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Application of Content-Based Filtering Method Using Cosine Similarity in Restaurant Selection Recommendation System

Fajar Christyawan[1], Arif Nur Rohman[2], Anggit Dwi Hartanto[3]

[1,2]Information System Department, Amikom University, Yogyakarta, Indonesia
Email: [1]fchristyawan@students.amikom.ac.id, [2]arifrahman@amikom.ac.id, [3]anggit@amikom.ac.id

Abstract

This research focuses on developing a restaurant recommender system designed to assist users in selecting restaurants based on preferences such as cuisine type and proximity, thereby enhancing the dining experience. The system employs a content-based filtering approach combined with the Cosine Similarity algorithm to calculate similarity values between restaurant addresses and categories, ensuring personalized and accurate recommendations. Data for the system was collected from TripAdvisor and Google Maps using a web scraping method, resulting in a comprehensive dataset that reflects a wide variety of dining options. An experiment involving 30 respondents was conducted to evaluate the system's performance under real-world conditions. The results demonstrated an accuracy rate of 88%, indicating that the recommender system effectively delivers highly relevant restaurant suggestions to users. These findings suggest that the system can serve as a valuable tool for culinary tourists and local residents, simplifying the process of discovering new dining experiences and aligning them with individual preferences.

Keywords: Recommendation System, Restaurant Recommendation, Content-Based Filtering, Cosine Similarity, Cuisine Type

1. INTRODUCTION

Culinary tourism has become a prominent aspect of today's foodie culture, with an abundance of culinary information available through various electronic media. However, this wealth of information does not necessarily assist culinary tourists in effectively selecting restaurants that meet their preferences [1]. Restaurants and eateries are critical to the tourism infrastructure, supporting the public and tourists in fulfilling their dining needs. Statistical data from five districts/cities from 2016 to 2019 indicate that the restaurant industry has generally experienced growth, despite various fluctuations. This growth is driven by intense competition within the sector, largely due to the relatively low barriers to entry in the restaurant business [2].

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Technological and economic developments have significantly transformed lifestyles, particularly in terms of food consumption patterns. Many individuals now prefer dining out, either due to time constraints or to experience a different ambiance. Dining at a restaurant offers a unique experience compared to cooking and eating at home, which may often feel monotonous. Restaurants provide a diverse range of menu options, including dishes that diners may not have tried before, and invest in creating a comfortable atmosphere for customers [3]. However, despite the vast amount of information available online, users often struggle to find restaurants that suit their preferences. This highlights the need for a more efficient and user-friendly restaurant search system.

Recommendation systems are software tools and techniques designed to suggest items that might interest users [4], [5]. For instance, a recommendation system implemented in a book search information service can simplify finding books that match visitors' preferences, speeding up the search process in libraries. Such systems have been widely employed in various applications, including movie suggestions by Netflix [6] and product recommendations by Amazon [7].

Recommendation systems can be categorized into four types based on the knowledge base they use [8]: (1) Collaborative Filtering: Relies on user ratings and identifies users with similar rating histories to provide recommendations based on the relationships between users. (2) Content-Based Filtering: Generates suggestions based on attributes related to the product and user ratings. It treats recommendations as classification problems, utilizing classifiers for positive or negative user feedback based on product features. (3) Demographic-Based Filtering: Offers product recommendations based on the consumer's demographic profile. (4) Knowledge-Based Filtering: Provides product recommendations by understanding consumer needs and preferences, utilizing specific practical knowledge about how certain product features meet those needs. Among these, a content-based filtering recommendation system is considered particularly suitable for addressing restaurant recommendation challenges [9].

Research by [10] demonstrates that content-based filtering can produce unbiased recommendations, making it ideal for platforms providing growing culinary information, as seen in the MANGAN application. The study's results show that the system can offer suggestions, including images, names, and distances to similar restaurants, based on content similarity when users select a specific restaurant. With a recommendation system, users can more easily find culinary options that match their tastes and preferences. This system processes information based on previous order history to suggest food aligned with user preferences [11].

In this context, the modern solution such as a web-based recommendation platform designed to help restaurant customers discover culinary destinations in

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Yogyakarta that match their preferences. Although numerous recommendation websites are available, many provide information covering too many categories, such as hotels, cafes, and restaurants, which can confuse users. The goal of the platform is to simplify the process of searching for and selecting restaurants, thereby providing a more efficient and satisfying experience for culinary enthusiasts in Yogyakarta. It is anticipated that the food and beverage industry in Yogyakarta will see an increase in customers who are more targeted and aligned with their preferences, contributing to local economic recovery and growth. Therefore, this study aims to provide a more segmented and targeted approach by focusing on restaurant recommendation systems using content-based filtering with the Cosine Similarity algorithm. Content-based filtering has been selected as the recommendation tool to facilitate users in discovering dining options based on the type of cuisine and proximity.

2. METHODS

2.1. System Design

In the design flow of the proposed restaurant recommender system, the process begins with the user accessing the initial starting point, or the "Start." The user is first presented with the homepage, which serves as the main navigation hub for the system. From here, the user is directed to the "Show Page," which offers various categories of restaurants to choose from. Once the user selects a preferred category, the system displays a list of restaurants that fall within that chosen category. At this stage, the user selects a specific restaurant to view more details.

Upon selecting a restaurant, the content-based filtering method is employed to analyze the restaurant's details, such as its cuisine type, address, and other relevant attributes. Based on this analysis, the system generates a set of recommended restaurants that match the user's preferences. These recommendations are presented to the user, who can then choose from the list of suggested restaurants. The user has the option to select one of the recommended restaurants or explore more options by navigating back to the previous steps and refining their choices.

The system's design flow, illustrated in Figure 1, highlights a user-friendly navigation process, starting from the homepage and progressing through the category and restaurant selection stages. The initial step involves the user accessing the category page, where they can browse various cuisine types or restaurant classifications. After the user selects a category, the system dynamically generates a restaurant page tailored to the user's choice, displaying a list of relevant dining options. At this point, the content-based filtering algorithm is applied to identify additional restaurants that share similar features to the selected restaurant, effectively expanding the range of personalized recommendations [12], [13].

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Following this, the recommended restaurants are displayed to the user, who then decides whether to select one of the suggested options or continue browsing. If the user chooses to go back and select another restaurant, the process iterates, allowing for multiple rounds of exploration and refinement. Conversely, if the user is satisfied with a recommended restaurant, they can proceed to finalize their decision, thereby concluding the process. This iterative design provides flexibility and ensures that users can continually refine their search until they find a restaurant that best matches their preferences [14].

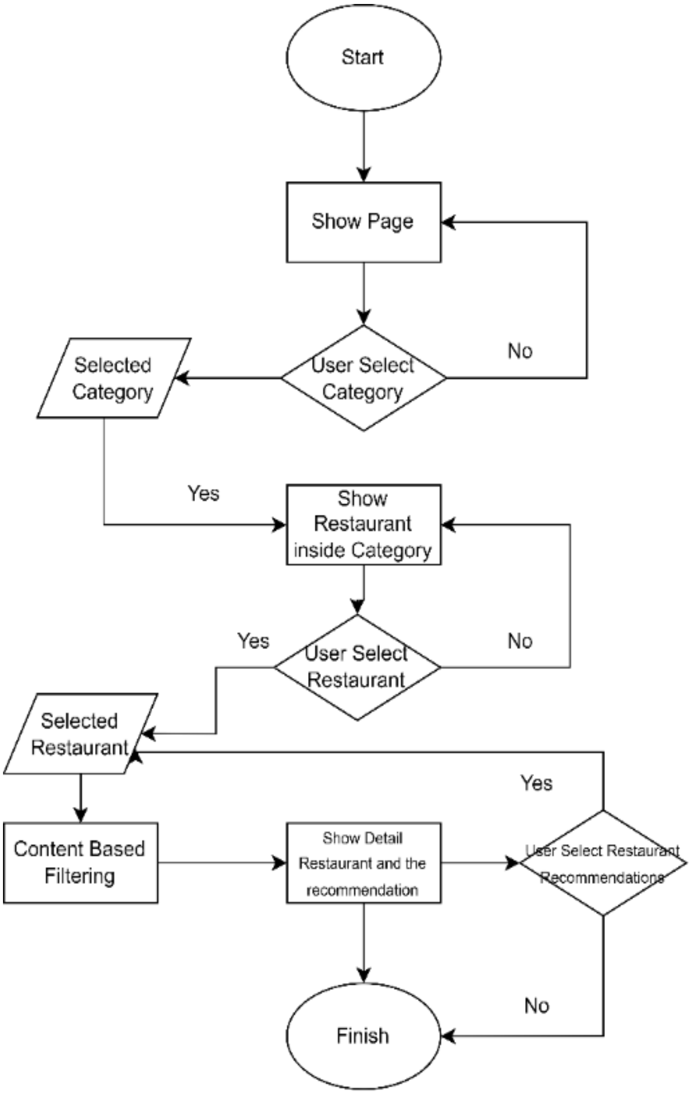

Figure 1. Flowchart System

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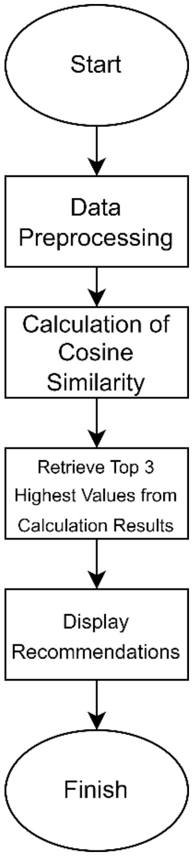

Figure 2. The Flow of the Method

Based on figure 2, the system waft for the content material filtering approach starts off evolving with the critical component step of facts preprocessing as defined earlier. This initial section entails preparing the facts to make sure that it is clean and appropriate for similarly analysis. After the data has been effectively preprocessed, the next step entails calculating cosine similarity, which measures the similarity among objects based on their homes. the use of this similarity calculation, the machine identifies and selects the top 3 gadgets with the highest similarity values. These 3 primary gadgets are then presented as pointers for the user. In addition, the specified information preprocessing procedure is shown in Distinct 3, which can be seen below. This determination provides a visual illustration of the stairs involved in cleaning and getting ready the facts for the following stages of similarity calculation and recommendation technology.

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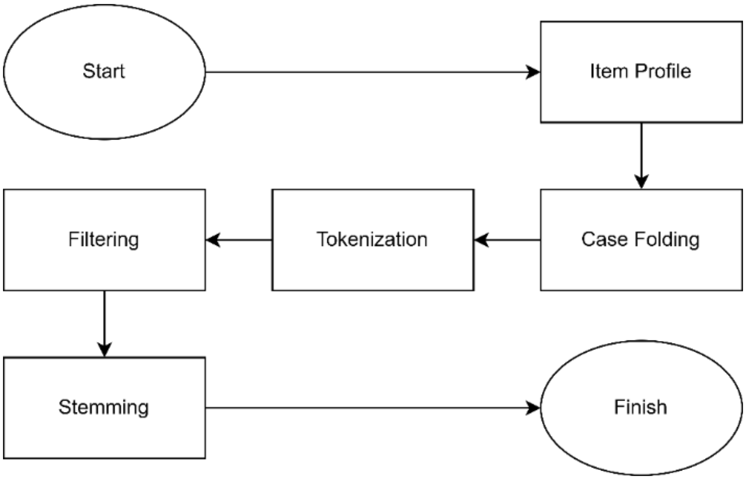

Figure 3. Preprocessing Data

Within the records preprocessing process, a sequence of meticulously planned steps is undertaken to put together the information for the following stages of analysis and advice generation formerly defined. The preliminary step involves importing the uncooked statistics into the gadget, which is crucial for developing the object profile. This object profile includes key attributes which include the eating place call, category, and deal with. once the statistics is effectively imported and the object profile is mounted, the process movements directly to Case Folding, which standardizes the text data by changing all characters to lowercase, ensuring uniformity.

Following this, the Tokenizing system is implemented, in which the text is damaged down into person tokens or words, facilitating less complicated analysis. the subsequent step is Filtering, where irrelevant or redundant information is removed to enhance the satisfactory of the records. finally, the procedure of Stemming is implemented, which reduces phrases to their root forms, in addition to refining the statistics for most appropriate performance inside the advice system. The comprehensive implementation waft of content material-based filtering, inclusive of these certain preprocessing steps, may be visualized in parent 4 below. This parent presents a clear representation of the systematic technique taken to put together the data, ensuring its readiness for correct similarity comparisons and a powerful recommendation era.

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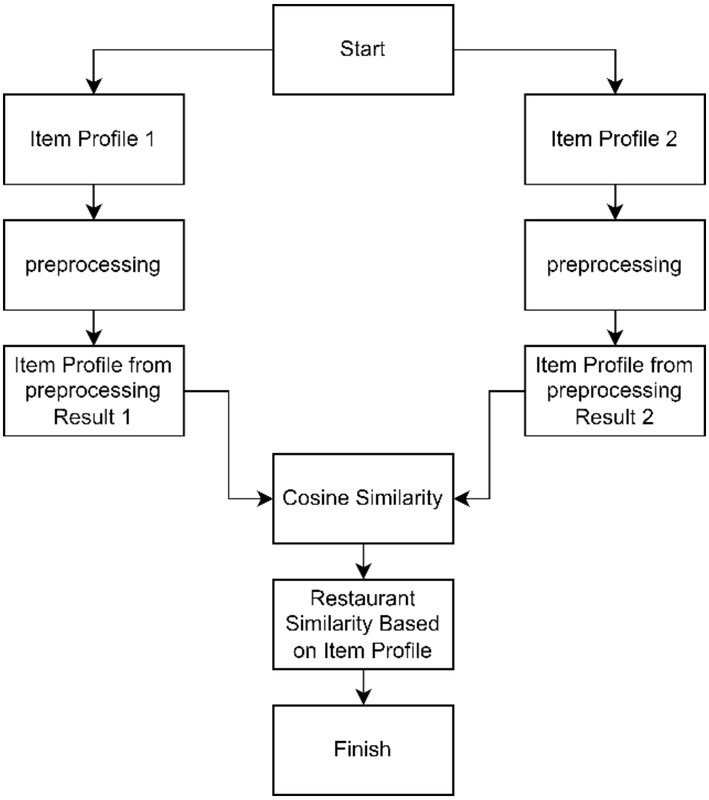

Figure 4. Implementation flow of content-based filtering

2.2. Data Processing

The preliminary stage of the technique involves a thorough statistics series. This crucial phase starts with gathering information through the usage of an immediate statistics scraper software program, which streamlines the extraction of big datasets from diverse online sources. Mainly, class data meticulously accrued from the TripAdvisor website online, presenting distinct facts about unique training of interest. simultaneously, cope with records sourced from Google Maps, ensuring accurate and complete place statistics. As quickly as those datasets are collected, they may be cautiously loaded and stored in an Excel spreadsheet, facilitating the clean dealing with and employer of the records. subsequently, the organized records are imported into a database, where it is stored securely for in addition processing and evaluation. This systematic approach to statistics series ensures that the facts are nicely organized and reachable for the subsequent levels of the content material primarily based on the Filtering technique.

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2.3. Data Preprocessing Process

The data preprocessing process has several stages, the first is the formation of an item profile, the item profile that is formed is then processed by case folding, after that the data is processed again by tokenizing, and then the data that has gone through the tokenizing process is filtered, entering the final stage, namely stemming, here the data that has been going through a process before being reshaped by changing the word into a base (removing prefixes, suffixes or word combinations).

2.4. Cosine Similarity Calculation Method

Based on similar product profiles, a fundamental concept of providing proposals is the cosine similarity content-based filtering approach [15], [16]. when a client selects an eating place, they will get hold of pointers inside the shape of a list of eating places that have profile objects just like the chosen eating place. Profile items are calculated for similarity using evaluating profile gadgets from the eating place selected with the aid of the person with profile gadgets from other eating places after going through the preprocessing level [17].

2.5. Testing Scenario

The testing phase checks whether the developed system meets the expected requirements and is relevant in providing the desired recommendations. Testing is performed by executing the testing scenarios and evaluating the similarity value. Top-N Recommendation. The output of the implementation should be cosine/similarity values between one restaurant and all other restaurants, that made use of method 1. What follows is using the similarity to recommend this content to users. These items have made their way into 3 items which in turn, hit the top-N recommendation with the highest similarity fee (higher most similar it is assumed between two compared restaurants). This will then show up as the list of 3 items that users are recommended to order when selecting a restaurant.

2.6. Implementation

The systems implementation phase for the JinjiDinner website will advance by deploying a content-based recommendation system, designed to offer personalized suggestions to users through an accessible web application. This will be developed using PHP and the Laravel 8 framework, ensuring a scalable, maintainable, and high-performance solution. The approach aims to deliver a seamless and enriching user experience with tailored recommendations based on individual preferences and behaviors.

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3. RESULTS AND DISCUSSION

3.1 Data Processing

Restaurant data is acquired by scraping category details from TripAdvisor and addresses from Google Maps, comprising a dataset of 100 entries stored in a file. This data is then imported into the system for subsequent preprocessing steps. Examples of data restaurants from the addresses can be seen in Table 1.

Tabel 1. Data Processing

Restaurant	Addresses	Category
Kesuma Restaurant	Road: Jl. Sartono No.829 District: Mantrijeron Sub-district: Kec. Mantrijeron Town: Kota Yogyakarta Province: Daerah Istimewa Yogyakarta Postal Code: 55143	Indonesian
Mediterranea Restaurant by Kamil	Road: Tirtodipuran St No.24A District: Mantrijeron Town: Yogyakarta City Province: Special Region of Yogyakarta Postal Code: 55143	Mediterranean
The House of Raminten	Road: Jl. Faridan M Noto No.7 Kotabaru District: Gondokusuman Town Yogyakarta Province: Daerah Istimewa Yogyakarta	Indonesian

3.2 Data Preprocessing Process

The data used in this stage includes information about restaurant categories and addresses. This stage is conducted to ensure the data is prepared and ready for subsequent stages. The processes carried out in this stage are as follows: Item Profile, Case Folding, Tokenizing, Filtering, and Stemming.

3.3 Item Profile

The item profile is subsequently created from the collected data. The item profile includes the restaurant name, category, and address, columns. The item profile is formed to serve as the content for each restaurant, which will be compared for similarity.

Tabel 2. Item Profile Tokenization

No	Item Profile		
	Kesuma Restaurant	Six Senses Restaurant	City Grill
1	Jl.	Jl.	Jl.
2	Sartono	DI Panjaitan	Parangtritis

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No	Item Profile		
	Kesuma Restaurant	Six Senses Restaurant	City Grill
3	No. 829,	No. 39,	No. 95,
4	Mantrijeron	Mantrijeron	Mantrijeron
5	Kota	Kota	Kec.
6	Yogyakarta	Yogyakarta	Mergangsan
7	Daerah	Daerah	Kota
8	Istimewa	Istimewa	Yogyakarta
9	Yogykarta	Yogyakarta	Daerah
10	55143	55143	Istimewa
11			Yogyakarta
12			55143

3.4 Case Folding

In this initial stage, all data is converted to lowercase and all punctuation marks are removed.

3.5 Tokenizing

In this stage, the data that has undergone the previous process is further processed by splitting the input string based on each word.

Tabel 3. Item Profile Tokenization

No	Item Profile		
	Kesuma Restaurant	Six Senses Restaurant	City Grill
1	jl	jl	jl
2	sartono	Di panjaitan	parangtritis
3	no 829	no 39	no 95
4	mantrijeron	mantrijeron	mantrijeron
5	kota	kota	kec.
6	yogyakarta	yogyakarta	mergangsan
7	daerah	daerah	kota
8	istimewa	istimewa	yogyakarta
9	yogyakarta	yogyakarta	daerah
10	55143	55143	istimewa
11			yogyakarta
12			55143

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3.6 Filtering

Next, the data that has undergone the previous process is processed again by removing words that are less important or do not have meaning in the processed data

3.7 Stemming

In the final stage, the data produced from the previous processes undergoes stemming, which converts words to their root forms by removing prefixes, suffixes, or any combination of affixes. The preprocessing results of the selected restaurants can be seen in Table 4 below.

Tabel 4. Preprocessing Results of Selected Restaurants

Restaurant	Addresses	Category
Kesuma Restaurant	jl sartono no 829 mantrijeron kota yogyakarta daerah istimewa yogyakarta 55143	indonesian

3.8 Cosine Similarity Calculation Method

In creating the Cosine Similarity calculation method for this recommendation system, there are several steps involved. The steps for calculating Cosine Similarity are as follows:

1) The first step is to compare the term frequency of each query in the selected restaurant, focusing on the category and address parameters. The next step is to calculate the similarity value for each parameter against the query. The similarity value is calculated using cosine similarity based on the weights obtained previously as shown in Equation 1.

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

2) The following step within the technique involves the meticulous calculation of the parameter weights. This section is essential as it determines the relative significance of various functions in the dataset.

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through calculating those weights, we are able to gauge the significance of every parameter, ensuring that the advice gadget can efficaciously prioritize and highlight the maximum relevant attributes.

This calculation is crucial for optimizing the performance and accuracy of the content-based filtering approach, ultimately enhancing the overall satisfactory and precision of the recommendations supplied to the customers. Through this specific and methodical approach, we make certain that the recommendation system is finely tuned to deliver the most pertinent and personalized guidelines primarily based on the calculated parameter weights.

3) The final step is to calculate the similarity fee for the deal with and class. that is accomplished via dividing the sum of the similarities via the square root of the fabricated from records a and statistics b, ensuing within the very last similarity value from the calculation.

3.9 Implementation of the Restaurant Page

The Restaurant page appears as shown in Figure 5. On this page, there are three navigation options: Home, About Us, and Categories. Home is the main page of the website, and About Us tells about JinjiDinner's purpose, Categories are categories of the restaurants. The user can first select a category to search for a desired restaurant. The advent of the eating place page can be visible in parent 5 beneath.

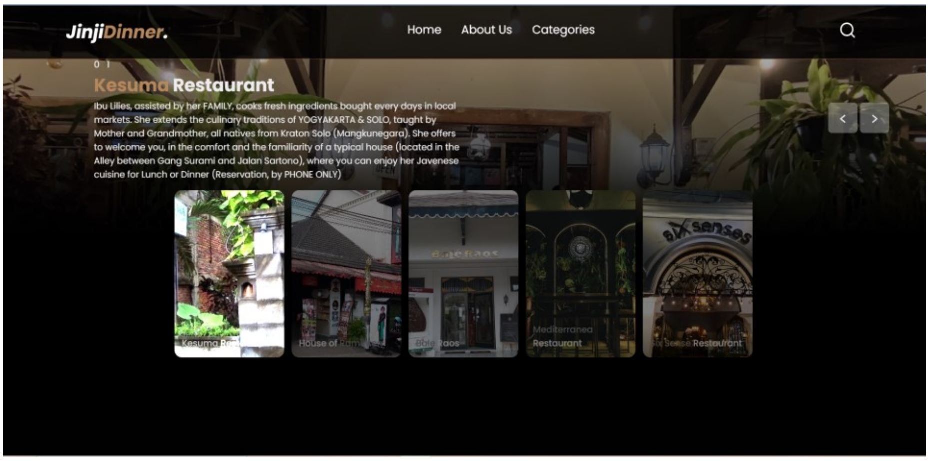

Figure 5. Restaurant Home Page

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3.10 Implementation of the Restaurant Category Page

The restaurant category page is designed to beautify consumer experience with the aid of allowing users to effects pick out their favored eating class. As soon as a category is chosen, customers are then provided with a list of eating places that fall within that chosen class. Upon selecting a particular eating place from the list, customers can view specific information approximately the eating place, which incorporates not best vital information along with the menu, hours of operation, and phone facts, however also a curated listing of encouraged restaurants. These pointers are tailored to match the first of all decided-on class and are readily positioned closest to the chosen eating place. This user-friendly interface guarantees that individuals can make properly-informed dining alternatives comfortably. The visible format and capability of the eating place category page are depicted in Figure 6, offering a clear example of the seamless navigation and complete information to be had to customers.

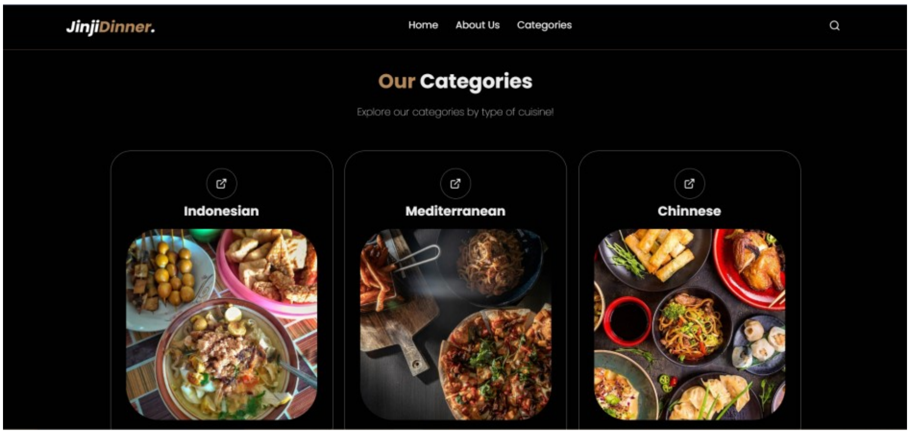

Figure 6. Restaurant Category Page

3.11 Implementation of the Detailed Restaurant Information Page

The detailed restaurant information page is designed to showcase comprehensive details about the restaurant chosen by the user. This page provides an in-depth view of the selected restaurant, featuring a high-quality image of the establishment, the type of cuisine it offers, a detailed description of its menu and ambiance, and the restaurant's precise location. Additionally, the page includes a section dedicated to recommendations, displaying three other restaurants that users might find appealing. Each recommended restaurant is represented with an image, a brief title, and its address, allowing users to easily explore alternative dining options. Users can click on any of these recommended restaurants to access their own detailed information pages, enabling them to make well-informed dining choices. For a visual representation of this layout, please refer to Figure 7.

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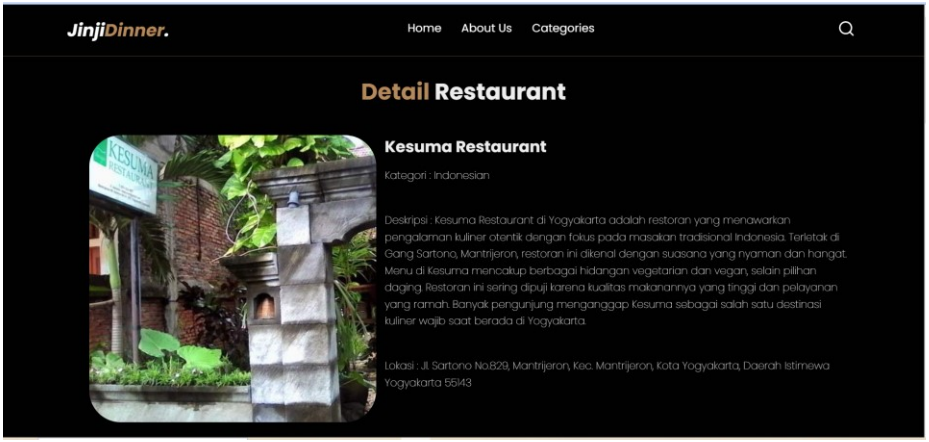

Figure 7. Detail Restaurant

Underneath is an image of the recommended eating place displayed consistent with the info of the restaurant selected by using the user. it could be visible in Figure 8 underneath. There are 2 recommendations, the primary is a recommendation primarily based on category and the second is advice primarily based on the nearest cope with

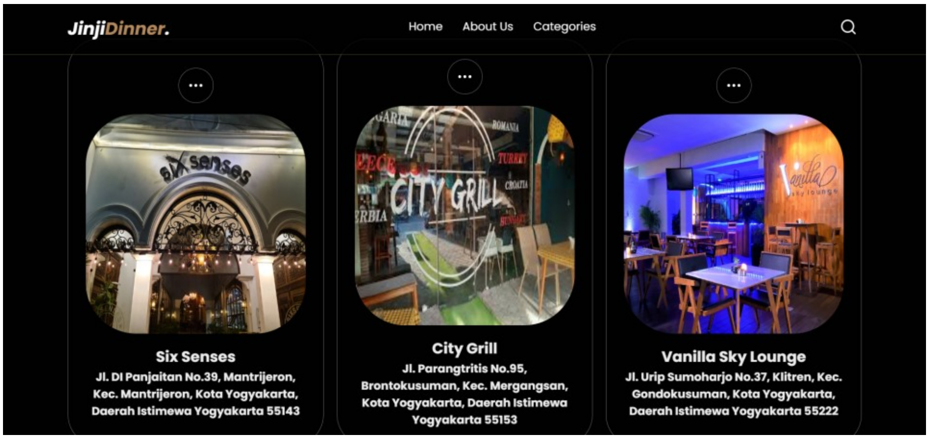

Figure 8. Detail Restaurant Category

Testing was carried out using the Top-N Recommendations test. At this testing scenario stage, 3 data were taken from different restaurants and also different categories, based on the closest address, and the similarity value are calculated. Then each restaurant has Three restaurants that are related or relevant to the same category of cuisine or the nearest address. The appearance of the Top 3 Recommendation page can be seen in Tabel 5.

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Table 5. Top 3 Recommendation

Restaurant	Similarity Value
Six Senses	0.80064076902544
City Grill	0.58333333333333
Vanilla Sky Lounge	0.5604485383178

From the recommendations obtained, then continued with the Top-N Recommendation testing process with the restaurants shown as follows:

1. Six Senses restaurant test scenario
   At restaurants, relevant recommendations are obtained. If you calculate the similarity value os **0.80064076902544**
2. City Grill restaurant test scenario
   At restaurants, relevant recommendations are obtained. If you calculate the similarity value is **0.58333333333333**
3. Vanilla Sky Lounge restaurant test scenario
   At restaurants, relevant recommendations are obtained. If you calculate the similarity value is **0.5604485383178.**

Based on the results obtained in the similarity test with the test scenario carried out, it was found that the value produced in system testing was 0.80064076902544. After testing There are 3 test results, which are all relevant.

3.12 Discussion

The content-based filtering method, leveraging Cosine Similarity, is a fundamental approach used in the restaurant selection recommendation system to provide users with personalized dining options. This method focuses on the specific attributes of restaurants, such as their categories (e.g., Indonesian, Mediterranean) and addresses, to determine their relevance to user preferences. By treating each restaurant and user query as a vector composed of its features, the system calculates the similarity between these vectors using the Cosine Similarity formula. This calculation measures the cosine of the angle between the two vectors in a multi-dimensional space, which effectively quantifies how similar a given restaurant is to what the user is searching for. A higher cosine value represents a closer match, allowing the system to rank restaurants based on their alignment with the user's criteria.

To implement this method, the recommendation system begins by preprocessing the restaurant data to create an item profile that includes all relevant features, such as name, address, and category. The preprocessing involves steps like case folding, tokenization, filtering, and stemming to standardize the data, ensuring that the comparison is accurate and efficient. For instance, case folding converts all text to

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lowercase, and tokenization splits the text into individual words or terms, which are then filtered to remove common or insignificant words. Stemming reduces words to their root form, unifying variations of the same word, which helps in creating a consistent dataset for analysis. This processed data forms the basis for calculating term frequencies for each restaurant attribute.

Once the data is preprocessed, the system calculates the term frequency of each word within the attributes, such as the restaurant category and location. These frequencies are then converted into numerical weights that reflect the importance of each term in defining the restaurant's profile relative to the user's query. The Cosine Similarity is determined by comparing these weighted vectors, focusing on the terms that overlap between the user's preferences and the restaurant profiles. The similarity score is computed using the formula that divides the dot product of the vectors by the product of their magnitudes, providing a normalized value between 0 and 1. This score indicates how closely a restaurant matches the user's input, with 1 representing an exact match.

The content-based filtering approach, specifically using Cosine Similarity, offers several advantages in the context of restaurant recommendation. It allows the system to deliver unbiased recommendations based solely on the content and features of the restaurants rather than relying on the collective behavior or preferences of other users. This is particularly useful for new or niche restaurants that may not have sufficient user ratings or historical data to be recommended through collaborative filtering methods. By focusing on the attributes that directly align with the user's preferences, the system provides highly relevant suggestions, which are more likely to satisfy individual tastes and requirements. Moreover, this method is dynamic and can adapt quickly to changes in the user's preferences or newly added restaurants in the database.

Ultimately, using a content-based filtering method with Cosine Similarity enhances the user experience by streamlining the process of selecting restaurants. It simplifies the search for dining options by filtering out irrelevant choices and highlighting those that best match the user's specific preferences, such as type of cuisine or proximity. The method also supports scalability, as it can handle large datasets and continuously update recommendations as new data becomes available. This approach ensures that users receive tailored recommendations that save time and effort, leading to a more efficient and satisfying dining decision-making process. Overall, the content-based filtering method, combined with the precision of Cosine Similarity, provides a robust solution for restaurant selection in a highly diverse culinary landscape.

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4. CONCLUSION

Content-based filtering techniques can be employed in the case study of JinjiDinner website's recommendation system, as indicated by conducted research. Recommendation results are influenced by the similarity of restaurant profile items selected by end users to other restaurant profile items. The completeness of content features also influences the similarity results. When Kesuma Restaurant is selected, the SixSenses restaurant is recommended to users because its profile item is similar to the Kesuma Restaurant profile item, namely with a similarity value of 0.80064076902544. Yammie Pathuk is not recommended or displayed because the similarity value is low, namely 0.48038446141526. Testing was carried out by comparing the recommendation results with comparative data for restaurants in the Indonesian Cuisine category, which is one of the categories in the Kesuma Restaurant profile item. The similarity calculation currently used is still based on per word, so the recommendations produced are not accurate enough. Further research can be developed by calculating the similarity value per sentence or by applying certain weights so that the resulting recommendations are more relevant.

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