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# Application of Content-Based Filtering for Moisturizer Recommendation System Based on Skin Type Suitability

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***Abstract*— Many users face significant challenges when trying to select the most suitable moisturizer for their skin. This difficulty often arises due to the overwhelming variety of available products on the market, combined with a lack of personalized information that could guide users toward the best choice. To address this issue, the present study aims to develop a recommendation system based on the Content-Based Filtering approach, which is specifically designed to align the benefits of moisturizer products with the unique needs of users' skin types. The data for this study were collected manually from 17 moisturizer products featured on the Sociolla e-commerce platform. Each product was carefully analyzed according to the descriptive information provided, including the benefits claimed and the skin types for which the product is recommended. The methodology involved several important steps: preprocessing the text from product descriptions, applying TF-IDF to assign term weights, and calculating cosine similarity scores between the user's skin profile and product attributes. The analysis revealed that products such as D10 and D6, which yielded the highest similarity values, are strongly aligned with particular skin types. The resulting system demonstrates its ability to generate relevant and personalized product suggestions without the need for prior user preference data. This study concludes that using descriptive content as the foundation for recommendation logic can significantly enhance accuracy and targeting. Future enhancements may involve expanding the product database, integrating user-generated reviews, and leveraging machine learning techniques to produce even more adaptive and intelligent recommendations.**

***Keywords*— Content-Based Filtering; Moisturizer; Skin Type; TF-IDF; Cosine Similarity;**

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## I. INTRODUCTION

Facial appearance is an important aspect that receives great attention from many individuals, especially women. This level of concern is influenced by various factors, such as genetic predisposition, overall body health conditions, and exposure to the external environment. Facial skin plays a vital role in protecting sensitive anatomical structures, including the eyes, nose, and mouth, from various potential external threats. To obtain healthy and aesthetic facial skin conditions, many individuals are willing to allocate significant financial resources in order to undergo various skin care procedures, both medical and cosmetic, as part of an effort to maintain facial health and appearance [1].

Facial skin is generally classified into five main types, namely normal, combination, oily, dry, and sensitive. Identifying skin type correctly is an essential step in determining appropriate and effective skin care products. Inaccuracy in recognizing individual skin types can lead to the use of inappropriate products, which can potentially trigger various dermatological problems. Common impacts include dull skin, irritation, blackheads, and acne. Therefore, understanding skin characteristics is an important basis for developing skin care strategies that are preventive, adaptive, and oriented towards long-term skin health [2].

In recent years, public awareness of the importance of skincare has increased rapidly. One of the most widely used products is moisturizer, because it functions to maintain skin moisture while strengthening its natural protective function. However, differences in skin types in each individual and the many variations of products on the market often make it difficult for users to determine the choice that best suits their skin needs.

Several previous studies have attempted to develop a skincare product recommendation system by utilizing the Content-Based Filtering approach. One of them was conducted by Safitri, Helilintar, and Wahyuniar (2021), who designed a skincare recommendation application based on past user preferences. The study combined a priori and content-based filtering algorithms in the product assessment process and formed relationships or associations between items to provide more relevant recommendations [3].

In a study conducted by Larasati and Februariyanti (2021), the cosine similarity method was used to measure the level of similarity between skincare products based on the description or characteristics of each product. This approach aims to identify products that have similar content, so that they can be recommended to users based on their previous preferences or needs. This method is applied in the development of a recommendation system for products from the Emina brand, with the hope of increasing the accuracy and relevance of recommendations given to users [4].

Meanwhile, research conducted by Azizah and Rozi (2024) applied the Term Frequency–Inverse Document Frequency (TF-IDF) method together with cosine similarity to measure the level of content similarity between skincare products. This approach is used in the development of a recommendation system based on the history of product use by previous users. By processing textual information from product descriptions, this system is able to identify products that have similar characteristics, so that it can provide recommendations that are more relevant and in accordance with the individual needs of users [5].

Although the Content-Based Filtering approach has been widely applied in skincare product recommendation systems, most of its implementations still focus on the history of user preferences or previous behavior, without considering the specific needs related to each individual's skin type. In addition, some recommendation systems also have limitations because they only cover products from a particular brand, thus reducing the diversity of choices for users. This study presents a different approach by matching the user's skin type profile with the description of the benefits of various skincare products. This matching process is carried out using the TF-IDF and Cosine Similarity methods, which allow the system to provide recommendations that are more personalized, contextual, and relevant to the user's skin condition.

## II. Research Methodology

The data in this study were obtained manually from the Sociolla e-commerce site (https://www.sociolla.com), by recording information from 17 moisturizer products. Each data includes brand name, product name, product benefits, and recommended skin types. The data is arranged in CSV format and used as a basis for building a Content-Based Filtering-based moisturizer recommendation system..

### A. Research Path

This research was conducted through five main stages, which include data collection, pre-processing stage, application of TF-IDF weights, similarity calculation using cosine similarity, and prototype creation, as shown in Figure 1.

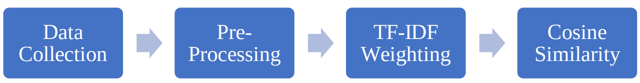


Fig. 1 Research Flow

### B. Data Collection

The collected data includes brand name, product, description/benefits, and recommended skin type, in order to obtain relevant information about the characteristics of moisturizers on the market. This data is the basis for the representation of product features and the development of a recommendation system according to the user's skin type.

### C. Data Pre-Processing

Data preprocessing is an early data mining practice that transforms raw data into a format suitable for analysis. It improves data quality through cleaning, normalization, transformation, and feature extraction, significantly improving the performance of machine learning algorithms [6]. At this stage, data is taken from the product benefits column in the form of text, which is cleaned through lowercasing, punctuation and special character removal, and stopword removal.

### D. TF-IDF Weighting

Term Frequency-Inverse Document Frequency (TF-IDF) is a statistical measure to assess the importance of words in a document relative to the set of documents, by combining term frequency (TF) and inverse document frequency (IDF) [7]. Each sentence is considered as a document, where the more frequently a word appears, the greater its weight, but the more frequently it appears in many documents, the smaller its weight [8].

Formula (1) calculates the Inverse Document Frequency (IDF), which indicates the importance of a word based on its frequency of occurrence compared to the total documents in the collection [9]. Formula (2) calculates the word weight in the TF-IDF model by multiplying the word frequency and the IDF value that has been increased by 1, to avoid division by zero or giving additional weight to words that appear in all documents [10].

$$1)\quad IDF = \left(\frac{D}{DF}\right)$$
$$2)\quad W = TF * (IDF + 1) \qquad (1)$$

Information:
TF: The frequency with which a word or term appears in a document.
IDF: The inverse of document frequency, which is calculated by the logarithm of the total number of documents divided by the number of documents containing the term.
D: Total number of documents.
DF: Number of documents containing the word or term.
W: Weight is assigned to each document.

### E. Cosine Similarity

Cosine similarity is a measure used to calculate the similarity between two items by determining the cosine of the angle between their vector representations in n-dimensional space. It ranges from -1 to 1, where 1 indicates identical directions, 0 indicates independence, and -1 indicates opposite directions. This function is widely used in applications such as recommendation systems and collaborative filtering, as it effectively captures the similarity of items based on their attributes while ignoring their magnitude [11] .

$$Cosine\ Similarity\ (Q, D) = \frac{Q \cdot D}{\|Q\|\,\|D\|} \qquad (2)$$

Information:
Q · D is the dot product between vectors Q and D.
‖ Q ‖ is the length (norm) of the vector Q.
‖ D ‖ is the length (norm) of the vector D.

## III. Results And Discussion

The moisturizer recommendation system was developed by collecting product data from Sociolla, including brand name, product, benefits, and skin type. The data was processed through text cleaning and word weighting using TF-IDF to identify important words in product descriptions.

Next, the Cosine Similarity algorithm is used to calculate the similarity between the user's skin needs and the product description. As a result, the system can recommend the appropriate moisturizer, for example for dry skin, products with benefits such as "hydrating" or "intense hydration" will be prioritized.

### *A. Text Preprocessing*

Pre -processing of the moisturizer product description to convert it into a numerical representation that can be calculated using the TF-IDF and Cosine Similarity methods. This stage includes tokenization, removing punctuation, special characters, and stop words that do not have important meaning.

Pre-processing is only applied to products with relevant keywords according to the user's skin type, making the recommendation process more efficient. In this way, only relevant descriptions are further processed in the recommendation system.

TABLE I
PRODUCT PRE-PROCESSING DATA

| Code | Product Name | Description |
|---|---|---|
| D1 | Intense Luminous Barrier Moisturizer | Moisturizer morning and night to brighten dull skin, even out skin tone and relieve redness. |
| D2 | Pure Radiance Barrier Moisturizer | Morning and night moisturizer to help fade dark spots on the face, tighten pores, and control oil. |
| D3 | Rich Skin Barrier Cream | Moisturizer that functions to lock in skin moisture and strengthen the skin barrier to maintain healthy skin. |
| D4 | Fresh Skin Barrier Cream | Moisturizer that functions to lock in skin moisture and strengthen the skin barrier to maintain healthy skin. |
| D5 | Lightening Day Gel | Morning moisturizer with a watery gel texture that is light & moisturizing with a fresh effect, and protects the skin from dullness. |
| D6 | Ms Pimple Acne Solution Moisturizing Gel | to maintain skin moisture and Rosebay Willowherb Extract which can reduce redness on the skin and prevent the growth of acne-causing bacteria. |
| D7 | Brightening Water Cream | A practical & hygienic moisturizer formulated to be a solution for dull skin and dark spots. |
| D8 | Gokujyun Ultimate Moisturizing Lotio | Locks moisture into the skin for better hydration. Skin feels smoother, softer and more elastic. |
| D9 | Daily Calm & Soothe Skin Moisturizer | skin moisturizer cream that can be used on the face & body. This product helps maintain skin moisture, helps brighten facial skin, can maintain healthy skin barrier and helps cool the skin. |
| D10 | Centella Asiatica Barrier Moisturizer | Good for treating acne-prone skin, reducing acne scars, maintaining the skin's natural moisture, and maintaining the skin barrier. |
| D11 | Yuja Symwhite 377 Dark Spot Moisturizer | helps brighten and disguise black spots from acne, provides moisture and soothes the skin. |
| D12 | Ceratinol Moisturizer | functions to help and care for the skin so that it feels tight, prevents signs of premature aging, as well as maintaining skin youth and helping to maintain the facial skin barrier. |
| D13 | Ultra Clarity Balancing Lotion | Suitable for oily skin, Alcohol-free with balanced pH levels. |
| D14 | Noni Probiotics Comfort Me Moisturizer | Moisturizes and provides a soothing effect, ideal for sensitive skin. |
| D15 | VinoHydra Sorbet Cream Moisturizer | formulated to provide hydration to the skin and help the skin regeneration process which is suitable for sensitive skin (redness). |
| D16 | Acne Expert Soothing Gel Moisturizer | Formulated with a balanced pH and a formula that absorbs quickly into the skin. Controls excess oil, maintains oil balance and helps hydrate the skin. |

### *B. TF-IDF Weighting*

In the document weighting process, each product description containing certain keywords will be given a weight value of 1. This weighting serves as an initial indicator that shows the semantic relevance between keywords and document content. The weight represents the level of information relevance in the context of a search system or recommendation system. Thus, documents that have relevant keywords will be considered more important and more worthy of being displayed as search results. This strategy is part of a simple approach to measuring document significance based on the appearance of keywords in the structure of descriptive text are written in Table 2.

Document Frequency (DF) is the number of documents in a corpus that contain a particular term or word. The Inverse Document Frequency (IDF) value is calculated using the mathematical formula IDF = log(n/DF), where n represents the total number of documents analyzed. Table 3 presents the IDF results. This formula is designed to give higher weighting to terms that rarely appear across documents, because they are considered to have stronger discriminatory power in identifying the relevance of documents to a search topic. Thus, IDF functions as a mechanism to reduce the influence of common terms and increase accuracy in information retrieval or recommendation systems.

TABLE 2
TERM WEIGHTING

| Terms | TF | | | | |
|---|---|---|---|---|---|
| | Moisturizer | Sensitive | Oil | Pimple | Skin |
| Q | 1 | 1 | 1 | 1 | 1 |
| D1 | 1 | 0 | 0 | 0 | 1 |
| D2 | 1 | 0 | 1 | 0 | 0 |
| D3 | 1 | 0 | 1 | 0 | 1 |
| D4 | 1 | 0 | 0 | 0 | 1 |
| D5 | 1 | 0 | 0 | 0 | 1 |
| D6 | 1 | 0 | 0 | 1 | 0 |
| D7 | 1 | 0 | 0 | 0 | 1 |
| D8 | 1 | 0 | 0 | 0 | 1 |
| D9 | 1 | 0 | 0 | 0 | 1 |
| D10 | 1 | 0 | 0 | 1 | 1 |
| D11 | 1 | 0 | 0 | 1 | 1 |
| D12 | 0 | 0 | 0 | 0 | 1 |
| D13 | 0 | 0 | 1 | 0 | 0 |
| D14 | 1 | 1 | 0 | 0 | 1 |
| D15 | 1 | 1 | 0 | 0 | 1 |
| D16 | 1 | 0 | 1 | 0 | 1 |
| D17 | 1 | 1 | 1 | 0 | 1 |

TABLE 3
IDF RESULTS

| Terms | DF | D/DF | IDF |
|---|---|---|---|
| Moisturizer | 15 | 1.133 | 0.054 |
| Sensitive | 3 | 5,667 | 0.753 |
| Greasy | 5 | 3,400 | 0.531 |
| Pimple | 3 | 5,667 | 0.753 |
| Skin | 14 | 1.214 | 0.084 |

The weight value of a term in a document (marked as wdt) is calculated using the formula wdt = tf × idf, where tf (term frequency) indicates how often the term appears in a document, and idf (inverse document frequency) reflects the rarity of the term across the entire document collection. The multiplication of these two components produces a weight value that represents the importance of a term in the context of a specific document and the corpus as a whole. This approach is commonly used in various information retrieval models to improve the relevance of search results or text-based content recommendations. The results obtained from this formula are presented in Table 4.

TABLE 4
WDT CALCULATION RESULTS

| Terms | Wdt = TF.IDF | | | | |
|---|---|---|---|---|---|
| | Moisturizer | Sensitive | Oil | Pimple | Skin |
| Q | 0.05 | 0.75 | 0.53 | 0.75 | 0.08 |
| D1 | 0.05 | 0 | 0 | 0 | 0.08 |
| D2 | 0.05 | 0 | 0.53 | 0 | 0 |
| D3 | 0.05 | 0 | 0.53 | 0 | 0.08 |
| D4 | 0.05 | 0 | 0 | 0 | 0.08 |
| D5 | 0.05 | 0 | 0 | 0 | 0.08 |
| D6 | 0.05 | 0 | 0 | 0.75 | 0 |
| D7 | 0.05 | 0 | 0 | 0 | 0.08 |
| D8 | 0.05 | 0 | 0 | 0 | 0.08 |
| D9 | 0.05 | 0 | 0 | 0 | 0.08 |
| D10 | 0.05 | 0 | 0 | 0.75 | 0.08 |
| D11 | 0.05 | 0 | 0 | 0.75 | 0.08 |
| D12 | 0 | 0 | 0 | 0 | 0.08 |
| D13 | 0 | 0 | 0.53 | 0 | 0 |
| D14 | 0.05 | 0.75 | 0 | 0 | 0.08 |
| D15 | 0.05 | 0.75 | 0 | 0 | 0.08 |
| D16 | 0.05 | 0 | 0.53 | 0 | 0.08 |
| D17 | 0.05 | 0.75 | 0.53 | 0 | 0.08 |

Each document is represented as a vector in the feature space, where the vector dimension is determined by the number of unique words (terms) contained in the corpus. Each component in the vector indicates the weight of each term contained in the document, and this weight is calculated based on the Term Frequency-Inverse Document Frequency (TF-IDF) value. This representation aims to describe the distribution of terms in a document numerically, thus allowing further analysis, such as measuring the similarity between documents in the vector space using statistical methods or text processing algorithms. The results obtained from this process are presented in Table 5.

TABLE 5
SWITCH CALCULATION

| Terms | WD*Wdi | | | | |
|---|---|---|---|---|---|
| | Moisturizer | Sensitive | Oil | Pimple | Skin |
| D1 | 0.0025 | 0 | 0 | 0 | 0.0064 |
| D2 | 0.0025 | 0 | 0.2809 | 0 | 0.0064 |
| D3 | 0.0025 | 0 | 0.2809 | 0 | 0 |
| D4 | 0.0025 | 0 | 0 | 0 | 0.0064 |
| D5 | 0.0025 | 0 | 0 | 0 | 0.0064 |
| D6 | 0.0025 | 0 | 0 | 0.5625 | 0.0064 |
| D7 | 0.0025 | 0 | 0 | 0 | 0 |
| D8 | 0.0025 | 0 | 0 | 0 | 0.0064 |
| D9 | 0.0025 | 0 | 0 | 0 | 0.0064 |
| D10 | 0.0025 | 0 | 0 | 0.5625 | 0.0064 |
| D11 | 0.0025 | 0 | 0 | 0.5625 | 0.0064 |
| D12 | 0 | 0 | 0 | 0 | 0.0064 |
| D13 | 0 | 0 | 0.2809 | 0 | 0.0064 |
| D14 | 0.0025 | 0.5625 | 0 | 0 | 0 |
| D15 | 0.0025 | 0.5625 | 0 | 0 | 0.0064 |
| D16 | 0.0025 | 0 | 0.2809 | 0 | 0.0064 |
| D17 | 0.0025 | 0.5625 | 0.2809 | 0 | 0.0064 |

The length of a document vector is calculated using the Euclidean norm formula, which is the square root of the sum of the squares of all term weights in the document vector, as shown in table 6. This calculation represents the magnitude or size of the vector, which provides an overview of the level of complexity or information density of a document. The higher the norm value, the higher the accumulation of term weights in the document, which indirectly reflects the relevance of the document to the entire collection. This value also plays an important role in the vector normalization process when measuring similarity between documents using methods such as cosine similarity in information retrieval systems.

TABLE 6
VECTOR LENGTH CALCULATION RESULTS

| Terms | Vector Length |
|---|---|
| D1 | 0.094 |
| D2 | 0.532 |
| D3 | 0.538 |
| D4 | 0.094 |
| D5 | 0.094 |
| D6 | 0.752 |
| D7 | 0.094 |
| D8 | 0.094 |
| D9 | 0.094 |
| D10 | 0.756 |
| D11 | 0.756 |
| D12 | 0.080 |
| D13 | 0.530 |
| D14 | 0.756 |
| D15 | 0.756 |
| D16 | 0.538 |

| D17 | 0.923 |
|---|---|

### C. *Cosine Similarity*

Cosine similarity is used as a method to measure the degree of similarity between two documents in a vector space. In the context of a ranking system, the similarity between the question document (Q) and each of the comparison documents (D1 to D17) is calculated based on the cosine angle between the two vectors. A higher similarity value indicates a greater degree of similarity, so that the document gets a higher ranking in the search results or recommendations. The results of this ranking process are presented in Table 7. This process reflects the implementation or testing stage of the system, where the effectiveness of the similarity measurement is tested to determine the relevance between documents in the analyzed corpus.

TABLE 7
RECOMMENDATION RESULTS RANKING

| TERMS | COSINE VALUE | RANKING |
|---|---|---|
| D10 | 2.519410697 | 1 |
| D6 | 2.516357676 | 2 |
| D17 | 0.667387547 | 3 |
| D13 | 0.522880029 | 4 |
| D14 | 0.447881782 | 5 |
| D2 | 0.443791232 | 6 |
| D11 | 0.314429912 | 7 |
| D15 | 0.314429912 | 7 |
| D3 | 0.078625082 | 9 |
| D16 | 0.055576778 | 10 |
| D5 | 0.000046394 | 11 |
| D8 | 0.000046394 | 11 |
| D9 | 0.000046394 | 11 |
| D4 | 0.000008130 | 14 |
| D12 | 0.000004335 | 15 |
| D1 | 0.000003680 | 16 |
| D7 | 0.000000416 | 17 |

Based on Table 7, the results of the cosine similarity calculation show that document D10 has the highest value of 2.5194, followed by D6 with a value of 2.5163. These two documents are ranked first and second because they have the highest level of similarity to the question document (Q). Meanwhile, documents D17, D13, and D14 are ranked third to fifth respectively with lower similarity values but still show significant relevance. This indicates that these documents have term weights that are in line with the query, both in terms of structure and content, so they are worthy of being the main recommendation in the system.

In contrast, documents with the lowest cosine similarity values, such as D7, D1, and D4, are ranked the lowest, namely 17th, 16th, and 14th. These three documents have similarity values close to zero, indicating that their content has little or no similarity to the query document. Documents with these low values tend to be irrelevant and are not recommended to be displayed at the top of search results or recommendation systems. Therefore, the calculation of cosine similarity has proven effective in identifying and ordering documents based on their degree of similarity to the reference or query document.

## IV. CONCLUSION

This study aims to build a moisturizer recommendation system based on Content-Based Filtering that considers the suitability of the user's skin type with the description of the product's benefits. As expected in the introduction, the developed system is able to produce relevant product recommendations through the TF-IDF and cosine similarity approaches to product description data. The test results show that products with the highest cosine similarity values, such as Centella Asiatica Barrier Moisturizer (D10) and Ms Pimple Acne Solution Moisturizing Gel (D6), can be recommended appropriately according to specific skin needs.

Thus, there is a match between the initial objectives of the study and the results obtained. This system shows effectiveness in producing more personalized content-based recommendations that are focused on specific user needs. For further development, this system can be expanded by integrating user review data, adding texture type and active content features, and implementing more complex machine learning models to improve the accuracy and flexibility of the recommendation system in real-world scenarios.

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