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Café Recommendation Using the Content-Based Filtering Method

Anggito Whiku Wicaksono[1], Arif Nur Rohman[2], Anggit Dwi Hartanto[3]

[1,2,3]Information System Departement, Amikom University, Yogyakarta, Idnonesia
Email: [1]awhiku2003@gmail.com, [2]arifrahman@amikom.ac.id, [3]anggit@amikom.ac.id

Abstract

The coffee industry has experienced rapid growth over the last decade. In this research, the content-based filtering approach is employed to suggest cafes by analyzing the similarity of different features or attributes. The degree of similarity is influenced by the similarity of item profiles between cafes. CW Coffee & Eatery had the highest similarity value of 0.4802 because it found 16 item profiles that were similar to Cosan Seturan. In contrast, Kelanaloka has a very low similarity value of 0.1844, because only 7 similar item profiles were identified when compared. This research shows that content-based filtering methods can be effectively applied to cafe recommendation systems.

Keywords: Recommendation Systems, Content-Based Filtering, Café Recommendation

1. INTRODUCTION

The coffee industry has experienced rapid growth over the last decade. Cafes are no longer merely places to drink coffee or socialize; they have evolved into productive spaces where students often study, discuss, and complete their assignments. As a result, there is a need for a more sophisticated system that can provide personalized cafe recommendations that align with individual consumer preferences.

Previous studies have explored various methods for generating cafe recommendations, each focusing on different attributes. For instance, research utilizing the Simple Additive Weighting (SAW) method revealed that facilities are the most significant factor influencing visitor choices, more so than location or price range [1]. Similarly, studies applying the Weighted Product method found that recommendations were heavily influenced by the highest preference values, derived from an analysis of quality, facilities, and location distance [2]. Another approach, the MOORA method, considered a comprehensive set of attributes—distance, food and drink prices, facilities, menu variety, and service quality—to evaluate cafes [3]. Research conducted in Pontianak using the SAW method reinforced these findings, identifying quality and facilities as the primary drivers for cafe recommendations [4]. In contrast, a study employing the collaborative

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filtering method focused on deriving recommendations from visitor reviews and specific parameters provided by the system [5].

While various recommendation methods have been applied, there is a noticeable gap in the integration of these approaches to leverage their complementary strengths. Existing studies often emphasize a single technique or a limited combination of attributes, leaving room for a more nuanced approach that could incorporate multiple factors and methods. Two main techniques underpin recommendation systems: collaborative filtering and content-based filtering. The collaborative filtering approach recommends items based on user preferences, identifying patterns and trends from user data, but it requires a substantial dataset for accuracy. In contrast, content-based filtering suggests items based on similarities to those previously liked or chosen by the user, making it effective even when user data is sparse [6].

Applications of these methods have been varied across different domains. For example, collaborative filtering has been applied to tourism destination recommendations in Yogyakarta, relying on user ratings [7], while a hybrid approach combining content-based and collaborative filtering was used to provide more specific recommendations for tourism attributes in Bali [8]. Content-based filtering has also been used to recommend books based on attributes like title, synopsis, and author [9] and for recommending skincare products based on product attributes such as name, composition, and skin type [10]. Each method presents its own set of advantages and limitations; collaborative filtering excels at uncovering patterns in large datasets, whereas content-based filtering offers flexibility with limited data.

Despite these advancements, there remains a lack of research on developing a comprehensive cafe recommendation system that combines multiple filtering techniques to optimize accuracy and relevance. This study aims to fill this gap by developing a cafe recommendation website that utilizes content-based filtering techniques, alongside cosine-similarity calculations, to accurately match user preferences with various cafe attributes such as descriptions, addresses, and operating hours [11], [12]. This approach not only facilitates personalized recommendations for users but also provides a platform for cafe owners to promote their offerings, thereby supporting the growth of the coffee industry. Thus, this research goes beyond the technology of delivering recommendations and contributes to the broader development of the cafe industry.

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2. METHODS

2.1. Waterfall System Development Method

This research employs the waterfall system development methodology, which is a traditional approach to software development that involves a sequential progression through distinct stages: needs analysis, design, implementation, testing, deployment and maintenance [12]. One of the key benefits of this method is its clear structure, which ensures an organized and systematic development process. However, in the context of this research, the application of the waterfall method is limited to the testing phase, meaning it does not extend to the deployment and maintenance stages.

2.1.1 Analysis

This stage initiates the process by thoroughly understanding the goals and objectives of the software that is to be developed. Developers start by analyzing the needs and expectations of the users, identifying the essential features and functionalities that the software must include. This comprehensive assessment ensures that the software will meet the users' requirements and align with their intended purposes.

2.1.2 Design

Once the needs and objectives are clearly understood, the developer applies the Waterfall Method to design the website's architecture, layout, and technical specifications. This phase includes crafting detailed flow charts and designing user interfaces to ensure a seamless user experience. Additionally, the website's flow diagram and the content-based filtering system, which are crucial components of the design process, are illustrated in Figure 1 and Figure 2.

2.1.3 Implementation

The implementation phase involves developing the visual aspects of the website's user interface, writing the necessary program code, and conducting testing to ensure the website's quality and functionality meet the required standards.

2.1.4 Testing

Once the website has been developed, the testing phase is conducted to verify that it functions correctly. This process ensures that the final product effectively meets the needs of users seeking cafe recommendations.

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2.2. System Design

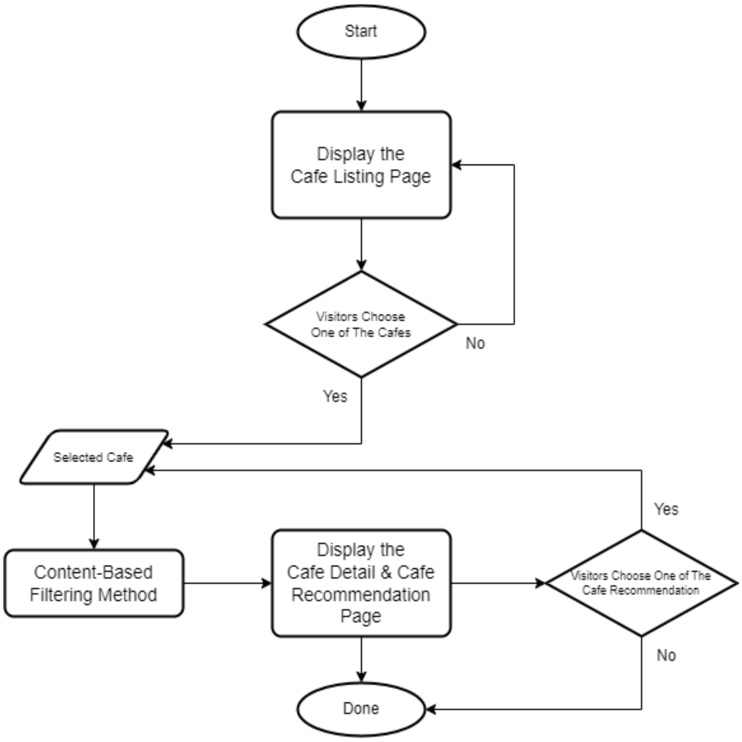

Figure 1. Website flow diagram

Based on Figure 1, the system design flow in this study begins by displaying a list of cafés to the visitor. The visitor selects a café from this list, triggering the application of the content-based filtering method to provide detailed information about the chosen café, as well as recommendations for other cafés that match the visitor's preferences. If the visitor selects a café from the recommended list, the system repeats the process for the newly selected café, displaying its details and generating further recommendations [13], [14]. If no café is selected from the recommendations, the process ends. The overall process flow of the content-based filtering method is illustrated in Figure 2.

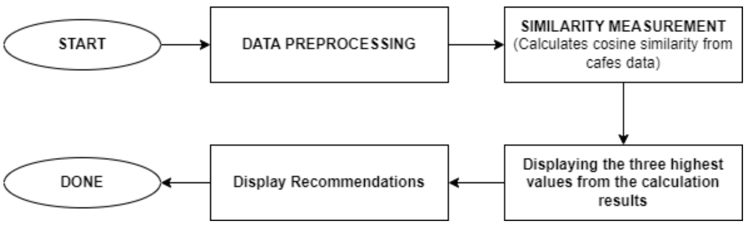

Figure 2. Content-Based Filtering

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Figure 2 provides a detailed view of the system flow for the content-based filtering method. The process begins with the first stage, Data Preprocessing, which prepares the data for subsequent analysis. After preprocessing, the system calculates the Cosine Similarity between the selected café and other cafés in the database. The top three cafés with the highest similarity scores are identified and presented as recommendations to the visitor. This iterative process ensures that the most relevant recommendations are displayed based on the visitor's initial selection.

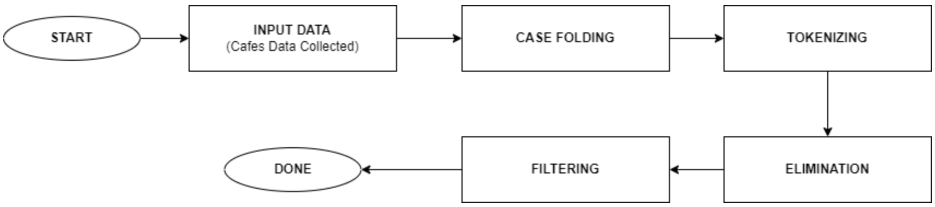

Figure 3. Data preprocessing

Figure 3 illustrates the Data Preprocessing stage in greater detail. During this stage, several steps are performed to ensure that the data is clean and suitable for analysis. The process begins with importing the café data into the system, followed by several key preprocessing steps: case folding to standardize text data, tokenizing to break down the text into individual components, eliminating irrelevant words or symbols, and finally filtering to retain only the most significant features for recommendation [15].

2.3. Data Collection

The collected data is obtained from scraping Google Maps and reviews from the Instagram accounts @referensikopi and @cafejogjakarta. The information gathered includes the name of the cafe, the address of the cafe, and the description of the cafe, with a total of 150 cafes documented. This data is then imported into the system for data preprocessing.

2.4. Method Implementation

The content-based filtering method operates on the principle of providing recommendations based on the similarity of item profiles[16]. When a user selects a café, recommendations are generated in the form of a list of cafés that have item profiles similar to the selected café. The similarity of item profiles is calculated by comparing the item profile of the chosen café with those of other cafés after undergoing preprocessing stages. Next, the similarity between item profiles is calculated the usage of the cosine similarity feature. Cosine similarity is a popular technique for measuring similarity. This method measures the cosine of the angle between two vectors and is frequently employed to evaluate the similarity between

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two documents [17]. This technique function between item A and item B is defined as shown in Equation 1.

$$sim(A,B)=\frac{n(A\cap B)}{\sqrt{n(A)n(B)}} \quad (1)$$

sim(A,B)	=	similarity value of items A and item B
n(A)	=	the number of content features of item A
n(B)	=	the number of content features of item B
n(A∩B)	=	the number of feature contents that are present in both item A and item B

The higher the cosine similarity result between the two evaluated cafés, the more similar they are considered to be, and vice versa. The implementation go with the flow of the content-based filtering method is illustrated in Figure 4.

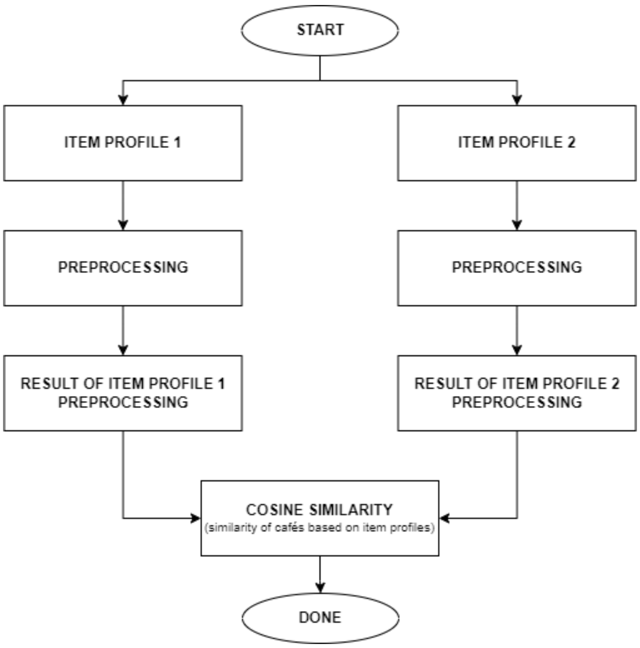

Figure 4. Implementation Content-Based Filtering Method

From Figure 4, its presents two item profiles with identical features but differing values. The first step is preprocessing these profiles by standardizing their formats and removing irrelevant features. Cosine similarity is then calculated to measure how similar the profiles are, with a range from 0 (completely dissimilar) to 1 (identical).

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2.5. Website Implementation

The interface of the cafe recommendation system will be implemented as an application accessible through a web browser using the PHP programming language and the Laravel 8 framework for scalable, maintainable, and high preformance solution for the website[18]. The interface will include a cafe listing page, a cafe detail page, and a cafe recommendation section.

3. RESULTS AND DISCUSSION

3.1 Data Preprocessing

The data preprocessing phase begins with data cleaning, a critical step to ensure that the data is accurate, reliable, and well-organized before analysis. Data cleaning focuses on removing errors and inconsistencies to enhance data quality, which is essential for achieving precise and meaningful analysis results. This process involves eliminating irrelevant words, such as conjunctions and affixes, to refine the dataset and improve the accuracy of subsequent analyses. After data cleaning, the next step is to create an item profile from the data in the feature content table. An item profile consists of two main columns: the café name and the feature content. The feature content data is extracted from the alamat_kafe (café address) and deskripsi_kafe (café description) tables in the database. To illustrate the implementation of the content-based filtering recommendation system, consider the example where a user selects the café "Cosan Seturan." The system generates an item profile for "Cosan Seturan" and then compares it with the item profiles of other cafés to identify similarities. For this purpose, cafés like "CW Coffee & Eatery" and "Kelanaloka" are used as case studies. The item profiles for each of these cafés, which include their names and corresponding feature content, are presented in Table 1.

Table 1. Item Profile

Cafes Name	Content Feature
Cosan Seturan	seturan raya kledokan caturtunggal depok regency sleman cosan coffee sanctuary cafe newest jogja worth visiting cafe street seturan raya kledokan caturtunggal depok sleman atmosphere comfortable cafe ideal working tasks free relieved sitting sharing table large tasks comfortable lingering lighting flexibility menu coffee food prices friendly atmosphere cozy fun relax work
CW Coffee & Eatery	seturan raya kledokan caturtunggal kec depok sleman cw coffee eatery jogja street seturan raya kledokan caturtunggal kec depok regency sleman

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Cafes Name	Content Feature
	cafe outdoor garden river fish splashing water comfortable calming indoor cozy wfc has ac spot sitting elegant internet fast facilities printer free relieved ideal tasks work menu coffee prices affordable cafe relax
Kelanaloka	street langenastran kidul panembahan regency kraton kota yogyakarta kelanaloka kafe atmosphere calm middle city street langenastran kidul panembahan regency kraton city yogyakarta concept retro homey warmth comfort menu lokal cuisine affordable prices variety coffee lovers coffee manual brew menu local selat solo timlo soto fied rice drinks kopsus og matcha black charcoal strawberry asri fresh prices menu friendly delicious hangout special collection vinyl songs culture old environment nostalgic dj night unique comfort coffee prefect relax

In Table 1, the cafe address and description data are transformed into item profiles to facilitate preprocessing. This process prepares the data for subsequent steps, including case folding, tokenization, elimination, and filtering.

3.2 Result of Data Preprocessing

Table 2. Item profile resulting from data preprocessing

No	Item Profile		
	Cosan Seturan	**CW Coffee & Eatery**	**Kelanaloka**
1	seturan	seturan	langenastran
2	raya	raya	kidul
3	kledokan	kledokan	panembahan
4	caturtunggal	caturtunggal	kraton
5	depok	depok	city
6	sleman	sleman	yogyakarta
7	coffee	coffee	cafe
8	cafe	eatery	atmosphere
9	jogja	jogja	calm
10	worth	cafe	retro
11	atmosphere	outdoor	homey
12	comfortable	garden	warmth
13	ideal	river	comfortable
14	work	fish	menu
15	tasks	splashing	local

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No	Item Profile		
	Cosan Seturan	CW Coffee & Eatery	Kelanaloka
16	free	water	prices
17	relieved	comfortable	coffee
18	sitting	indoor	brew
19	sharing	cozy	manual
20	large	wfc	selat
21	tasks	ac	solo
22	lighting	spot	timlo
23	menu	sitting	soto
24	coffee	elegant	fried
25	foods	internet	rice
26	prices	fast	drinks
27	friendly	printer	kopsus
28	atmosphere	free	og
29	cozy	relieved	matcha
30	relax	ideal	black
31		tasks	charcoal
32		work	strawberry
33		menu	asri
34		prices	fresh
35		affordable	delicious
36		cafe	hangout
37		relax	special
38			vinyl
39			songs
40			culture
41			old
42			environment
43			nostalgic
44			dj
45			night
46			coffee
47			perfect
48			relax

In Table 2, case folding is performed as an initial step in the preprocessing process. The sentences in the feature content column are converted to lowercase to ensure that the data used is more consistent. Next, tokenization is applied by separating the sentences into individual words. After tokenization, some similar words are still found in the item profiles. Elimination is performed by removing these similar words. In the final stage, filtering is done by removing words considered irrelevant or that may interfere with the similarity calculation process.

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3.3 Method Implementation

Content-based filtering method operates on the principle of providing recommendations based at the similarity of object. Once item profiles have been appropriately prepared through the preprocessing stages, they are compared to determine their similarities. The degree of similarity between item profiles is measured using the cosine similarity function.

3.3.1 Similarity Calculation

The first calculation involves comparing the item profile of Cosan Seturan with the item profile of CW Coffee & Eatery. Each café's item profile from Table 2 is compared, and several similarities are identified as shown in Table 3.

Table 3. Similarity of item profile

No	Item Profile	
	Cosan Seturan	CW Coffee & Eatery
1	seturan	seturan
2	raya	raya
3	kledokan	kledokan
4	caturtunggal	caturtunggal
5	depok	depok
6	sleman	sleman
7	coffee	coffee
8	jogja	jogja
9	free	free
10	relieved	relieved
11	work	work
12	tasks	tasks
13	sitting	sitting
14	coffee	coffee
15	cozy	cozy
16	relax	relax

Total item profile of Cosan Seturan, $n(A)$=30,
Total item profile of CW Coffee & Eatery, $n(B)$=37,
Total number of similar item profiles, $n(A \cap B)$=16,
The similarity value is calculated using Equation (1).

$$sim(A,B)=\frac{16}{\sqrt{30.37}}$$

$$sim(A,B)=0.4802$$

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The similarity value for the two cafes is 0.4802.

The second calculation involves comparing the item profile of Cosan Seturan with the item profile of Kelanaloka. The item profiles for these cafés, shown in Table 2, are compared, and several similarities are identified as presented in Table 4.

Table 4. Similarity of item profile

No	Item Profile	
	Cosan Seturan	**Kelanaloka**
1	cafe	cafe
2	atmosphere	atmosphere
3	kledokan	kledokan
4	menu	menu
5	environment	environment
6	coffee	coffee
7	relax	relax

Total item profile of Cosan Seturan, $n(A)$=30,
Total item profile of Kelanaloka, $n(B)$=48,
Total number of similar item profiles, $n(A \cap B)$=7,
The similarity value is calculated using Equation (1).

$$sim(A,B)=\frac{7}{\sqrt{30.48}}$$

$$sim(A,B)=0.1844$$

The similarity value for the two cafes is 0.1844.

The degree of similarity is influenced by the similarity of item profiles between cafés. CW Coffee & Eatery has the highest similarity value of 0.4802 because 16 item profiles were found to be similar to those of Cosan Seturan. In contrast, Kelanaloka has a very low similarity value of 0.1844, as only 7 similar item profiles were identified when compared.

3.3.2 Top-C Recommendation

The implementation continues for all cafés until all similarity values are obtained. When a user selects Cosan Seturan, they are provided with a top-C recommendation list sorted by the highest similarity values. The five recommendations given to the user are presented in Table 5.

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Table 5. Top-5 cafes recommendation

Cafes Name	Similarity
CW Coffee & Eatery	0.4802
Lars Flagship	0.4176
Lestari Corner Coffee	0.3547
XYZ Coffee & Collabs	0.3538
Bolivar Coffee	0.3512

Table 5 shows that CW Coffee & Eatery is included in the top-N recommendations due to its highest similarity value, while Kelanaloka is not included in the recommendations because its similarity value is very low.

3.4 Website Implementation

The implementation of the cafe listing page, as depicted in Figure 5, serves as the starting point for users to explore a variety of cafés. This page provides a visually engaging overview, featuring a gallery-style display of café images, along with essential details such as the name and address of each café. This layout enables users to quickly browse and identify cafés that align with their preferences or interests.

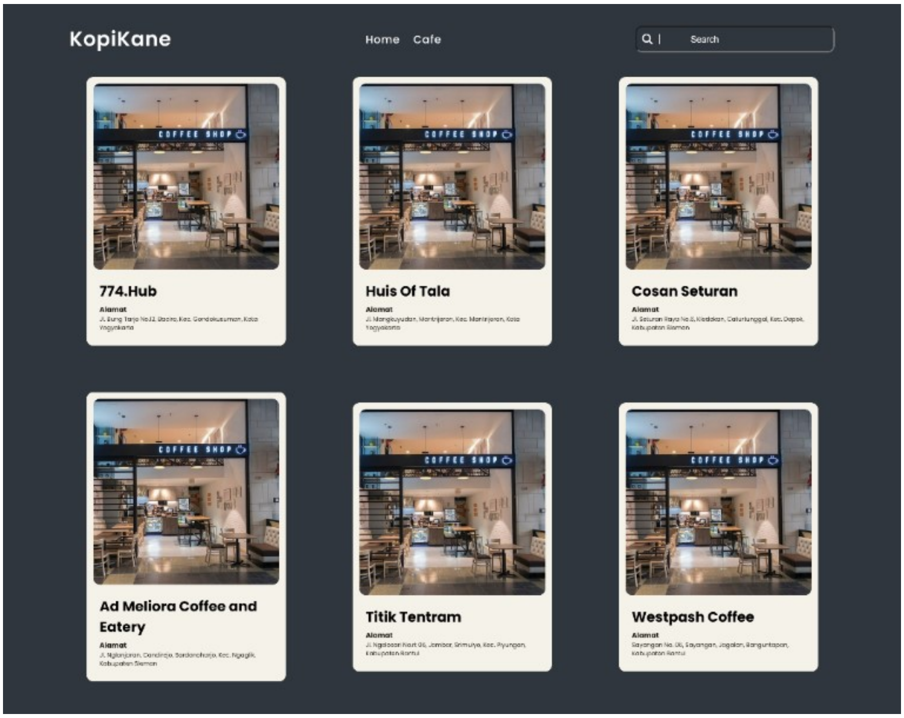

Figure 5. Café listing page

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When a user selects a café from this listing page, they are immediately redirected to the café detail page, as illustrated in Figures 6 and 7. This detail page is designed to provide comprehensive information about the selected café, enhancing the user's decision-making process.

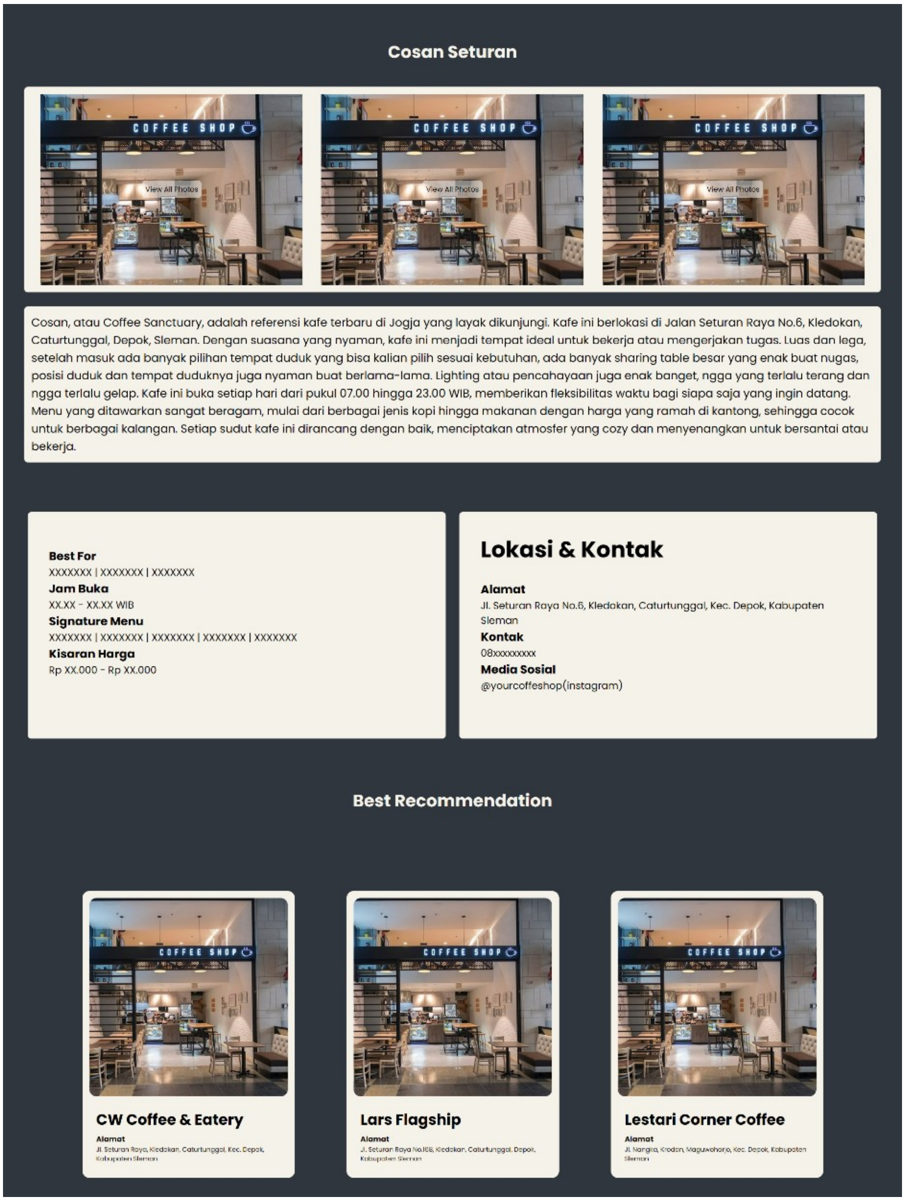

Figure 6. Cafe detail page

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Figure 6 presents the main café detail page, which includes vital information such as the café's name, a brief description, complete address, contact details, and links to the café's social media profiles. The detailed information section is designed to offer a deeper understanding of the café's unique characteristics. It includes the café's classification (e.g., coffee shop, bakery, or lounge), operating hours, signature menu items, and price range. This structured presentation helps users quickly grasp the café's offerings and decide whether it meets their needs. At the bottom of the café detail page, a recommendation section is prominently displayed, as shown in Figure 7. This section plays a crucial role in enhancing the overall user experience by providing personalized suggestions for similar cafés.

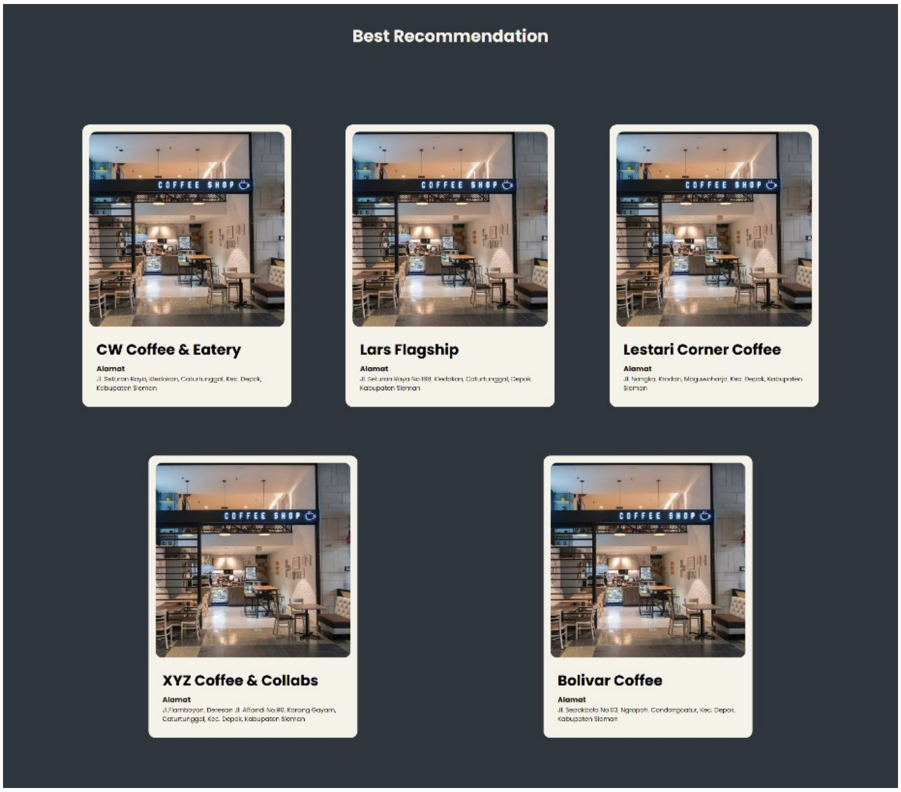

Figure 7. Café detail page – recommendation section

3.5 Discussion

This study implemented a content-based filtering recommendation system to enhance user experience by providing personalized café recommendations. The system operates by comparing item profiles of cafés based on data extracted from their addresses and descriptions. These profiles undergo a series of preprocessing steps including case folding, tokenization, elimination, and filtering to standardize

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the data and remove any irrelevant content. Once the data is prepared, the cosine similarity metric is used to calculate the degree of similarity between the item profiles of different cafés.

The core principle behind the content-based filtering method is to provide recommendations based on the similarity of objects—in this case, the cafés. After preprocessing, the item profiles are compared to determine their similarities. The cosine similarity function calculates the angle between two vectors (representing item profiles) in a multidimensional space, which reflects the degree of similarity between them. A higher cosine similarity value indicates a greater degree of similarity between the cafés. For example, the similarity calculation between "Cosan Seturan" and "CW Coffee & Eatery" yielded a cosine similarity value of 0.4802, indicating a moderate level of similarity between the two cafés. This result was derived from 16 matching item profiles between them (as shown in Table 3). In contrast, the similarity value between "Cosan Seturan" and "Kelanaloka" was only 0.1844, with only 7 matching item profiles (as shown in Table 4). The significant difference in similarity values demonstrates how the number of shared attributes directly impacts the degree of similarity. Cafés with higher similarity scores are more likely to share similar characteristics, such as ambiance, menu offerings, or location attributes.

The content-based filtering system continues this similarity calculation process for all cafés in the database. Each café's item profile is compared against the user-selected café, generating a similarity score. Based on these scores, a top-C recommendation list is created, ranking the cafés in descending order of similarity to the user-selected café. As illustrated in Table 5, "CW Coffee & Eatery" appears at the top of the recommendation list with a similarity score of 0.4802, followed by "Lars Flagship" (0.4176), "Lestari Corner Coffee" (0.3547), "XYZ Coffee & Collabs" (0.3538), and "Bolivar Coffee" (0.3512). This ranking allows the system to provide the user with the most relevant café options based on their initial choice. The effectiveness of the recommendation system is evident from the generation of the top-5 recommendations, where cafés with higher similarity values are prioritized, ensuring that the suggested options closely match the user's preferences. Conversely, cafés with lower similarity values, such as "Kelanaloka," are not included in the recommendations, as their attributes do not align as closely with the selected café.

The practical application of this recommendation system is integrated into a user-friendly website interface. The website begins with a visually engaging café listing page (Figure 5) that allows users to browse a variety of cafés based on their preferences. When a user selects a café, they are redirected to the detailed café page (Figures 6 and 7), where they can find comprehensive information, such as the café's name, description, address, contact details, social media links,

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classification, operating hours, signature menu items, and price range. This detailed presentation enhances the decision-making process by providing users with all the necessary information in a structured format. At the bottom of the café detail page, a recommendation section (Figure 7) displays the top five cafés with the highest similarity values to the selected café. This feature enhances the overall user experience by offering personalized suggestions based on the user's initial choice. The dynamic and responsive nature of this recommendation system encourages users to explore new cafés, contributing to higher user engagement and satisfaction.

While the current implementation effectively utilizes content-based filtering to provide personalized café recommendations, there are several opportunities for further enhancement. Incorporating additional user data, such as preferences and feedback, could significantly improve the recommendation accuracy. By learning from user interactions and adjusting recommendations based on real-time feedback, the system can become more adaptive and responsive to individual tastes. Furthermore, exploring alternative similarity measures, such as Jaccard similarity or Pearson correlation, could offer new insights into the relationships between café profiles, potentially leading to more refined recommendations. Additionally, incorporating a broader range of café features—such as user reviews, ratings, or environmental attributes (e.g., noise levels, seating arrangements)—could make the recommendations more comprehensive and aligned with diverse user preferences. The combining content-based filtering with collaborative filtering could create a hybrid recommendation system that leverages both user-item similarities and user-user similarities. This hybrid approach could further enhance the robustness and flexibility of the recommendation engine, allowing it to perform well in different contexts, whether data is sparse or abundant.

4. CONCLUSION

This research demonstrates that the content-based filtering method can be effectively applied to a cafe recommendation system. The results of the recommendations are influenced by the similarity between item profiles, such as cafe addresses and descriptions, selected by users and other cafe item profiles. For instance, when Cosan Seturan is selected, CW Coffee & Eatery is recommended because its item profile is similar to that of Cosan Seturan, with a similarity value of 0.4802. In contrast, Kelanaloka is not recommended or included in the top five recommendations due to its lower similarity value of 0.1844. The current similarity calculation method is based on individual words, which results in recommendations that may lack accuracy. Future research could explore alternative methods or incorporate additional attributes and features to enhance the relevance and accuracy of the recommendation results.

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