Facial Skincare Product Recommendation Using Deep Learning Techniques

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Abstract- *Skincare products are essential cosmetics for women, especially in the modern era. To make the process easier and more effective, an innovative skincare product recommendation system has been developed. the system revolutionizes personalized skincare solutions by seamlessly integrating image processing and advanced deep learning techniques like Efficient net B0. The system goes beyond traditional classifications, accurately identifying diverse skin types, including normal, oily, dry, sensitive, or combination. In return, they receive intricate recommendations tailored not only to their specific skin types but also addressing individual concerns such as acne, pigmentation and dark circles. The suggestions provided are comprehensive, spanning a range of products including cleansers, moisturizers, serums, and more. Beyond being a mere product recommendation tool, the system says the routine to the user. By offering personalized recommendations and valuable skincare education, the innovative system becomes your trusted companion in achieving a skincare routine tailored to your unique needs, fostering a glowing and confident complexion with an over all is accuracy of 92.34%.*

Keywords- Skin care, Efficient net B0, Deep Learning, Recommendations, Acne, Skin Types

I. INTRODUCTION

In the modern world, personalized skincare are more important. The integrated system utilizes cutting edge technology, leveraging Convolutional Neural Networks and Efficient-net B0 transfer learning. the powerful combination ensures the accurate classification of facial images into categories such as Dry, Oily, Normal, Sensitive or combination, while also adeptly identifying specific concerns like dark circles and needs. Remarkably, the model maintains heightened accuracy even when faced with challenges related to image quality.

To enhance its capabilities, the system employs a region-based skin detection method within the HSV and YCbCr color spaces. the innovative approach categorizes skin tones using the six Fitzpatrick scale categories, now extended to include detailed information on dark circles. Acne classification is seamlessly integrated into the system, utilizing a Convolutional Neural Network (CNN) structure with transfer learning. Powered by a specialized dataset, our recommended system employs cosine similarity to provide tailored product suggestions.

These suggestions are intricately aligned with diverse skin metrics, encompassing considerations for dark circles. the holistic framework aims to revolutionize skincare by offering a curated selection of products designed to effectively address specific individual needs. Through the amalgamation of advanced technology and personalized insights, our system aspires to redefine the skincare experience and empower users with targeted solutions for a radiant and healthy complexion.

II. OBJECTIVES

An innovative skincare product recommendation system, driven by Convolutional Neural Networks and Efficient-net B0 transfer learning, transforms personalized skincare. Seamlessly integrating image processing, it accurately classifies diverse skin types and addresses specific concerns such as acne, pigmentation and dark circles. Users easily engage through a user-friendly interface, receiving comprehensive product recommendations spanning cleansers, moisturizers, serums and more. Beyond product suggestions, the system educates on effective skincare routines and ingredient benefits, empowering users for healthier and more confident skin. With a commitment to open-source principles, the practical system offers personalized recommendations, becoming a trusted companion in achieving a tailored skincare routine. The advanced technology, including region-based skin detection and acne classification, ensures heightened accuracy in assessing individual skincare needs. By revolutionizing the skincare experience, the holistic framework aims to redefine beauty routines, providing targeted solutions for a radiant and healthy complexion.

III. METHODOLOGY

The primary objective the research t is to develop an advanced Skincare Product Recommendation System, integrating image processing and deep learning techniques.

The system aims to provide personalized skincare recommendations by accurately identifying users' diverse skin types, including normal, oily, dry, sensitive, or combination skin. Beyond the, the system evaluates skin tones and addresses specific skincare concerns like acne, pigmentation, dark circles. To achieve precise skin type identification, employing Convolutional Neural Network (CNN) models, incorporating transfer learning with state-of-the-art architectures such as EfficientNet B0. the ensures a robust and accurate analysis of individual skin characteristics. Additionally, implement a region-based skin detection method based on color segmentation and clustering to determine skin tone, adding a comprehensive layer to the system's understanding of users' unique skincare profiles. The heart of our recommender system lies in a specialized dataset that links skincare products to specific attributes. the dataset allows us to offer users a tailored selection of products aligned with their individual skincare needs.

A. Dataset Collection & Preprocessing

Collected 1800 skin issue images, enhancing quality through noise removal and exposure normalization. Data augmentation diversified the dataset for robust model training.

B. Feature Extraction

Customer demographics and product attributes inform feature extraction. Demographics like age and skin type, alongside product details, tailor recommendations. External data integration enhances personalization.

C. Skin Type Detection

Utilized a CNN with Efficient Net B0, extracting color, texture, and statistical features for skin type classification. The model categorizes skin types such as oily, normal, dry, and sensitive.

D. Product Recommendation Engine

A content-based recommendation system prioritizes ingredient similarity within product categories, ensuring personalized skincare suggestions aligned with individual skin types.

E. Cosine Similarity Of Products

Utilized t-SNE to visualize ingredient similarities, facilitating effective product comparisons. Cosine similarity aids in assessing ingredient alignment between products, enabling tailored skincare routines.

F. Matrix Factorization

Matrix Factorization simplifies the product recommendations considering the user input and skin concerns. The method suggests products based on similarities in brand, skin type and ingredients.

IV. ARCHITECTURE

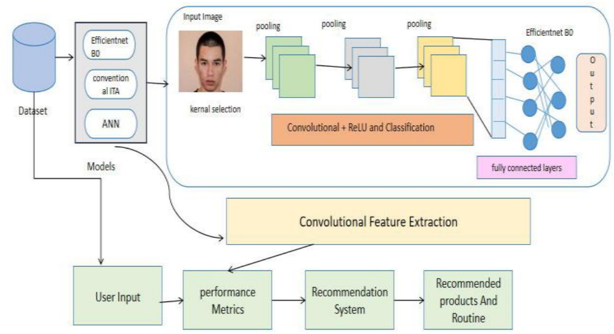

Fig.1. Proposed System Architecture

The architecture of the facial skincare products recommendation system with deep learning begins with user input, where a facial image is either captured by a camera or uploaded from a device. The heart of the system lies in the Efficient net BO convolutional neural network (CNN) architecture, specifically designed for efficient feature extraction from facial images. Convolutional layers within the architecture analyze the input image, identifying intricate facial features like the nose, eyes, mouth and the overall facial structure.

A. CONVOLUTION NEURAL NETWORK

CNN is a specialized type of neural network designed for image-related tasks. It excels in learning hierarchical features from visual data, making it well-suited for tasks like facial skincare and skin type classification. In the Facial Skincare Recommendation System, a CNN is employed for facial lesion detection, allowing the system to identify key features such as acne, dark circle and pigmentation . the information is crucial for assessing specific areas of the face, understanding facial structure and providing targeted skincare recommendations.

B. Efficient Net B0

Efficient Net is a family of neural network architectures that are known for their efficiency in terms of model size and computational resources while maintaining high accuracy. Efficient Net B0 is the baseline model of the family. It systematically scales the network in multiple dimensions, balancing model depth, width and resolution. In the Facial Skincare Recommendation System, Efficient Net B0 is used for skin type classification. By extracting features from skin images, including color, texture and statistical characteristics, the model classifies skin types into categories such as oily, normal, dry and sensitive. Efficient Net B0's efficiency is particularly beneficial for deploying the model in real-world scenarios, ensuring that it can run efficiently on various devices and platforms.

C. Facial Acne Detection (CNN)

The Convolutional Neural Network (CNN) is instrumental in identifying and detecting facial acne in the Facial Skincare Recommendation System. By training the CNN on a dataset that includes images annotated with acne regions, the model becomes adept at recognizing patterns and features indicative of acne lesions. The CNN's role is crucial in precisely pinpointing the location and severity of acne on the face, enabling a detailed analysis of skin conditions. the acne detection capability enhances the system's ability to tailor skincare recommendations by targeting specific areas affected by acne, providing users with more focused and effective skincare advice based on their individual needs.

D. Skin Type Classification

Efficient Net B0, on the other hand, contributes to the understanding of skin types. By leveraging color, texture and statistical features extracted from skin images, the model classifies users into different skin types. the classification forms the basis for recommending skincare products and routines tailored to the individual's specific skin characteristics and needs.

E. Personalized Recommendations

The combined role of CNN and Efficient Net B0 enables the system to provide personalized skincare recommendations. The facial landmarks detected by the CNN help in understanding facial structure, while the skin type classification ensures that the skincare routine suggestions are customized based on the user's unique skin attributes.

V. DATA AUGMENTATION

Data augmentation in skin tone, type and acne predictions involves artificially diversifying the training dataset by applying transformations such as rotation, flipping and color adjustments. the process increases the model's exposure to varied skin tones, enhancing its ability to generalize and predict accurately. Augmentation aids in mitigating bias and improves the model's robustness to different lighting conditions and skin variations.

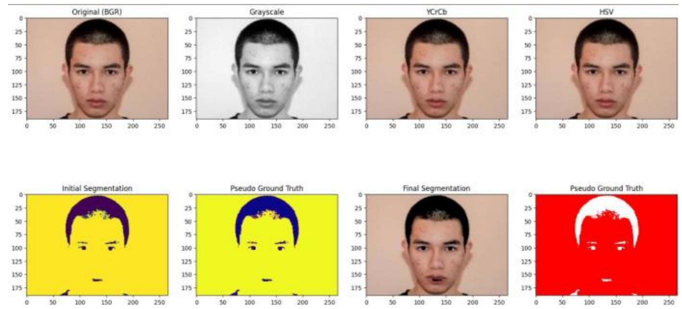

Fig.2. Data Augmentation

1. Original (BGR) - Color Information

The Original (BGR) representation allows for the analysis of different skin tones present in the image based on variations in the blue, green and red channels. the color information can be crucial for distinguishing between individuals with different complexions and identifying regions with specific tones associated with various skin types.

2. Grayscale - Intensity Analysis

The Grayscale version simplifies the image to a single intensity channel, providing insights into the overall brightness and darkness of different regions in the original image. the can be valuable for detecting subtle variations in skin tone, identifying areas with higher or lower pigmentation and potentially revealing patterns associated with certain skin conditions.

3. YCrCb - Luminance and Chrominance Separation

YCrCb separation allows for a more nuanced analysis of skin features. The Y channel, representing luminance, can highlight variations in skin brightness associated with different skin types. The Cr and Cb channels, capturing chrominance information, can be useful for discerning color variations indicative of diverse skin tones and identifying areas of interest related to skin conditions.

4. HSV - Hue, Saturation and Value

The HSV representation is particularly valuable for analyzing color-related information. Hue can help identify specific skin tones, saturation can reveal the intensity or vividness of those tones and value can provide insights into the brightness of the skin. the breakdown can be beneficial for distinguishing skin types, detecting anomalies in coloration and assessing the severity of skin conditions such as acne.

5. Initial Segmentation - Skin Regions Identification

The Initial Segmentation results demonstrate how the segmentation algorithms have initially divided the image into different regions. In the context of skin analysis, the step can help identify regions of interest related to different skin types, tones, or potential areas affected by acne.

6. Pseudo Ground Truth - Manual Reference for Skin Attributes

The Pseudo Ground Truth serves as a manually created reference for desired segmentation results. In the context of skin analysis, it can be designed to highlight specific characteristics such as skin types, tones and acne-affected areas. the serves as a benchmark for evaluating the accuracy and effectiveness of the segmentation algorithms in capturing relevant skin attributes.

7. Final Segmentation - Refined Results

The Final Segmentation represents the refined outcome of the segmentation algorithm after adjustments based on the Pseudo Ground Truth. the step is crucial for enhancing the accuracy of the segmentation process, ensuring that the algorithm aligns closely with the desired identification of skin tones, types and acne-affected regions.

VI. IMAGE HISTOGRAM

The process of skin detection involves several key steps to accurately identify skin pixels within an image. Initially, segmentation is performed, followed by the prediction of skin pixels and k-means clustering.

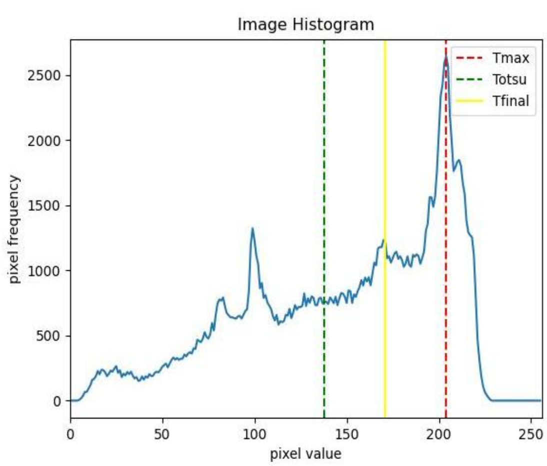

Fig.3. Image Augmentation

The initial segmentation begins with thresholding the grayscale image using a specific threshold value, which is calculated as the average of TOTSU, TFINAL and TMAX obtained from the image histogram. the thresholding process helps in separating the foreground (skin) from the background. For images with a resolution of 224 by 224 pixels, the segmentation ensures that each pixel within the image is individually evaluated based on its grayscale intensity.

The HSV and YCrCb color spaces, potential skin color pixels are selected based on predefined criteria. Typically, these criteria involve specific ranges for the Hue, Cr, and Cb components. For example, skin pixels may be identified if (Hue <= 170) and (140 <= Cr <= 170) and (90 <= Cb <= 120). These criteria ensure that only pixels within the specified color ranges are considered as potential skin pixels, allowing for precise detection within the image.

VII. RECOMMENDATION SYSTEM

The model needs to know the user's skin features to deliver the products corresponding to the top values of similarity (skin vector, product vector) for the items in the dataset that are classified into that particular category. the can be seen in the figure, It would be an intelligent move to search for products with features compatible with the skin measurements and concerns of the consumer. The user's automated cosine similarity between the user skin attribute vector and the product feature vector is used to determine the similarity of ingredients between products, the t-SNE technique is employed, leading to the reduction of the dimensionality in the data. By preserving the similarities between instances, t-SNE effectively visualizes high-dimensional data on a two-dimensional plane. Similarities are calculated based on the distances between data points and cosine similarity is used to find similarities between non-zero vectors. Unlike distance-based measures, Cosine Similarity captures more information about vector direction. In the developed system, the technique is applied when the user selects a known brand on the recommended system. The system then analyses ingredient similarities based on skin type and skin concern and recommends a complete skincare routine with up to five products in each category, based on t-SNE and Cosine Similarity.

VIII. CONCLUSION

In summary the Facial Skincare Recommendation System represents a comprehensive and intelligent solution for personalized skincare guidance. Leveraging Convolutional Neural Network (CNN) models, including Efficient Net B0, the system excels in facial skincare recommendations system and skin type classification. By extracting features from diverse facial images, it provides accurate insights into individual skincare needs, allowing for the formulation of tailored product recommendations. The system's success lies in its ability to handle various scenarios, including different skin types, lighting conditions and the presence of makeup or accessories. The inclusion of test cases ensures the robustness and reliability of the model across diverse real-world situations. It emerges as a valuable tool for users seeking personalized and effective skincare routines.

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