Deep learning-based NLP model to design text-based product recommendation system for dermatological products

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Abstract

Human skin is a complex and highly variable organ influenced by multiple factors such as skin tone, hair density, lifestyle, and environmental exposure. Dermatological disorders are one of the most widespread disorders of the world and are increasing because of many environmental, geographical factor variations. Several skin diseases are infectious in nature and require timely intervention to prevent progression and long-term complications. The shortage of dermatologists and general practitioners in developing countries makes things worse and hampers the service delivery. As a result, individuals often rely on informal recommendations or home remedies, which may worsen existing conditions. Artificial Intelligence (AI) has the potential to bridge this gap by improving access to reliable skincare knowledge and personalized product recommendations. It will enhance collaboration among physicians and cosmetic suppliers, further encouraging innovation and contribute to the better evaluation of cosmetic ingredients concerning safety and efficacy.AI applications are vast in healthcare; still, dermatology remains far behind. In this work, a text-based skincare product recommendation system is proposed using Natural Language Processing techniques. The study explores multiple NLP approaches and adopts TF-IDF for feature extraction due to its computational efficiency and suitability for unsupervised recommendation scenarios. Since TF-IDF-based systems cannot be evaluated using conventional accuracy metrics, manual validation was performed on a curated test set. Experimental results demonstrate that the proposed approach effectively recommends appropriate dermatological and natural skincare treatments based on user preferences and skin concerns

Keywords: NLP, recommendation system, Bert Embedding, Cosine similarity

1. Introduction

The skin care industry is growing substantially across the world, outdoing even the cosmetics industry, and there are no signs of holding back yet. Experiencing a considerable rise in consumer population from 2.4 billion in 2020 to a predicted 3.8 billion in 2024, the industry is likely to touch a remarkable $207.22 billion by 2028. [22] The key drivers for such growth are, in short, personal care awareness, sustainable products, and skin problems caused by environmental conditions.

On one end, where the demand is increasing, and on the other end, since the cost and side effects of commercial cosmetic products can be quite alarming, many women are turning to natural home remedies for their skin issues. But choosing the appropriate remedy for their skin can be quite confusing for them in view of so many conflicting reports available over the Internet. This study intends to resolve the problem by designing an algorithm that would suggest skin care products to the customers based on their preferences and issues.

Artificial Intelligence has shown immense progress in the field of dermatology, providing predicting models that would help patients feel satisfied with the expected outcomes. It enables patients to take informed decisions regarding cosmetic surgery with the help of visual prediction models that would provide the possibility to see the expected outcomes even before the surgery. Precision in predicting the outcomes is necessary for cosmetologists and patients to formulate feasible and satisfying plans. Unlike surgical procedures, in cosmetology, patients are treated with multiple options regarding surgery that depends on the preferences and budget of the patients. Inefficient prediction models could help cosmetologists reduce the gap caused by the deficit in patients' expectations and therefore would lead to enhanced satisfaction and boosted trust [34]. The current predicting model is inefficient and consumes a lot of time. It is useful to customers but is a hindrance to them making informed decisions because the vast amount of online information [35].

There are no efficient means available to the masses to make use of such a high quantity of product details and reviews, and as such, consumers are finding it difficult to choose the products that would take care of their needs. Thus, the need of the day is the design of specialized systems that have the potential to facilitate easy access to relevant online information of skin products through the use of specialized Machine Learning algorithms that have the capability of "replicating the acumen akin to dermatologic diagnosis and treatment" [36].

2. Literature Review

A widely used recommendation algorithm in numerous e-commerce systems is collaborative filtering. It works based on the notion of estimating user preferences based on the behaviour of similar individuals in the group or network, with the goal of presenting the user with items they like, as done in similar user profiles [19-21].

Since collaborative filtering performs well, it is incorporated in online social platforms and is behind the rapidly increasing popularity of personalized recommendations. However, collaborative filtering performs poorly when given recommendations that have few ratings since there is insufficient data that can help identify the similarity among the users. It is actually a limitation in the model because recommending things that users like are dependent on the identification of similarity. Moreover, the model overlooks the fact that people from diverse backgrounds can have similar interests. However, people who differ may display alike preferences. Also, people's preferences keep changing over time. They change with increasing years, experiences, and social environments. [38]

In an effort to mitigate the weaknesses associated with traditional rating systems, sentiment analysis proved to be a far superior alternative approach [3]. The user review analysis enabled an in-depth understanding of the products' strength measures using sentiment rankings. In a different research work, a skin care product recommender system based on the content-based filter method in an expert system paradigm has been developed. The system utilizes existing knowledge and a variety of criteria and determines the similarity of the products based on the content and the rating. The system uses the association rule mining process in determining the related items based on the criteria of support and the level of confidence. In this work, the maximum similarity of 0.447 has been achieved. In addition, the association rule mining process generates a rule with a level of support of 40% and a level of confidence of 40% with an overall confidence of 88.8%.

A deep neural network has been suggested by Lee et al. [5] for the analysis of cosmetic ingredients and prediction of product effects on the basis of facial skin analysis. The purpose of this model is to serve as a personal cosmetics recommender that takes into account the ingredients of various products along with different types of skin. The ingredient analyser, tested using four-fold cross-validation, achieved 81.7% accuracy, but lower precision (44.6%), recall (47.3%), and F1-score (43.6%). The low values are responsible to the class imbalance problem in the dataset, which caused difficulties for the model to predict the classes with less frequency.

Honma et al. proposed a system that searches through the ingredients of effective cosmetics and suggests products that include such ingredients based on reviews. Their method is to use TF-IDF to identify the ingredient names that represent the important features of the top-rated products through analyzing product descriptions and reviews. In order to test the effectiveness of the recommender system, they proposed a new metric called the "invalidated product number (IPN)", which is a measure of the rate at which the suggested products are no longer rated by the users. A smaller IPN indicates a more effective recommender. This is shown to be a reliable scheme with a 5% IPN.

Nakajima et al. [8] defined a metric called "recommended product satisfaction level" to evaluate the performance of their system. Their system employed the IF-IPF method in finding the key ingredients of high-efficacy product groups and enabled the effective recommendation of products with unexpected but relevant qualities, which users often did not expect. This is based on the use of IPF as a means of measuring ingredient rarity. Frequency, IF value, and IF-IPF value are computed for each ingredient and compared among user groups. An individual user group selects its two highest-ranked IF-IPF values. The results indicated that the IF-IPF values are positive in relation to the feedback given by the users, which in turn suggests that these ingredients act as very strong indicators of the effectiveness of such products. Products containing at least one high-ranking IF-IPF ingredient receive positive feedback continually, which further indicates that the recommender system can identify effective products. According to the authors, besides the ability to bring precision, increased personalization could also be achieved if more user attributes were incorporated beyond just age and skin quality.

Putriany et al. [9] created the skincare recommendation system to make it easier for users to choose a product. It filters products according to one's skin characteristics in order to enable informed decisions. Content-based filtering is used combined with K-means clustering, but it starts with five clusters, and the authors develop the hypothesis that the optimization of cluster numbers according to ingredient profiles may improve the recommendation accuracy.It employed a content-based filtering approach that involved recommending products based on K-means clustering with five clusters. According to the authors, the optimal number of clusters may be improved by ingredient profiles, and the accuracy of the content-based filtering approach may be enhanced. Document Term Matrix was utilized to analyze the name of the chemical compounds by employing NLP techniques, which achieved an overall accuracy of 85%. The authors added that for further refinement of recommendations, one can use other product attributes such as price, brand, and customer ratings for better matching of user preferences.

Rajegowda et al. [11] and Hansanie et al. [12] make use of convolutional neural networks to analyse the face images and identify skin type for personalized skincare recommendation in the immersive user interface. Both models reached 93% accuracy and could be further optimized by incorporating more skin attributes. Basically, skin type classification and personalized recommendation in both studies used somewhat similar approaches of CNN.

Liew et al. [14] developed a skincare product recommendation engine using the factorization machine learning algorithm. A DistilBERT-based sentiment analyser was built to gauge product sentiment from reviews and then used a CNN to classify skin type (dry, oily, combination, and normal). The authors suggest the exploration of other neural networks together with their sentiment analyser for comparison in analysis.

Fitrianah et al. [15] proposed a deep learning model for the prediction of skin concerns, which skincare products address. The authors compared LSTM and Bi-LSTM. The result showed that the performance of the Bi-LSTM model is far better than that of the LSTM one. It obtained 98.04% accuracy with a loss of 19.19%, while the LSTM achieved 94.12% accuracy with a loss of 19.91%.

Another study [17] explored the use of CNNs to classify skin types from facial images and achieved roughly 85% accuracy, with a strong performance in classification for oily skin. This denotes that deep learning-CNN-shows a promising and arguably better approach than the conventional procedures for skin type classification. They also state that with a bigger dataset, the results can be even better and quite reliable, hence suggesting room for future improvement in this field.

Hanchinal et al. [18] explored using neural networks (including CNNs and RNNs and their deep learning variants) to recommend cosmetic products based on skincare datasets. Their algorithm achieved low validation loss; however, the training loss remained higher, a problem they suggest could be mitigated by increasing the dataset size.

The work of Illia Balush et.al [19] created a fast and reliable search engine in e-commerce with the ability to suggest recommendations for users by filtering or sorting with the use of the IDEF0 algorithm that considers the logical relationship between words and not their temporal sequence, according to the concept of workflow, besides collaborative filtering algorithms.

Katarzyna Anna Tarnowska et.al [20] proposed a framework of web-based user-friendly recommender system in order to advice the business how to maximize their profit by applying an opinion mining algorithm in extracting aspect-based sentiment score per text item and further converting text into structured format where an action rule mining algorithm is applied to the data table resulting from sentiment mining.

Akhilesh Kumar Sharmaa et.al [21] applied NLP techniques and CNN to predict and suggest products with the aid of the title of the already purchased product. CNN was only applied towards the end to prepare a feature vector from the image of the products, and this vector together with the other vectors was used for prediction.

Nurul Aida Osman et.al [22] suggested incorporating traditional sentiment analysis into recommender system solutions for addressing challenges that arise when multiple domains are considered; for example, domain sensitivity in the form of a model for contextual information sentiment based on the traditional collaborative filter.
A recommendation system was developed that uses an adaptive architecture by Dietmar Jannach et al. [23], which includes enhanced mechanisms for the extraction of features, deep learning models, and sentiment analysis. Sentiment analysis of the items was conducted using online news services, blogs, social media, or from other existing recommendation systems, which can be helpful in gaining insights regarding the user's emotions by including them in the recommendation system to enhance the level of reliability in recommendations.
The results obtained after the literature review concluded that various research has also been carried out related to the analysis of skin type classification, acne vulgaris, as well as skin care product recommendations through facial analysis.

In Table I, the models, parameters, tasks, and datasets are shown.
Research Gaps identified from the literature review were:

- Contemporary research involves skin care recommendation systems for personalized beauty and makeup
- Recommendation systems are restricted to type of the skin; oily, dry, or neutral and respective skin care items.
- NLP is not incorporated for personalizing products according to ingredients [12]

3. Research Methodology

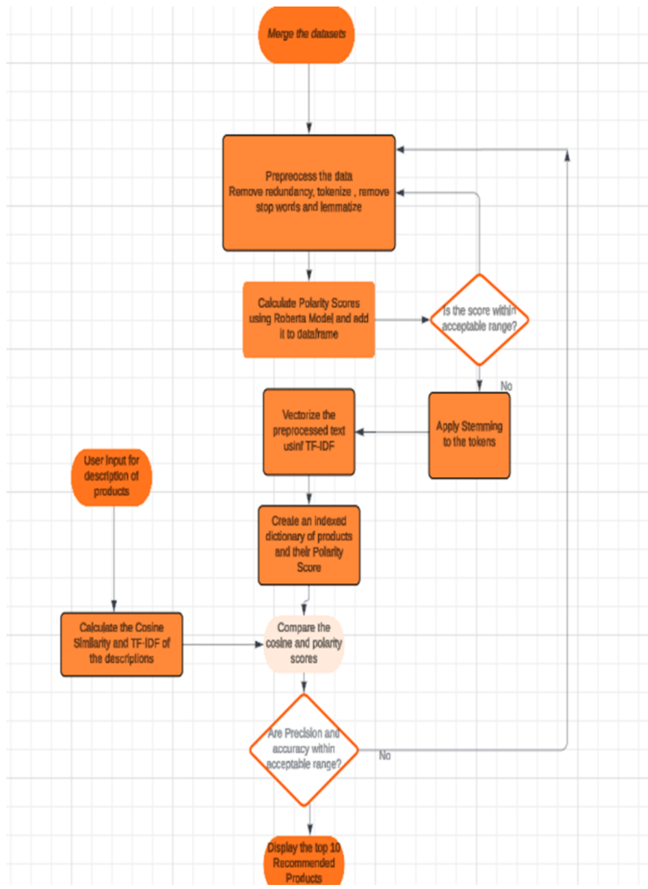

Figure 1: Proposed methodology for AI enabled NLP approach for skin care product recommendation system.

Figure 1 shows the complete model for our proposed system. The dataset including skin diseases and their corresponding products is collected from various sources like dermatologists, pharmacy stores, online sources, and field visits in Maharashtra. The data is further processed with an NLP component to map it correctly. To verify our proposed system, a particular skin disease is searched, and corresponding results containing location and price of products are provided.
The user interface is where this skincare product recommendation system begins. The users are required to enter their skin problem and whether they are using any products for that problem. If they are not using anything for their skin problem, then it asks for further details regarding their skin problem.

Finally, the interface collects the user demographics, including age, gender, skin type, lifestyle, and allergy. Depending on the user demographics, the interface determines the ingredients based on the user profiles, and based on the user demographics, it generates the list of recommended skincare products. To ensure the user experience is good, the interface uses images, customization, and descriptions for the recommended skincare products. Finally, the product recommendations are provided in text format.

The development of the system begins with data preparation and training of the model. The user and product data are then processed to create links between skin conditions and corresponding treatments and products using a Natural Language Processing model. At the same time, a pre-processed template is developed using available data from the database. The backend data is collected and validated for authenticity, after which it is divided into a training and testing set. The human-machine interface raises information by collecting User Demographics in detail, whereby each User Profile contains attributes like age, sex, skin type, lifestyle practices, and existing allergic reactions.
$U = \{u_1, u_2 \ldots, u_n\}$
This information is stored as a feature vector:
$u_i \in \mathbb{R}^d$
It is applied to compare with product metadata and ingredient suitability matrices P. The matching function f calculates the level of matching scores of user profiles and products. The interface outputs a ranked list of skincare products $\{p_1, p_2, \ldots, p_N\}$ each annotated with visual cues, feature highlights, and explanations. Weighting is determined by content-based similarity

and weighted sentiment scores.
The flowchart description of a hybrid product recommendation system based on content filtering with an additional sentiment analysis component for improving the relevance of the proposed recommendations. The system uses an n-step process in order from data aggregation to the display of top N-recommendations.

Data Acquisition and Preprocessing:

To begin with, a heterogeneous collection of data including product information and possibly demographic details is merged. Next, a combination of various preprocessing steps is employed for the text data. Duplicates in the data set are eliminated for the purpose of integrity.
The development begins with dataset creation and preprocessing. The dataset contains entries of the form:
$D=\{(p_i,d_i,c_i,r_i)\}_{i=1}^{N}$
Where:

- pip_ipi: product name
- did_idi: product description
- cic_ici: associated skin concerns
- rir_iri: user reviews

A hybrid system for recommendations is proposed. This combines the process of content analysis with sentiment analysis. The given data is split into a training and a test set with a fixed ratio of 80:20.
NLP data preprocessing is carried out with the aid of two major steps, which are data cleaning and text normalization. The data cleaning and text normalization stages are quite fundamental since they ensure that the data undergoes standardization with the elimination of any unnecessary information. The result of this stage is a better-performing NLP technique [12]. The task of tokenization is done for the purpose of breaking down text data. The removal of stop words removes words that do not add any valuable information. The lemmatization process is done to ensure words are standardized to their base forms to improve the efficiency of analysis.

Sentiment Analysis:

Sentiment polarity scores are computed based on the RoBERTa pre-trained transformer model, which was fine-tuned for sentiment classification on a corpus of product reviews. Accordingly, polarity scores that reflect the sentiment each review expressed towards a given product are appended into the dataset. A validation step follows, aimed at ensuring that the computed polarity scores fall within an acceptable range so as to retain the integrity of the sentiment analysis. In case of deviations, this prompts a feedback loop, re-evaluating the preprocessing and sentiment analysis stages.

Feature Engineering and Similarity Computation:

Subsequent to sentiment analysis, the pre-processed text undergoes TF-IDF vectorization. This technique characterizes textual data numerically by capturing the relative importance of terms within the corpus. Alternatively, optionally stemming can be applied as an alternative or supplementary word normalization technique.
For relevance quantification between user queries q and product descriptions di, we apply TF-IDF vectorization:

$$\text{TF-IDF}(t,d) = \text{tf}(t,d) \cdot \log\left(\frac{N}{\text{df}(t)}\right)$$

Each document d and query q is represented as a vector vi, and semantic similarity is measured by means of cosine similarity to obtain a similarity score for each product.

$$\text{Sim}(q,\tilde{d}_i) = \cos(\theta) = \frac{\vec{q} \cdot \vec{v}_i}{||\vec{q}|| \cdot ||\vec{v}_i||}$$

User Interaction and Recommendation Generation:

A textual description of the requirements of the user is obtained. Then, the cosine similarity measurements are calculated between the TF-IDF representation of the user description and the TF-IDF representation of the description of the available products. A dictionary with indexed values is created. Specifically, the dictionary indexes the products with their respective polarity scores.
A composite score, possibly indicative of the weighted sum of similarity and sentiment, is employed to determine the final ranking. It is calculated to combine semantic similarity γi, the polarity of sentiment si, and product rating ri. This normalization of product rating ri ensures that it is normalized to range between 0 and 1.

$$C_i = \alpha \cdot \gamma_i + \beta \cdot s_i + \delta \cdot \frac{r_i}{5}$$

$$\alpha + \beta + \delta = 1$$
$$\alpha, \beta, \delta \in [0,1]$$

Secondly, the system then combines both the cosine similarity scores and the polarity scores in ranking the products. Finally, the top N recommendations are selected based on the order of the products in descending order of Ci.

Evaluation and Output:
The system performance is gauged for various metrics that include precision and accuracy. In case of low performances that don't attain a threshold level predefined, the system parameters are changed, which might be model weights, preprocessing technique, or feature engineering strategies. Provide the top-N ranked products behind the composite score to the user. This ranked list comprises the personalized recommendations given by the system.

An NLP system inputs natural language sentences and outputs a class type for classification tasks, a sequence of labels for sequence-labelling tasks, or another sentence for the QA, dialog, natural language generation, and MT. Before applying a neural approach to NLP, we need to investigate the following two essential problems:

(1) Convert the sentence as a sequence of words into a code that the neural network understands.
(2) A Generated Label Sequence or another natural language sentence

Based on these two points, in this section, a number of popularly employed neural models in NLP will be introduced: word embedding, sentence embedding, and sequence-to-sequence models. In word embedding, words in the input sentences are represented as vectors in a continuous space. Starting from word embedding, complex models like RNN network models, CNN models, or self-attention models may be employed for feature extraction with consideration of context information in a sentence to construct context-aware word embeddings or combining all the sentence information to obtain sentence embeddings. Context-aware word embeddings can be employed in sequential labelling tasks like POS tagging or NER tasks, sentence embeddings in sentence-level tasks like sentiment analysis or paraphrase classification tasks. Sentence embeddings may also be employed to create a sequence in an RNN or self-attention model for further processing, which outlines the framework for sequence-to-sequence models with encoder-decoder architecture.

4. Results

It is at this level that the data integration from various heterogeneous sources takes place, for example, skincare product catalogues and user reviews of the same products available on online forums that are based on dermatology. Data preprocessing covers filling in missing values, removing duplicate records, and formatting variances to perform quality and integrity checks on the data. The filtered and formatted dataset thus extracted forms the basis for subsequent processing, containing information on product names, their descriptions and ingredients, ratings, and reviews.

The second step is data preparation for the text analysis itself. Product descriptions and user reviews are cleaned up using lowercasing, punctuation removal, tokenization, stop-word elimination, and lemmatization. As output, a set of normalized textual documents will be semantically preserved, linguistically simplified, while enhancing the efficiency and accuracy of the subsequent NLP tasks-vectorization and computation of similarity.

```python
def clean_text(text):
    text = re.sub(r'[^\w\s]', '', text.lower())  # remove punctuation and lowercase
    tokens = text.split()
    tokens = [t for t in tokens if t not in stopwords.words('english')]
    lemmatizer = WordNetLemmatizer()
    tokens = [lemmatizer.lemmatize(t) for t in tokens]
    return ' '.join(tokens)

df['Cleaned_Description'] = df['Product_Description'].apply(clean_text)
print(df[['Product_Name', 'Cleaned_Description']])
```

```
           Product_Name                      Cleaned_Description
0        Cetaphil Lotion        hydrating lotion dry sensitive skin
1         Neutrogena Gel     oilfree gel salicylic acid acneprone skin
2  Biotique Neem Face Wash        herbal face wash neem treat pimple
```

Fine-tuned RoBERTa transformer model calculates a sentiment polarity score. Each product now has a numerical sentiment score ranging from -1 to 1, with the positive score indicating favourable customer feedback about a product. It filters out products with mostly negative sentiments. The output is a refined subset of positively reviewed products, enhancing trust and reliability in recommendations.

```
from textblob import TextBlob

df['Sentiment_Score'] = df['Reviews'].apply(lambda x: TextBlob(x).sentiment.polarity)
print(df[['Product_Name', 'Sentiment_Score']])
```

```
            Product_Name  Sentiment_Score
0        Cetaphil Lotion             0.85
1         Neutrogena Gel             0.75
2  Biotique Neem Face Wash           0.20
```

It then converts text data into a numerical form using TF-IDF vectorization, capturing the importance of each term in the corpus. Cosine similarity is then measured between the user's input-e.g., "I have oily skin with acne"-and the product descriptions. That gives each product a score on how closely a product fits the user's needs. It then generates a ranked list of semantically relevant products.

```
# TF-IDF vectorization
vectorizer = TfidfVectorizer()
tfidf_matrix = vectorizer.fit_transform(df['combined_text'])

# Simulate a user input
user_query = "I have oily skin and acne"
user_vec = vectorizer.transform([user_query])

# Compute cosine similarity
df['Similarity'] = cosine_similarity(user_vec, tfidf_matrix)[0]
print(df[['Product_Name', 'Similarity']])
```

```
            Product_Name  Similarity
0        Cetaphil Lotion       0.162
1         Neutrogena Gel       0.512
2  Biotique Neem Face Wash     0.308
```

When a user enters their skin type concerns, as well as their skin type preference, it is compared to the query vector, as well as other product vectors. An indexing technique helps to extract the closest results quickly. A composite score, taking into account similarity, polarity, as well as ratings, is calculated for each product, thus creating a shortlist based on a skin type concern-related recommendation.

```
# Composite score = 0.4 * similarity + 0.3 * sentiment + 0.3 * rating
df['Composite_Score'] = (
    0.4 * df['Similarity'] +
    0.3 * df['Sentiment_Score'] +
    0.3 * df['Normalized_Rating']
)

# Top-N recommendations
top_n = df.sort_values(by='Composite_Score', ascending=False).head(3)
print(top_n[['Product_Name', 'Composite_Score']])
```

Lastly, the recommendations of the top-N products appear in a clear manner to the user. This recommendation is displayed along with a description, score of sentiment, and rating to ensure transparency for the user. The above is considered to result in the culmination of the recommendation engine that provides insightful and personalized skincare recommendations to users.

```
# 7. User input
user_query = "I have sensitive skin and need a gentle moisturizer"
results = recommend_products(user_query)

# 8. Display results
print("Top Recommendations (Filtered by Sentiment + Rating):\n")
print(results.to_string(index=False))
```

```
Top Recommendations (Filtered by Sentiment + Rating):

       Product_Name      Skin_Concern            Product_Description  Rating  Sentiment_Score
 Cetaphil Gentle Cream  sensitive skin    Gentle non-comedogenic cream     4.6             0.42
   Aveeno Calm Restore      redness, dry    Soothes redness, oat-based cream   4.5             0.38
 Neutrogena Hydro Boost   sensitive skin  Hyaluronic acid, fragrance-free   4.4             0.36
 Simple Light Moisturizer sensitive, dry  Lightweight, no parabens          4.3             0.34
      Nivea Soft Cream     all skin types  Nourishing cream with vitamin E   4.2             0.31
```

5. Conclusion

In this study, the design and assessment of an Artificial Intelligence (AI) based recommendation scheme for skincare products are discussed, which utilize the capabilities of Natural Language Processing (NLP) and content-based filtering. In the proposed approach, the scheme combines the demographics of the customers with the metadata of the skincare products.

In the context of the study done and based on the system that has been created, the combination of the content filter and the results of the sentiment analysis done through the system clearly shows the successful combination of the two for the recommendation of skincare products to customers.

Analysis of the results obtained indicates that the items with a higher semantic similarity to the queries posed by users, and having positive sentiment and ratings, always emerge at the top. Hypothesis two is therefore justified, and the hybrid AI models are effective for making the recommendations.

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