method predicts student-industry compatibility by uncovering latent patterns in the rating data, while constraint-based filtering ensures that recommendations meet specific criteria such as major compatibility, skill alignment, and availability of industry capacity. The system was implemented as a web-based application using Python and MySQL, providing real-time recommendations with response times between one and three seconds. Testing with data from 344 students and more than 120 industry partners at SMK Negeri 2 Banda Aceh demonstrated the system's ability to generate accurate and relevant recommendations. For example, although an industry with a predicted rating of 0.58 matched the student's major and skills, it was not recommended due to full capacity. Instead, another industry with a lower predicted rating of 0.44 was recommended because it met all the required constraints. This system helps schools carry out internship placements more objectively, efficiently, and in alignment with student profiles and industry.

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INTRODUCTION

Vocational High School (SMK) is a form of formal education unit that provides vocational education at the secondary education level that prepares students primarily to work in certain fields (Hadi, 2022). Vocational schools play an important role in preparing students to be ready to work after they graduate from their education (Huda et al., 2019). Vocational High School is a level of education that plays a role in producing graduates who have the skills and knowledge appropriate to the fields that will be needed in the world of work (Santika et al., 2023).

In February 2024, the unemployment rate for vocational school graduates reached 8.62%, followed by general high school (SMU) graduates at 6.73%, D4-S3 graduates at 5.63%, and D1-D3 at 4.87% (Mahardika et al., 2023). This is in accordance with a survey conducted by the Central Statistics Agency (BPS) in 2021-2024, vocational school graduates are in first place with the highest number of unemployed (Rizkylillah et al., 2024). Even though vocational school graduates have relevant technical skills, they often have difficulty finding job vacancies that match their skills (Abitha et al., 2025). This is due to several factors, including a lack of information about relevant job vacancies and a misalignment between the skills taught in schools and industry needs (Wijaya & Utami, 2021).

The internship placement process at SMK Negeri 2 Banda Aceh is still carried out manually, so that competency mapping and distribution through the Special Job Exchange (BKK) is not yet optimal and less objective. This makes it difficult to match students and industry partners. With 344 students from 11 vocational programs and more than 120 industry partners, a scalable and efficient recommendation system is needed to support the placement process. One method that can be applied to overcome this problem is the Singular Value Decomposition (SVD) algorithm combined with a constraint-based approach.

Singular Value Decomposition (SVD) is known for its effectiveness in addressing scalability issues and is particularly well suited for large datasets (Sitanggang, 2023). It has the ability to uncover latent patterns in data, making it useful for generating relevant recommendations even in sparse data environments. Meanwhile, the constraint-based approach ensures that recommendations meet certain pre-defined criteria. (Jong & Herwindiati, 2024).

Research conducted by (Aswilyarti & Fauzi, 2025), This study implements the Singular Value Decomposition (SVD) algorithm to build a beauty treatment product recommendation system at Tyalashes Studio UMKM. This study aims to overcome the constraints of low product sales target achievement by providing relevant recommendations based on consumer rating data. With a dataset of 300 rating data and 7 products, the SVD model built showed good performance with an RMSE value of 0.9324. These results indicate that the SVD approach is able to provide fairly accurate predictions of user preferences even though the data is highly sparse.

Research conducted by (Juseva et al., 2023) applied the EDAS (Evaluation based on Distance from Average Solution) method to provide recommendations for mid-range smartphones based on various technical criteria such as battery capacity, RAM, camera, and price. Using 34 smartphone data samples, the study successfully identified the five best smartphones, with the highest score of 1.2431 for Redmi 8. The system was also developed in the form of a web application that takes data from the GSM Arena API and processes it using EDAS calculations. Although the study used a different domain, namely consumer devices, the EDAS approach makes an important contribution in the context of multi-criteria-based recommendation systems. This is an interesting comparison to the Singular Value Decomposition (SVD) approach used in this study, where SVD emphasizes more on learning hidden patterns (latent factors) from user preference data. Thus, this study attempts to combine the strengths of factor-based predictive models (SVD) with the addition of constraint-based filtering, in order to produce relevant and measurable internship recommendations.

Taking into account the strengths and weaknesses of each method, this study combines the SVD algorithm with a constraint-based approach. The constraint-based component ensures that the recommendation results meet certain requirements, including compatibility of majors with industry, skill alignment, industry capacity, and the highest score predicted through the decomposition of the obtained SVD matrix. This system is designed to support students in obtaining personalized and relevant internship placements, while also assisting schools in implementing a more objective and efficient placement process.

METHODS

1. Research Flow

This study adopts a methodological framework consisting of literature review, requirements analysis, data collection, system design, and system implementation. The sequence of these stages follows the waterfall model, as illustrated in Figure 1.

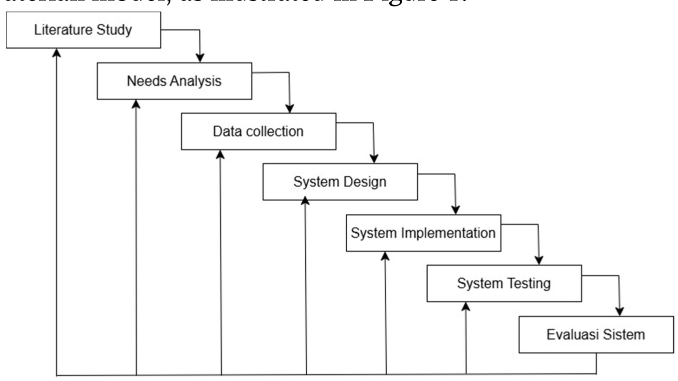

Figure 1. Research Flow

2. System Scheme

The system workflow illustrates the processes involved in implementing a recommendation system for vocational internship placements for vocational high school students, utilizing the Singular Value Decomposition (SVD) method in combination with a Constraint-Based Recommendation approach. The system is designed to deliver relevant recommendations that adhere to predefined constraints. The stages of the process are outlined as follows and are illustrated in Figure 2.

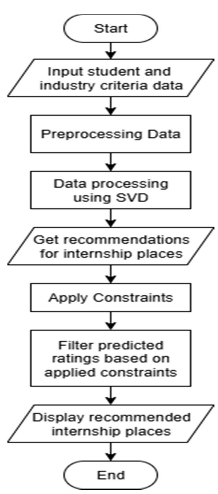

Figure 2. Scheme System

3. Singular Value Decomposition

Singular Value Decomposition (SVD) is a matrix decomposition technique that breaks down the user–item interaction matrix into three special matrices (Zhao & Ye, 2022). Using SVD, the rating matrix R is of size $m\ x\ n$ represented as items of an orthonormal matrix and a smaller diagonal matrix. Thus, SVD can condense the information in the initially large-dimensional R matrix into a more compact form (Setiawan, 2021). Secara matematis, dekomposisi SVD dinyatakan dalam persamaan berikut:

$$R = U \times \Sigma \times V^T \qquad (1)$$

The decomposition of the matrix R becomes $U \Sigma V^T$, where U and V are orthonormal matrices and Σ is a diagonal matrix containing singular values (non-negative components) that indicate the contribution of each component to the latent representation (Widyasprana et al., 2024). Dalam In the context of recommendation systems, the input matrix R is generally a matrix of user ratings of items, so that U contains the latent factors of users and V contains the latent factors of items.

In recommendation system practice, truncated SVD decomposition is often applied to improve efficiency (Przystupa et al., 2021). By simply maintaining k top latent factors k < min (m,n), matrix R reconstructed close to the original based on k greatest singular value. The result of this reduction is expressed by the equation:

$$R_k = U_k \times \Sigma_k \times V^T{}_k \qquad (2)$$

Where $U_k \in R\ m \times k\ U_k\ \in R\ m{\times}k$, $\Sigma_k \in R\ \ k{\times}k\ \Sigma\ k\ \ \in R\ k{\times}k$, *and* $V_k \in R\ n \times k\ V_k$ is a matrix cut based on k greatest singular value. This reduction step retains the key information of the original matrix while significantly reducing the computational dimension, so that the recommendation system can focus on the latent factors that are most influential in predicting user ratings (Priady et al., 2025).

4. Min-Max Normalization

Min-Max normalization is a data pre-processing technique that maps feature values into ranges [0,1] (Ariawan et al., 2023). Each feature is scaled linearly so that the original minimum value becomes 0 and the maximum value becomes 1. This approach ensures that all features have the same scale [0,1] and facilitates comparison between features (Allorerung et al., 2024). The commonly used Min-Max normalization formula is:

$$X' = \frac{x - \min(x)}{\max(x) - \mathrm{mi}\ \ (x)} \qquad (3)$$

Where x is the original value, and min(x), max(x) are respectively the minimum and maximum values in the data. This formula produces x′ = 0' when x = min(x) and x′ = 1 when x = max(x), with other values lying between 0 and 1 (A. Rahim et al., 2023). This Min-Max normalization is used to ensure that all predicted values obtained from the SVD decomposition process are within a uniform scale range, namely [0,1], thus facilitating the process of interpretation, comparison between items, and consistent recommendation ranking. In addition, this normalization also plays a role in reducing scale bias and maintaining the stability of the input data distribution used in the evaluation stage of the recommendation system results.

RESULTS AND DISCUSSION

1. Implementation of Singular Value Decomposition Method

In the initial stage, the data is processed based on the degree of compatibility between student criteria and the criteria defined by each industry. Once the matching process is completed, a rating matrix R R is generated. This matrix represents the rating values assigned by each student to various industries. The rating is calculated according to the number of matching criteria between a student and an industry where a higher number of matched criteria results in a higher rating score. The criteria considered in this process include: location, major, skill set, facilities, industry type, benefits, and capacity. The resulting rating matrix R R serves as the primary input for the decomposition process using the Singular Value Decomposition (SVD) method. A sample of the student–industry rating table derived from this matching process is presented as follows:

Table 1. Student Ratings on Industry

Student	**Industry**												
Id	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	…	I120
S1	6	0	3	1	5	4	0	2	0	0	0	…	2
S2	4	2	1	1	1	2	2	6	7	0	4	…	1
S3	0	0	0	3	3	1	0	0	2	6	0	…	1
S4	4	1	7	0	1	1	6	3	1	0	4	…	0
S5	6	3	1	0	7	0	3	1	1	1	6	…	2
S6	7	2	1	1	6	2	2	1	2	0	7	…	1
S7	5	0	1	1	6	1	0	1	0	2	5	…	1
S8	1	1	1	2	2	0	1	6	7	1	1	…	0
S9	1	0	2	1	0	2	0	6	5	0	1	…	1
S10	1	3	1	0	2	0	3	6	6	3	1	…	2
…	…	…	…	…	…	…	…	…	…	…	…	…	…
S344	4	6	1	0	1	3	1	2	1	0	4	…	5

The rating data obtained from the matching between student and industry criteria forms the basis for constructing the rating matrix R. This matrix reflects how well each student aligns with each industry based on the number of matched criteria. To ensure fairness and stability in the recommendation process, the matrix is normalized. Normalization scales all ratings to a uniform range, reducing bias from differing data scales and enhancing the accuracy of matrix reconstruction during prediction. The normalized rating matrix is presented below:

Table 2. Normalized Rating Matrix

Student	**Industry**												
Id	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	…	I120
S1	0.86	0	0.43	0.17	0.71	0.67	0	0.33	0	0	0	…	0.4
S2	0.57	0.33	0.14	0.17	0.14	0.33	0.33	1	1	0	0.57	…	0.2
S3	0	0	0	0.5	0.43	0.17	0	0	0.29	1	0	…	0.2
S4	0.57	0.17	1	0	0.14	0.17	1	0.5	0.14	0	0.57	…	0
S5	0.86	0.5	0.14	0	1	0	0.5	0.17	0.14	0.17	0.86	…	0.4
S6	1	0.33	0.14	0.17	0.86	0.33	0.33	0.17	0.29	0	1	…	0.2
S7	0.71	0	0.14	0.17	0.86	0.17	0	0.17	0	1	0.71	…	0.2
S8	0.14	0.17	0.14	0.33	0.29	0	0.17	1	1	0.17	0.14	…	0
S9	0.14	0	0.29	0.17	0	0.33	0	1	0.71	0	0.14	…	0.2
S10	0.14	0.5	0.14	0	0.29	0	0.5	0.33	0.14	0	0.14	…	0.4
…	…	…	…	…	…	…	…	…	…	…	…	…	…
S344	0.57	1	0.14	0	0.14	0.5	0.17	0.33	0.14	0	0.57	…	1

After the rating data is normalized using the Min-Max technique, the next step is to apply the Singular Value Decomposition (SVD) method. SVD is used to decompose the normalized rating matrix into three component matrices: U, Σ, and V^T. The matrix U represents the latent features of the students, Σ is a diagonal matrix containing singular values that indicate the importance of each latent feature, and V^T represents the latent features of the industries. The following is a visualization of the decomposition process, showing how the rating matrix is broken down into the three matrices.

$$
U = \begin{bmatrix}
0.08 & -0.09 & 0.08 & -0.01 & -0.02 & 0.02 & 0.06 & -0.05 & -0.06 & -0.08 & -0.01 & \cdots & 0.0 \\
0.03 & -0.02 & -0.02 & -0.07 & -0.03 & 0.09 & -0.18 & -0.01 & -0.08 & 0.06 & 0.04 & \cdots & 0.0 \\
0.06 & 0.02 & -0.02 & -0.08 & 0.03 & -0.11 & 0.08 & -0.03 & 0.05 & 0.06 & -0.08 & \cdots & 0.0 \\
0.04 & 0.06 & 0.1 & -0.03 & -0.05 & 0.07 & -0.09 & 0.01 & -0.01 & -0.04 & -0.07 & & 0.0 \\
0.09 & -0.09 & 0.01 & 0.09 & 0.02 & -0.04 & -0.04 & -0.0 & 0.06 & 0.03 & -0.0 & \cdots & 0.0 \\
0.06 & -0.13 & 0.05 & -0.03 & -0.02 & 0.02 & -0.05 & 0.07 & -0.03 & 0.03 & 0.02 & \vdots & 0.0 \\
0.07 & -0.11 & 0.05 & 0.01 & 0.0 & -0.03 & 0.04 & 0.0 & 0.01 & -0.04 & 0.01 & \cdots & 0.0 \\
0.03 & 0.01 & -0.01 & -0.03 & -0.01 & 0.07 & -0.12 & -0.13 & 0.03 & 0.09 & -0.04 & \cdots & 0.0 \\
0.06 & 0.02 & -0.0 & -0.05 & -0.01 & 0.07 & -0.1 & -0.16 & -0.11 & -0.08 & -0.03 & \vdots & 0.0 \\
0.07 & 0.02 & -0.06 & 0.05 & 0.02 & 0.02 & -0.17 & -0.1 & 0.02 & 0.05 & -0.01 & \cdots & 0.0 \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
0.03 & 0.0 & -0.07 & -0.02 & -0.16 & 0.07 & -0.0 & 0.06 & 0.03 & -0.04 & 0.01 & & 0.0
\end{bmatrix}
$$

$$
\Sigma = \begin{bmatrix}
33.2 & 0 & 0 & 0 & \cdots & 0 \\
0 & 15.03 & 0 & 0 & \cdots & 0 \\
0 & 0 & 11.83 & 0 & \cdots & 0 \\
0 & 0 & 0 & 10.04 & \cdots & 0 \\
\cdots & \cdots & \cdots & \cdots & \ddots & 0 \\
0 & 0 & 0 & 0 & 0 & 0.0
\end{bmatrix}
$$

$$
V^T = \begin{bmatrix}
0.1 & 0.08 & 0.09 & 0.08 & \cdots & 0.09 \\
-0.21 & -0.01 & 0.12 & 0.01 & \cdots & 0.01 \\
0.08 & -0.16 & 0.19 & -0.06 & \cdots & -0.15 \\
-0.11 & 0.06 & -0.03 & -0.08 & \vdots & 0.09 \\
\cdots & \cdots & \cdots & \cdots & & \cdots \\
0.0 & 0.0 & -0.0 & 0.0 & \cdots & -0.0
\end{bmatrix}
$$

The matrices , Σ , and V^T obtained from the SVD decomposition are subjected to dimensionality reduction by selecting a number of principal components corresponding to the highest singular values in Σ Σ. The matrices , Σ , and V^T are then truncated based on these selected components to reconstruct an approximate rating matrix. This reconstructed matrix is utilized by the recommendation system to predict user preferences for items that have not yet been rated. The following presents the reconstructed matrix after dimensionality reduction:

$$
U = \begin{bmatrix}
0.08 & -0.09 & 0.08 \\
0.03 & -0.02 & -0.02 \\
0.06 & 0.02 & -0.02 \\
0.04 & 0.06 & 0.1 \\
0.09 & -0.09 & 0.01 \\
0.06 & -0.13 & 0.05 \\
0.07 & -0.11 & 0.05 \\
0.03 & 0.01 & -0.01 \\
\cdots & \cdots & \cdots \\
0.03 & 0.0 & -0.07
\end{bmatrix}
$$

$$
\Sigma = \begin{bmatrix}
33.2 & 0 & 0 \\
0 & 15.03 & 0 \\
0 & 0 & 11.83
\end{bmatrix}
$$

$$V^{T} = \begin{bmatrix} 0.1 & 0.08 & 0.09 & 0.08 & \dots & 0.09 \\ -0.21 & -0.01 & 0.12 & 0.01 & \dots & 0.01 \\ 0.08 & -0.16 & 0.19 & -0.06 & \dots & -0.15 \end{bmatrix}$$

The next step is to reconstruct the matrix by multiplying the truncated matrices , Σ , and V^T. The resulting reconstructed matrix is then used to predict the values or preferences of users toward the items. Below is the reconstructed matrix representing the predicted preferences of students toward the industries:

Table 3. Matrix Reconstruction

Student	**Industry**												
Id	**I1**	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**I8**	**I9**	**I10**	**I11**	**…**	**I120**
S1	0.75	0.2	0.36	0.25	0.76	0.27	0.33	0.28	0.26	0.23	0.31	…	0.21
S2	0.28	0.24	0.14	0.21	0.26	0.21	0.19	0.17	0.2	0.18	0.18	…	0.21
S3	0.26	0.33	0.29	0.3	0.28	0.3	0.32	0.26	0.25	0.28	0.28	…	0.25
S4	0.18	0.03	0.59	0.16	0.28	0.17	0.42	0.3	0.13	0.24	0.34	…	0.35
S5	0.71	0.35	0.23	0.32	0.69	0.33	0.3	0.27	0.31	0.26	0.29	…	0.08
S6	0.77	0.18	0.17	0.2	0.74	0.21	0.18	0.2	0.24	0.15	0.21	…	0.35
S7	0.73	0.22	0.23	0.24	0.71	0.25	0.24	0.23	0.26	0.19	0.25	…	0.17
S8	0.18	0.22	0.2	0.21	0.19	0.21	0.22	0.18	0.18	0.19	0.2	…	0.22
S9	0.23	0.28	0.32	0.27	0.25	0.27	0.32	0.25	0.22	0.26	0.28	…	0.23
S10	0.23	0.41	0.21	0.34	0.23	0.33	0.3	0.24	0.27	0.29	0.27	…	0.03
S11	0.22	0.08	0.49	0.18	0.29	0.19	0.37	0.27	0.15	0.23	0.31	…	0.43
…	…	…	…	…	…	…	…	…	…	…	…	…	…
S344	0.15	0.35	0.06	0.26	0.12	0.25	0.17	0.16	0.22	0.21	0.16	…	0.35

2. Application of the Contraint-Based Method

The recommendation system does not directly present all predicted results as final recommendations. This is because not all high predicted scores can automatically be considered relevant or appropriate in real-world conditions. Therefore, the system applies a Constraint-Based Recommendation approach as a final filtering stage to ensure that the recommended results satisfy a set of predefined constraints or requirements.

The constraints applied in this system include the following:

- Major Compatibility: Internship placements are recommended only if the student's field of study matches the major required by the industry.
- Skill Compatibility: In addition to major, specific skills possessed by the student are also critical. A company will only be recommended if the student's skills align with the industry's required competencies.
- Internship Capacity Availability: Recommendations are limited to industries that still have available capacity to accept student interns.

The following presents the ordered list of industry recommendations for the student with ID 130, ranked from the highest to the lowest predicted rating. These recommendations are derived from the predicted rating values generated using the Singular Value Decomposition method, refined through the application of the Constraint-Based approach:

Table 4. The highest score of student id 130

No	Industry ID	Required Major	Required Skill	Capacity Available	Predicted Rating
1	117	TBSM	Motorcycle Maintenance	Available	0.63
2	119	TBSM	Motorcycle Maintenance	Available	0.62
3	118	TBSM	Motorcycle Maintenance	Not Available	0.62
…	…	…	…	…	…
11	64	TITL	Electrical Installation	Not Available	0.58
…	…	…	…	…	…
65	31	TITL	Electrical Installation	Available	0.44
66	88	TM	Manufacturing	Available	0.44
…	…	…	…	…	…
120	5	TDPIB	Architectural Design	Not Available	0.24

Based on the data shown in the table above, the student with ID 130 obtained the highest predicted score of 0.62 for the industry with ID 117. The second-highest predicted rating was for the industry with ID 119.

129	MUHAMMAD RAFIF AZKA	Soeltan Sakti Motor	Best Score (0.31)
130	MUHAMMAD THAIFUR	Metro Motor Service	Best Score (0.63)
131	RIFAN SABIRIN	CV. PENTAGONAL CONSULTANT	Best Score (0.29)

Figure 3. Highest Rating Value of Students Id 130.

Based on Table 4 and Figure 3, although there are industries with higher predicted ratings, the system does not automatically recommend them. For example, the industry with ID 31 achieved the highest score of 0.63, and the industry with ID 64 obtained a score of 0.58. While both industries align with the student's preferences, they are not recommended because their capacities are already full and they can no longer accommodate interns. Therefore, the system recommends a similar industry with the next highest score that still meets the constraints defined by the constraint-based approach. In this case, the system recommends the industry with ID 31 with a score of 0.44. The following is the final recommendation result for student ID 130:

31	**ICT Universitas Syiah Kuala**	• MUHAMMAD RAFIF AZKA (0.23) • MUHAMMAD THAIFUR (0.44) • RIFAN SABIRIN (0.21)

Figure 4. Final Results Student Recommendations Id 130

3. Website Implementation

The website is designed to present a visualization of the results produced by the internship recommendation system, which applies Singular Value Decomposition with a constraint-based approach. This implementation also serves to evaluate whether the system performs as expected or if further adjustments and enhancements are needed to improve its functionality.

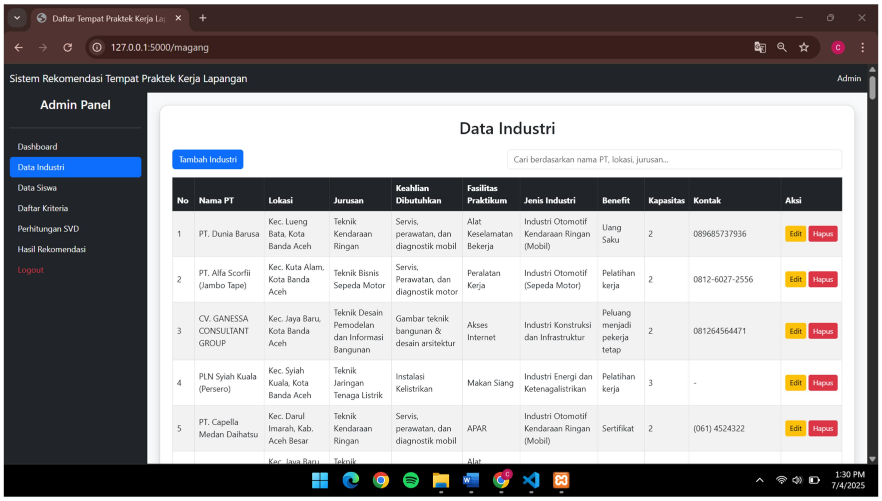

Figure 1. Industry Data Page

This page displays industry data and functions as a tool for managing industry information within the system. Through this page, the admin can not only view but also add or update industry data, including criteria such as the required majors, the necessary skills, and other relevant attributes. This ensures that the system generates recommendations based on complete and accurate industry profiles.

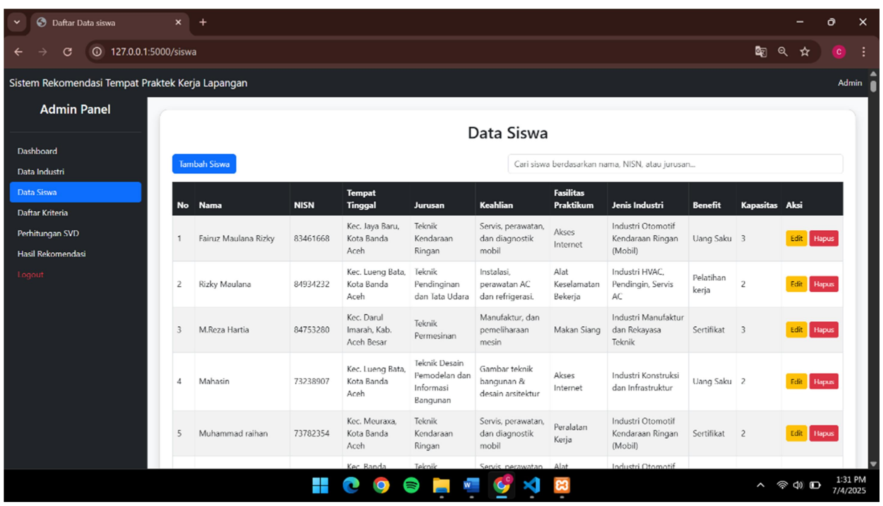

Figure 2. Student Data Page

This page displays student data and serves as a platform for managing student information within the system. Through this page, the admin can not only view but also add and update student data, including details such as their major, skills, preferences, and other relevant attributes. This feature ensures that the system's recommendations are based on accurate and up-to-date information.

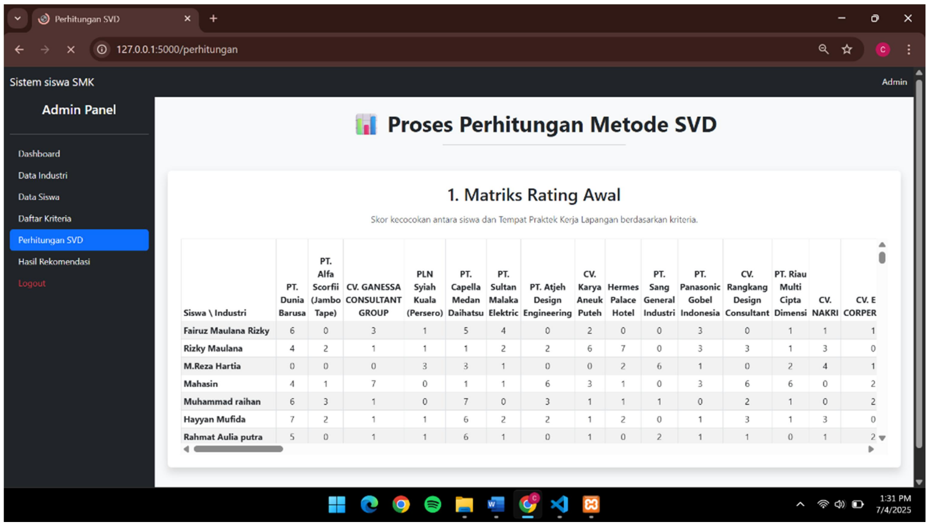

Figure 3. SVD manual calculation page

The above display shows the web interface of the manual SVD calculation process. On this page, the admin can see the student ratings, as well as the U, Σ, and V^t matrices which are the results of the decomposition of the rating matrix. This page also allows the admin to see the predicted results of the student ratings generated from the matrix reconstruction. In addition, this interface provides clear visualization to help the admin analyze how the system processes the data.

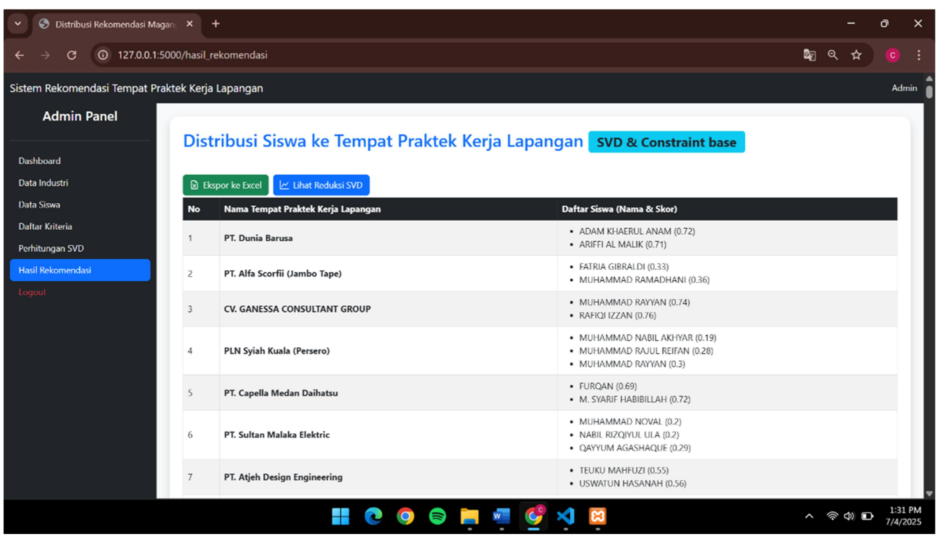

Figure 4. Recommendation Results Page

On this page, the admin can view the final internship recommendations for students across all available industries. In addition to listing recommendations, the page provides a summary of key information, such as the highest scores and how each student is matched to an industry. This display also provides information about the highest scores, as shown in the figure below, helping the admin evaluate the quality of the recommendations produced by the system.

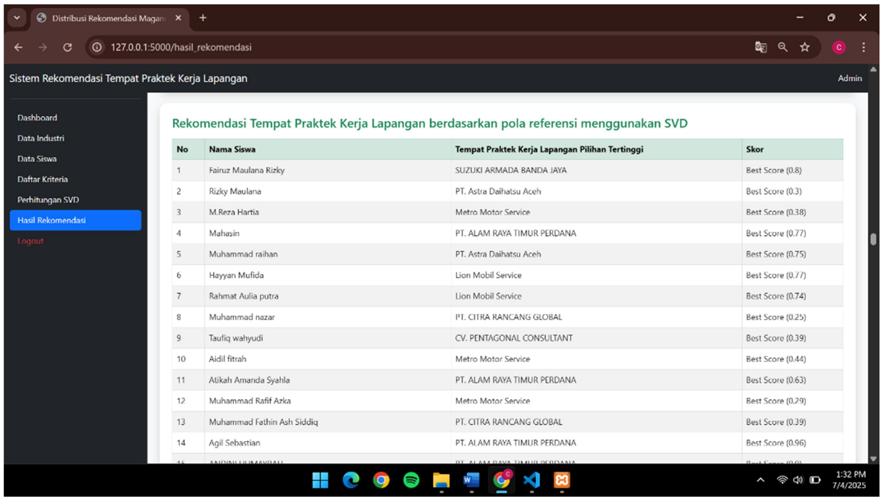

Figure 5. List of Students Highest Scores

4. System Architecture

The internship recommendation system was developed using a client-server architecture with Python as the backend language and MySQL as the database. The frontend is accessed through a web browser, while the backend handles data processing, SVD calculations, constraint-based filtering, and recommendation generation. The system separates the user interface, business logic, and data layers to ensure scalability and ease of maintenance. Data privacy is maintained by securing student and industry information, applying session-based authentication, and validating input to prevent unauthorized access or SQL injection. Performance tests show that recommendations and rating predictions are generated within 1 to 3 seconds, depending on data volume and constraint complexity.

CONCLUSION

This study shows that the integration of the Singular Value Decomposition (SVD) method with the Constraint-Based Recommendation approach is able to provide more accurate, objective, and industry-needed internship placement recommendations for Vocational High School (SMK) students. By utilizing data from 344 students and 120 industries, the system produces a rating-based internship match prediction which is then normalized and reconstructed through a matrix decomposition process. The experimental results show that the highest predicted value produced reaches 0.63 on a scale of 0–1, indicating a high level of match between students and the industry. However, thanks to the implementation of constraint-based rules such as suitability of majors, skills, and industry capacity, the system intelligently filters the final results and only recommends industries that meet all the criteria. For example, a student with ID 130 is recommended to industries with ID 117 and 119 with a predicted value of 0.62 each, because both are still available and in accordance with their field of expertise. The implementation of the system in a Python and MySQL-based web platform also succeeded in producing fast performance, with a recommendation processing time of only 1–3 seconds. These findings prove that the proposed approach can be an efficient and scalable solution in helping schools optimize the internship placement process that matches student potential and industry needs.

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