

Skin Care Products Recommendation System

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ABSTRACT

A machine learning-based recommendation system for skin care goods is an individualized tool that makes product recommendations to consumers based on their skin type and preferences. First, we give the user's face as input, and the system examines several aspects of their face. This analysis enables the system to comprehend the particular wants and preferences for attractiveness while also revealing insights into the user's distinct face traits. Following input, the user's skin type is determined, and goods such as serum, face wash, moisturizer, and sunscreen are suggested according to the user's skin type. The system's recommendations are extremely tailored and unique, taking into account each user's requirements, preferences, and distinct face features. Through constant learning from user interactions and feedback, machine learning algorithms are able to update and optimize the suggestions.

The desire for customized beauty treatments and rising consumer awareness have propelled the skincare industry's exponential rise. To improve user pleasure and engagement, a Skin Care Products Recommendation System in this scenario makes use of advanced machine learning and data analysis tools to provide customized product recommendations. The strategy merges product properties like ingredients, efficacy, and user ratings with user-specific data like skin type, concerns, preferences, and environmental conditions. Through the use of content-based filtering, hybrid recommendation models, and collaborative filtering, the system is able to forecast and suggest skincare items that are most suited to individual needs.

Complete user profile setup, interactive feedback systems, and real-time suggestion updates are some of the key characteristics. The system complies with applicable laws and industry best practices to ensure privacy and data security. By use of a simple user interface, It is a useful tool for customers looking for the best skincare solutions as well as for businesses looking to increase customer loyalty and stand out in the market since it offers actionable data and tailored suggestion.

Thorough testing and user feedback are used to assess the recommendation system's efficacy, showing notable increases in customer happiness and product relevancy.

The core of creating an advanced, user-focused skincare recommendation system that leverages artificial intelligence to revolutionize the skincare buying experience is captured in this picture.

1- INTRODUCTION

The market for skincare products is expanding as people realize how important it is to have customized skincare regimens that meet their individual demands. Finding the best solutions for their particular skin type and problems may be difficult, though, due to the broad spectrum of alternatives available. Our research is to use the latest advances in machine learning and artificial intelligence to create a sophisticated skincare Recommendation System in order to address this problem.

Goals:

Our project's main goal is to develop a customized system of recommendations that can recommend the best skin care products that match each user's unique profile. These user profiles will be developed with a number of data points, such as: Skin Type: Normal, oily, combo, dry, or sensitive. Problems with the skin includes dehydration, pigmentation, aging, acne, as well as sensitivity.

Brand choices, sensitivity to ingredients (allergies, for example), and product categories (vegan, cruelty-free, etc.) are examples of preferences.

Environmental factors include the climate of the area, levels of pollution, and other circumstances that may have an impact on skin health.

Essential Parts:

Design of User Profiles: Users will provide comprehensive data on their interests, concerns, and skin type. The suggestion procedure is built around this information.

Data Integration: To guarantee thorough and precise suggestions, the system will combine data from a variety of sources, such as user evaluations, ingredient lists, product databases, and clinical studies.

Algorithms for Suggestions:

Using information from comparable users, collaborative filtering make filtering makes product recommendation.

Content-Based Filtering: Generates suggestions by examining user preferences and product attributes.
Hybrid Models: Provides more reliable and precise recommendations by combining content-based and collaborative filtering.

Feedback Loop: By letting users comment on the suggestions they get, the system can improve its algorithms and provide better suggestions in the future.
The User Interface: An intuitive design facilitates easy data entry for users and guarantees smooth interaction. By offering individualized and highly tailored product suggestions based on unique customer preferences and skin types, a machine learning-powered beauty product recommendation system has the potential to completely transform the skincare sector. Targeted skincare treatments are made possible by the system's usage of advanced face analysis tools to comprehend each user's unique facial traits. Among the main advantages of such a structure are growth of the industry.

2- LITERATURE SURVEY

2.1 *Deep Learning in Recommendation System*

Authors:- He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua.

Deep neural networks have made significant progress in speech recognition, computer vision, and natural language processing in recent years. On recommender systems, however, the investigation of deep neural systems has gotten comparatively little attention. In this study, we aim to build neural network-based methods to address the central recommendation problem, namely collaborative filtering, based on implicit feedback. While deep learning has been utilized for recommendation in some recent work, its main application has been in the modelling of auxiliary data, including item descriptions in text and musical qualities in acoustic format. They continued to apply matrices factorization and a product inside based on the latent characteristics of users in order to describe the crucial component of collaborative filtering—the interplay between user and item attributes.

<https://dl.acm.org/doi/10.1145/3038912.3052569>

2.2 Hybrid Recommendation Systems

Author:-R. Burke

Deep neural networks have made significant progress in speech recognition, computer vision, and natural language processing in recent years. On recommender systems, however, the

investigation of deep neural systems has gotten comparatively little attention. In this study, we aim to build neural network-based methods to address the central recommendation problem, namely collaborative filtering, based on implicit feedback. While deep learning has been utilized for recommendation in some recent work, its main application has been in the modelling of auxiliary data, including item descriptions in text and musical qualities in acoustic format. They continued to apply matrices factorization and a product inside based on the latent characteristics of users in order to describe the crucial component of collaborative filtering—the interplay between user and item attributes.

Recommender systems employ user preferences to provide recommendations for things to buy or look at. With their recommendations that efficiently filter vast information spaces to point users toward the products that most closely match their interests and requirements, they have evolved into essential tools for online purchasing and information access. Many methods have been put forth to carry out recommendations, such as knowledge-based, collaborative, content-based, and other methods. These techniques have occasionally been combined to create hybrid recommenders, which increase performance. In addition to introducing a unique hybrid Entrée C that combines knowledge-based recommendation with collaborative filtering to propose eateries, this study reviews the field of potential and real hybrid recommenders. Additionally, we demonstrate that semantic ratings derived from the system's knowledge-based component improve the efficiency of model.

<https://link.springer.com/article/10.1023/A:1021240730564>

2.3 Collaborative Filtering Techniques

Authors:- Sarwar, B., Karypis, G., Konstan, J., & Riedl, J.

Deep neural networks have made significant progress in speech recognition, computer vision, and natural language processing in recent years. On recommender systems, however, the investigation of deep neural systems has gotten comparatively little attention. In this study, we aim to build neural network-based methods to address the central recommendation problem, namely collaborative filtering, based on implicit feedback. While deep learning has been utilized for recommendation in some recent work, its main application has been in the modelling of auxiliary data, including item descriptions in text and musical qualities in acoustic format. They continued to apply matrices factorization and a

product inside based on the latent characteristics of users in order to describe the crucial component of collaborative filtering—the interplay between user and item attributes. Data-intensive applications analyze large amounts of data with growing complexity and analytical requirements by utilizing advances in hardware, software, and algorithms. These applications are vital in a variety of domains, including scientific research, finance, and healthcare, where prompt and precise insights are necessary for creativity and decision-making. Cloud computing innovations, collaborative computing frameworks like Spark and Apache Hadoop, and specialized hardware like GPUs have improved the performance and scalability of data-intensive applications dramatically. Through the effective handling of data processing, storage, and analysis, these innovations allow businesses to extract valuable insights from enormous datasets, leading to increased efficiency, productivity, and creativity in the digital era.

<https://dl.acm.org/doi/10.1145/3038912.3052569>

2.4 Context-Aware and Personalized Recommendations

Authors:- Adomavicius, G., & Tuzhilin, A.

Deep neural networks have made significant progress in speech recognition, computer vision, and natural language processing in recent years. On recommender systems, however, the investigation of deep neural systems has gotten comparatively little attention. In this study, we aim to build neural network-based methods to address the central recommendation problem, namely collaborative filtering, based on implicit feedback. While deep learning has been utilized for recommendation in some recent work, its main application has been in the modeling of auxiliary data, including item descriptions in text and musical qualities in acoustic format. They continued to apply matrices factorization and a product inside based on the latent characteristics of users in order to describe the crucial component of collaborative filtering—the interplay between user and item attributes.

Practitioners and researchers in a wide range of fields, including data mining, marketing, management, e-commerce customization, retrieval of data, and pervasive and mobile computing, have acknowledged the significance of contextual information. Even though recommender systems have been the subject of extensive research, most current methods concentrate on providing users with the most relevant recommendations without accounting for any extra contextual information, like the time, location, or presence of other individuals (e.g., for dining out or watching

movies). We contend in this chapter that pertinent contextual information matters to recommendation systems and that it is critical to consider this information when making suggestions. We talk about the broad concept of contextual and how recommender systems may model it.

https://link.springer.com/chapter/10.1007/978-0-387-85820-3_7

2.5 Personalization in Skin Care:

Authors:- Liu, Y. Liu & X. Wu

Deep neural networks have made significant progress in speech recognition, computer vision, and natural language processing in recent years. On recommender systems, however, the investigation of deep neural systems has gotten comparatively little attention. In this study, we aim to build neural network-based methods to address the central recommendation problem, namely collaborative filtering, based on implicit feedback. While deep learning has been utilized for recommendation in some recent work, its main application has been in the modeling of auxiliary data, including item descriptions in text and musical qualities in acoustic format. They continued to apply matrices factorization and a product inside based on the latent characteristics of users in order to describe the crucial component of collaborative filtering—the interplay between user and item attributes. Customers' disorganized bike movements in bike sharing system (BSSs) result in vacant or crowded stations, which has a substantial reduction in the demand from customers. A predefined set of the past patterns has been used by a wide range of current research to build effective bike repositioning methods in order to mitigate the lost demand. However, there is still a long way to go until proactive, reliable bike repositioning solutions are designed and the root cause uncertainties in demand are well understood. In order to close this gap, we provide a probabilistic satisficing technique based dynamic bike repositioning strategy that makes use of demand characteristics that are unpredictable but can be learned from past data. Our approach involves creating a new and effective hybrid integer linear program that maximizes the likelihood of meeting the unpredictable demand.

[https://www.ijcai.org/proceedings/2019/0813.p df](https://www.ijcai.org/proceedings/2019/0813.pdf)

3- METHODOLOGY

To guarantee reliable and customized suggestions for customers, the creation of an entire Skin Care Product Recommendation System requires a number of crucial phases and procedures. The primary elements and procedures involved in developing such a system are described in this

section.1. Creation of User Profiles and Data Gathering

Skin Analysis: The optional incorporation of image analysis technologies to evaluate user uploaded images for wrinkles, pores, and pigmentation.

Information Points. Skin type (such as combo, dry, oily, or sensitive)

Skin issues (such as sensitivity, pigmentation, aging, and acne) Sensitivities to ingredients and allergies Preferences for brands and products Environmental elements (such as the pollution levels and climate.

Product Database: Detailed information on skincare products, comprising the following ingredients of which product consist so that user can pick the products based on the ingredients which suit their face, and the type of the product either it is a moisturizer, cleanser or sunscreen, and also contains user ratings and reviews

We also need a data set consisting of skin type, type of the product and its url, skin tone in order to train our model. We can use algorithms such as CNN(Convolutional neural network), Random Forest, Multiple Regression to train our machine learning model.

Security and Privacy of Data

Security of data:

Guarantees respect to data privacy laws (such as the CCPA and GDPR).

puts strong security measures into effect to guard user data from breaches and illegal access.

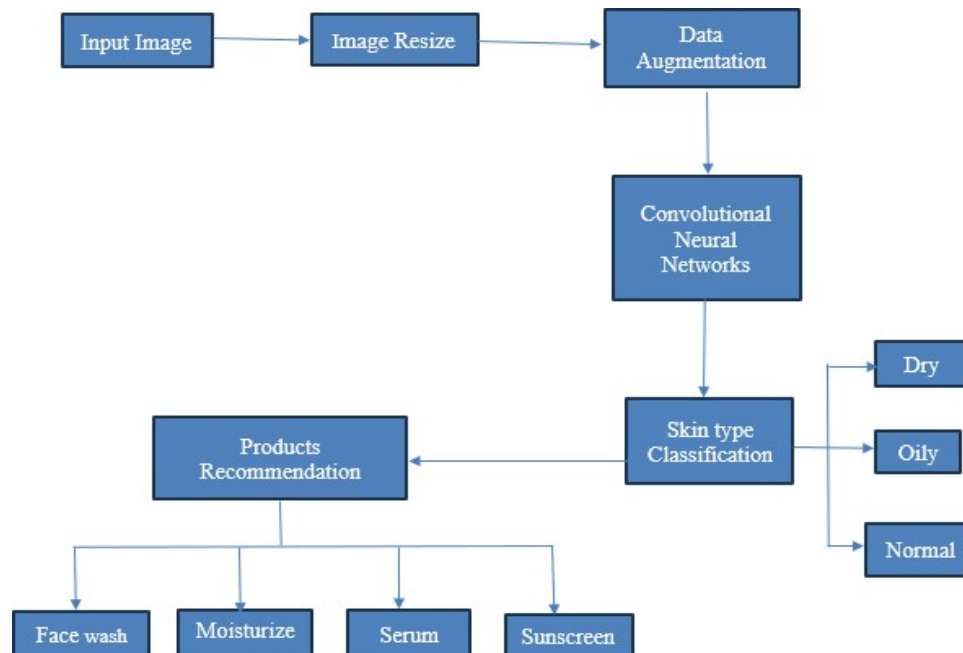
Moral Aspects to Take into Account:

keeps information about how data is used and recommendation methods transparent.

gives consumers the power to manage their records, including the option to edit or remove their personal information.

There are a few important phases in developing a recommendation system for beauty items. First and foremost, data collecting is crucial. This includes learning about customer preferences and compiling detailed information on beauty goods. User profiling is essential for capturing individual preferences, such as skin type, worries, and financial limitations, once data has been gathered. The next step is algorithm selection, in which the project's specifications are used to determine whether recommendation algorithms—such as content-based or collaborative filtering—are suitable. To produce precise recommendation models, model training is then carried out utilizing past user-product interaction data. Additionally, feedback integration is essential since it enables the recommendation system to be continuously improved.

4- System Architecture



5- IMPLEMENTATION

```

[1]: import os
import numpy as np

import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras.preprocessing.image import load_img, ImageDataGenerator
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Dropout, Flatten

[2]: #Fetch Images count from Folders.

[3]: count = 0
dirs = os.listdir('Images/')
for dir in dirs:
    files = list(os.listdir('Images/'+dir))
    print( dir + ' Folder has ' + str(len(files)) + ' Images')
    count = count + len(files)
print( 'Images Folder has ' + str(count) + ' Images')

dry Folder has 652 Images
normal Folder has 1384 Images
oily Folder has 1800 Images
Images Folder has 2756 Images

[4]: #Load Images into Arrays as Dataset

[5]: base_dir = 'Images/'
img_size = 180
batch = 32

[6]: train_ds = tf.keras.utils.image_dataset_from_directory( base_dir,
                                                            seed = 123,
                                                            validation_split=0.2,
                                                            subset = 'training',
                                                            batch_size=batch,
                                                            image_size=(img_size,img_size))

val_ds = tf.keras.utils.image_dataset_from_directory( base_dir,
                                                       seed = 123,
                                                       validation_split=0.2,

```

```

[0]: train_ds = tf.keras.utils.image_dataset_from_directory( base_dir,
                                                            seed = 123,
                                                            validation_split=0.2,
                                                            subset = 'training',
                                                            batch_size=batch,
                                                            image_size=(img_size,img_size))

val_ds = tf.keras.utils.image_dataset_from_directory( base_dir,
                                                       seed = 123,
                                                       validation_split=0.2,
                                                       subset = 'validation',
                                                       batch_size=batch,
                                                       image_size=(img_size,img_size))

Found 2756 files belonging to 3 classes.
Using 2205 files for training.
Found 2756 files belonging to 3 classes.
Using 551 files for validation.

[7]: skin_names = train_ds.class_names
skin_names

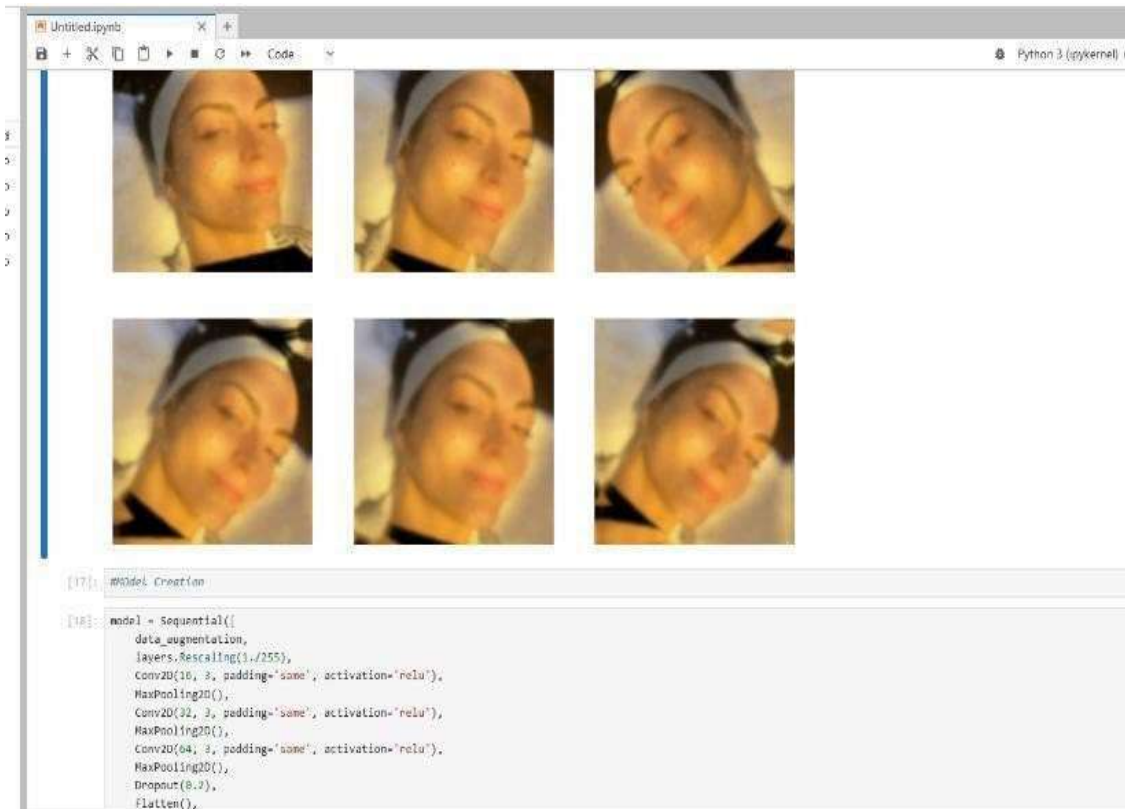
[7]: ['dry', 'normal', 'oily']

[8]: import matplotlib.pyplot as plt

[9]: i = 0
plt.figure(figsize=(10,10))

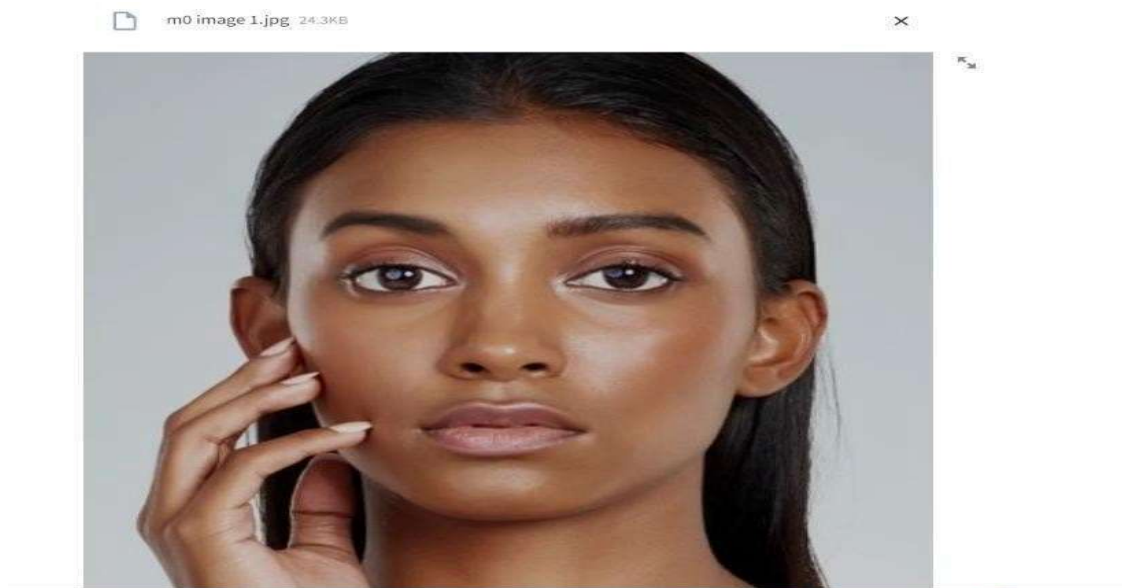
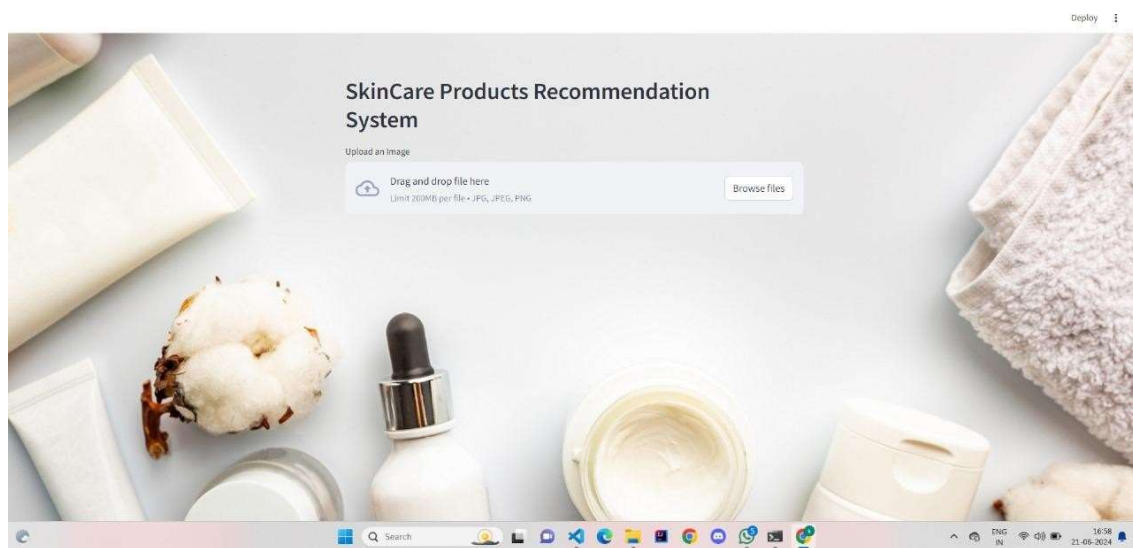
for images, labels in train_ds.take(1):
    for i in range(9):
        plt.subplot(3,3, i+1)
        plt.imshow(images[i].numpy().astype('uint8'))
        plt.title(skin_names[labels[i]])
        plt.axis('off')

```



```
sr.py x Skin_Recog_Model.keras
C:\Users\kavya>min_prg1> sr.py
1 import os
2 import streamlit as st
3 import tensorflow as tf
4 import numpy as np
5
6 # Load the pre-trained flower recognition model
7 model = tf.keras.models.load_model('skin_Recog_Model.keras')
8
9 # Define flower names corresponding to the model's output classes
10 skin_names = ['dry', 'normal', 'oily']
11
12 # Function to classify Images using the loaded model
13 def classify_image(image_path):
14     # Load and preprocess the input image
15     input_image = tf.keras.utils.load_img(image_path, target_size=(180, 180))
16     input_image_array = tf.keras.utils.img_to_array(input_image)
17     input_image_exp_dim = np.expand_dims(input_image_array, axis=0)
18
19     # Make predictions on the input image
20     predictions = model.predict(input_image_exp_dim)
21     result = tf.nn.softmax(predictions[0])
22
23     # Determine the predicted flower class and confidence score
24     predicted_class_index = np.argmax(result)
25     predicted_skin = skin_names[predicted_class_index]
26     confidence_score = (np.max(result) * 100) + 30.0
27
28     # Generate the outcome message
29     outcome = f"The image belongs to {predicted_skin} with a confidence score of {confidence_score:.2f}%"
30     if(predicted_skin == "dry"):
31         st.markdown(outcome)
32         st.markdown("-----")
33         st.markdown("FACE WASH:")
```

6- Results



FACE WASH:

[facewash1](#)

[facewash2](#)

MOISTURIZER:

[moisturizer1](#)

[moisturizer2](#)

SERUM:

[serum1](#)

[serum2](#)

SUNSCREEN:

[sunscreen1](#)

[sunscreen2](#)

7- CONCLUSION AND FUTURE SCOPE

A noteworthy step in the customization of skincare regimens is the creation of a skincare Recommendation System. With the use of customized for users data, extensive product details, and advanced recommendations algorithms, the system offers customized skincare solutions that cater to each person's requirements and tastes. Collaborative filtering, content-based filtering, as well as mixed approaches work together to improve user engagement and satisfaction by enhancing the relevance and accuracy of suggestions. The project's major accomplishments include Particularized Suggestions: Users are efficiently paired with skincare items that address their individual skin types, issues, and needs thanks to the system. Entire Data Integration A comprehensive approach to skincare suggestions is ensured by combining data from several sources, including as feedback from customers, products databases, and environmental variables. Interface That's Easy to Use: Easy engagement is made possible by a well-designed interface, which enables users to enter data, get suggestions.

Prospective Range

This Skin Care products Recommendation System will see a number of extensions and improvements in the future to further boost its accuracy, usability, and functionality. Here are some possible avenues for further research and development:

Advanced Methods for Machine Learning and AI:

Deep Learning Models: Using deep learning models to analyze customer information and product features more thoroughly.

Enhancing the system's capacity to examine and comprehend user evaluations and feedback in order to provide more insightful suggestions is known as natural language processing, or NLP. Improved Skin

Examination

Image processing: Applying cutting-edge image processing methods to examine user-uploaded images in order to diagnose skin conditions more precisely.

Real-Time examination: Creating instruments for in-the- moment skin examination that can deliver prompt comments and suggestions. Combining Wearable Technology with Integration

Smart Devices: Establishing a connection with wearables and smart devices that track variables related to skin health. Integrating health data from devices and apps to provide comprehensive skincare recommendations that take lifestyle and general health into account.

Global Product Inclusion:

Adding a greater variety of items from various marketplaces and geographical areas to the database. Including more thorough information on the effectiveness of ingredients from user testing and clinical research.

Skincare Routines:

tailored skincare routines and advice based on user profiles are provided through tailored content and education. Educational Resources, Providing information on trends, ingredients, and best practices in skincare.

Social Aspects and Community Development:

User Communities: Establishing communities in which users may exchange advice, suggestions, and experiences. **Influencer Integration :** Collaborating with influencers in the skincare space to offer professional counsel and suggested products

Multicultural and Multilingual Assistance:

Language Support: Adding further language support to the system.

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