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Recommendation of Skincare Product using Deep Learning Techniques

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Abstract:
Faced with a booming facial skincare market fueled by economic growth and an aging population, consumers struggle to navigate the overwhelming product selection. Misinformed choices based on individual skin variations can lead to adverse reactions. To address this challenge, we propose a novel virtual skincare advisor powered by machine learning and deep learning. Our system utilizes EfficientNet with convolution neural networks to analyze user-submitted selfies, extracting detailed features and inferring key skin metrics i.e. skin tone, skin type and acne. These metrics are then processed by a machine learning engine trained to recommend suitable skincare products, fostering a personalized approach to skincare routines. CNN is compared with various optimisers and activation functions. It is found that softmax with Adam optimiser and 20 epochs achieved 99.14% accuracy compared to others.
***Key Word**: Machine learning, Deep learning, Neural Networks EfficientNet B0, Skin recognition, Skincare product recommendation*

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I. Introduction

The pursuit of optimal skincare can be a daunting task. Consumers face an overwhelming array of products and often lack access to personalized guidance. Traditional in-store consultations can be time-consuming and may not cater to individual needs. Current virtual skincare advisors utilize two main approaches: form-based and image processing. While form-based systems offer user-friendly questionnaires, they rely on collaborative filtering, potentially overlooking unknown skin concerns. Image processing systems leverage machine learning, but currently focus solely on skin type, neglecting other crucial aspects of skin health. Present skincare recommendation systems are limited only to these : Brand-centricity creates information silos, while an absence of generic recommendations restricts user choice. Additionally, common algorithms introduce bias or echo chambers, and "bestseller" recommendations neglect individual skin needs. These shortcomings necessitate the development of more comprehensive and personalized systems.

This paper proposes a recommendation system that utilizes deep learning for superior skin analysis and personalized product suggestions. This system leverages Convolutional Neural Networks (CNNs) in tandem with the cutting- edge EfficientNet model. By analysing user- submitted selfies, the system extracts detailed features and infers key skin metrics, such as tone and the presence of acne or wrinkles. These metrics are then fed into a machine learning engine that recommends suitable skincare products, fostering a user-centric and personalized approach to skincare routines. Unlike traditional consultations this system offers readily accessible, personalised recommendations anytime, anywhere. Our initial evaluation with different activation functions and optimizers demonstrates promising results, with adam optimizer and softmax function producing 99% accuracy. This paves the way for a more effective and individualized approach to skincare.

II. Related Work

Numerous studies have been conducted in the field of skin condition identification, primarily utilizing CNN, computer vision, and other machine learning algorithms. Some authors emphasized the significance of obtaining accurate results through data augmentation, while others discussed the method of image processing for identifying skin conditions. Here are some examples of such studies: The author, S. Saiwaeo et al., proposes a deep learning system to classify human skin types from images. Preprocessing is done with CLAHE and augmentation, and features are extracted using GLCM. The system achieves high accuracy and has potential applications in skincare and dermatology. However, it mainly focuses on Asian skin tones, leading to bias in the model's performance for other ethnicities. The study only evaluated normal, oily, and dry skin types, neglecting potential variations in real-world scenarios.

The author A. Alagić et al., explore the use of AI in skin type classification. They propose two methodologies: image processing and data integration. However, they acknowledge limitations like bias and neglecting non-facial factors. They envision a future where precise and personalized skin health analysis fuels preventative and proactive skincare strategies.

The author T.-Y. Lin et al., proposes a system that uses advanced computer vision to analyze facial features, skin conditions, and preferences to recommend personalized skincare products. However, it only considers acne severity and data collected for client identification, such as finger veins and financial information, raises data security concerns.

The author P. Vatiwutipong et al., examines AI's potential in improving cosmetic skin care, including product development, skin assessment, diagnosis, treatment recommendation, and outcome prediction. However, it only considers studies published between 2018-23 with limited attention given to ethical considerations and biases that could arise.

The author N. Al Abbadi et al., presents a method for training neural networks with a diverse dataset of skin textures. This helps in achieving accurate and efficient skin texture recognition, which can be useful in the field of computer vision applied to dermatology. The work holds implications for improving the understanding of skin conditions through computational methods.

The author S. Bhadula et al., presents an IoT-based system that utilizes sensors to collect data related to various skin parameters. The system enables real- time monitoring of skin conditions and offers enhanced monitoring capabilities for healthcare professionals. The system has potential applications in healthcare, wellness, and dermatology and could contribute to advancements in healthcare technology.

The author T. A. Putra et al., aims to improve skin condition prediction models by addressing challenges associated with changing data distributions and adapting to evolving data patterns. The methodology involves collecting a diverse dataset of skin images, preprocessing the data, and utilizing a machine learning model, such as a convolutional neural network. The paper introduces dynamic training strategies and testing augmentation techniques to enhance the model's adaptability, robustness, and accuracy in real-world scenarios.

The author P. Afshar et al., introduces a new method to improve the accuracy of beauty product recommendations. It assesses face illumination quality to refine the precision of recommendations. The authors' collaboration indicates a multidisciplinary approach, likely involving machine learning, computer vision, and e-commerce expertise. The goal is to optimize user satisfaction and engagement on e-commerce platforms like Amazon, by considering varying lighting conditions. This work has implications for both computer vision and the beauty industry.

The author S. Solanki et al., introduces a deep learning technique to choose appropriate beauty care products for different skin types. The authors aim to develop a model that can analyze individual skin types and recommend suitable beauty care products. This work has implications for the convergence of technology and beauty care, aligning with the growing demand for personalized and data-driven approaches in the skincare industry.

The author N. H. Hazani et al., explores the application of machine learning in analyzing human skin texture. It provides insights into potential advancements for accurate and efficient analysis of skin texture, with implications for skincare research and medical imaging technologies. The work holds significance for the convergence of technology and healthcare, addressing the need for non-invasive and technologically-driven solutions in skin texture analysis.

III. Material and Methods

Consumers face a rapidly growing selection of skincare products, with limited guidance to choose the most effective ones. Traditional recommendation systems, often reliant on demographics or subjective reviews, fail to capture the unique needs of individual skin. This disconnect between product promises and individual requirements leads to frustration and wasted resources. There is a critical need for a personalized skincare recommendation system that goes beyond superficial factors and offers data- driven product suggestions tailored to each user's unique skin characteristics.

This proposed skin assessment model aims to evaluate three critical aspects: acne severity, skin type and tone. To achieve this, we employ a combination of well-established algorithms such as K-Means, EfficientNet and a content-based recommendation system. The components of the architecture are shown in Figure 1. Initial segmentation, skin pixel prediction and the process of achieving desired skin tones using k- means clustering are the main phases. Here the focus is on collecting skin pixels effectively, which is fundamental for accurate skin tone detection. The proposed model employs a thresholding technique for image segmentation, wherein a threshold value is determined to convert the grayscale or color image into a binary representation, effectively separating the pixels of interest from the background. This threshold value is calculated by averaging the Totsu and Tmax values obtained from the image histogram of the grayscale image. We emphasize that image segmentation is a crucial aspect of image

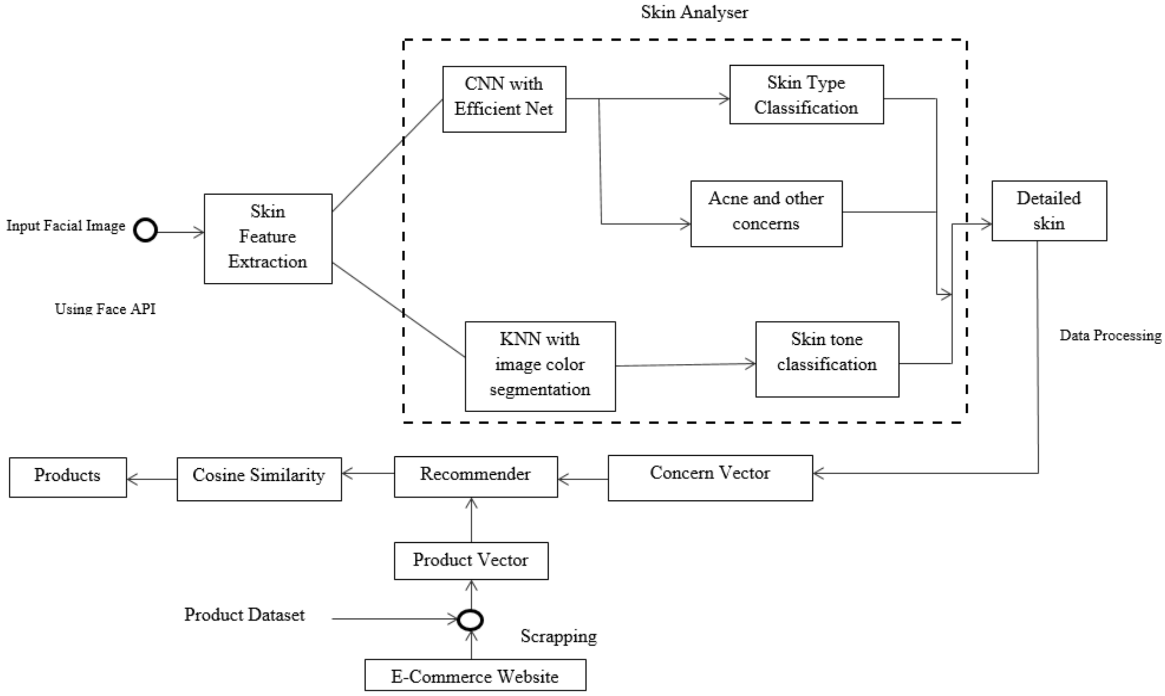

Figure 1. Proposed System Architecture

A: Skin Tone:

The process of achieving desired skin tones in the proposed method involves several key steps, namely analysis and pattern recognition, various other techniques including thresholding, clustering, transform and texturing algorithms. In this work, we specifically utilized histogram-based thresholding due to its simplicity and effectiveness. By adjusting the intensity values of the threshold, the discrimination between the background and the objects of interest can be optimized. The equation (1) illustrates the process of averaging Totsu and Tmax values to determine the threshold value, denoted as "Average."

$$\text{Average} = (\text{Totsu} + \text{Tmax})/2 \quad \text{--- (1)}$$

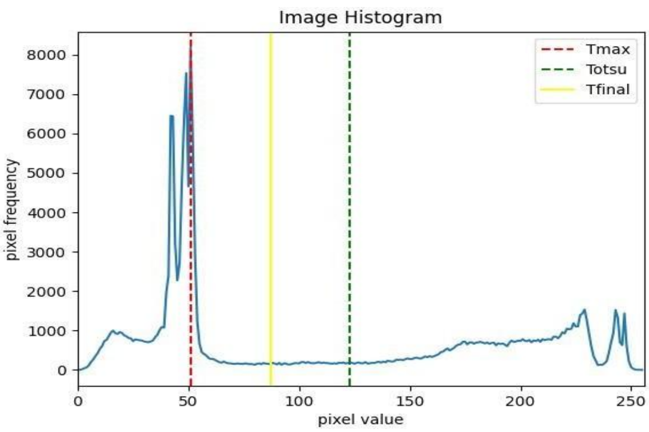

Figure 2. Histogram plot

The initial segmentation process employs a threshold value calculated as the average of Totsu and Tmax, obtained from the histogram of the grayscale image as shown in Figure 2. Subsequently, the thresholded image undergoes conversion to HSV and YCrCb color spaces, known for their reduced sensitivity to light variations. Identification of potential skin color pixels is executed using criteria such as (Hue <= 170) and (140 <= Cr <= 170) and (90 <= Cb <= 120). This selection process is preceded by plotting a histogram and image preprocessing, all laying the groundwork for the subsequent extraction of preprocessed features from the image. Utilizing K-means clustering, the final segmentation of the image is accomplished, leading to its categorization into one of six distinct skin tones. In recommendation systems, K-means clustering plays a pivotal role in grouping similar products or customers based on their characteristics or preferences. This clustering approach is particularly valuable in collaborative filtering-based recommendation systems, where users or products with akin traits or preferences are grouped together. Leveraging these groups, personalized recommendations can be generated by analyzing the behaviors and preferences of other users with similar skin types, concerns, and preferences.

By applying collaborative filtering techniques, the algorithm scrutinizes the actions and interests of a cluster of users sharing common characteristics. This analysis enables the system to suggest skincare products that align with a user's skin type, concerns, and preferences, based on the experiences and choices of other users within the same cluster. Ultimately, skincare product recommendation systems rely on predictive modeling to anticipate user behavior and preferences, tailoring recommendations that are likely to resonate with each individual's unique skincare needs.

B: Skin Type:

The analysis and categorization of facial skin types into standard, oily, and dry categories are conducted through the utilization of convolutional neural networks (CNN). Our model showcases a notable training accuracy of 87.10% and a validation accuracy of 80%, both of which attest to the robustness of our approach. To further bolster the model's performance, we employ transfer learning with EfficientNet B0, a method renowned for its effectiveness in enhancing accuracy.

EfficientNet represents a paradigm shift in the realm of convolutional neural network construction and scaling. It introduces a compound coefficient that uniformly adjusts depth, breadth, and resolution parameters, ensuring seamless integration of images with a resolution of 224 by 224 pixels into the network architecture. The term "MBConv" encapsulates a crucial component of EfficientNet's architecture—an innovative depth-wise separable convolution layer with an inverted linear bottleneck. This architectural element optimizes computational efficiency while maintaining high classification accuracy, making it a cornerstone of our model's design.

The equation $y = f7(f6(f5(f4(f3(f2(f1(x)))))))$ represents the EfficientNet-B0 design, where x is the input picture, $f1$ through $f7$ are the layers of the neural network, and y signifies the output classification label or probability distribution over the classes. This equation embodies the intricate layering and computations that drive the efficiency and accuracy of our model in classifying facial skin types.

C: Acne Severity:

The acne model evaluates skin using the acne concern level metric, categorized as Low, Moderate, and Severe. It has attained a 68% accuracy on both training and validation image sets through transfer learning, mirroring the architecture of the Skin Types CNN model. This design employs EfficientNet-B0, featuring MobileNetV2 inverted bottleneck residual blocks and squeeze-and-excitation blocks for skin tone and acne severity determination.

D: Recommender System:

The Recommender System takes two vectors for both identified skin concerns and available products, then cosine similarity is calculated between the concern and product vectors which is used to recommend products. By leveraging the cosine similarity metric, the system can identify the products that are most similar to the user's needs, which significantly improves the chances of successful product recommendations.

IV. Result & Discussions

The main objective of this stage is to determine the model with the highest accuracy for classifying skin type and skin acne. To achieve this, we experimented with different numbers of epochs, optimizers, and activation functions used to train the model.

A: Skin Type Classification:

This phase involves using a transfer learning model called EfficientNet B0 to classify skin type into three classes: oily, normal, and dry. We tested this model on multiple epochs, optimizers, and activation functions to identify the parameters that yield the highest accuracy.

B: Skin Acne Classification:

Similar to skin type classification, this phase includes several model trainings on optimisers like Adam and Adamax with different activation functions such as softmax, tanh and relu. Table 1 below shows the accuracy of different model.

Table 1: Comparison of Accuracy

Optimiser	epochs	Activation function	Training Accuracy	Validation accuracy
Adam	10	softmax	86.43 %	79.41 %
		relu	21.34 %	25.00 %
		tanh	22.23 %	21.93 %
	20	softmax	99.14 %	96.88 %
		relu	22.75 %	25.00 %
		tanh	24.03 %	25.00 %
Adamax	10	softmax	87.45 %	85.03 %
		relu	23.43 %	21.08 %
		tanh	83.56 %	75.23 %
	20	softmax	97.00 %	87.5 %
		relu	22.75 %	25.00 %
		tanh	96.99 %	87.5 %

Based on the table 1 presented, it is evident that the model trained with 20 epochs, using softmax activation function optimized with Adam optimizer, achieves an accuracy of 99.14%. As the difference between the training and validation accuracy is not significantly large, the model can be considered satisfactory

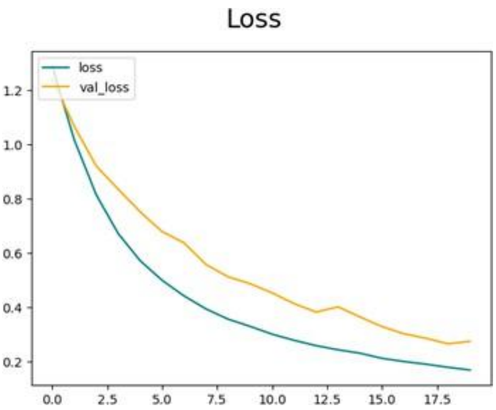

Figure 3: Training Loss vs Validation Loss

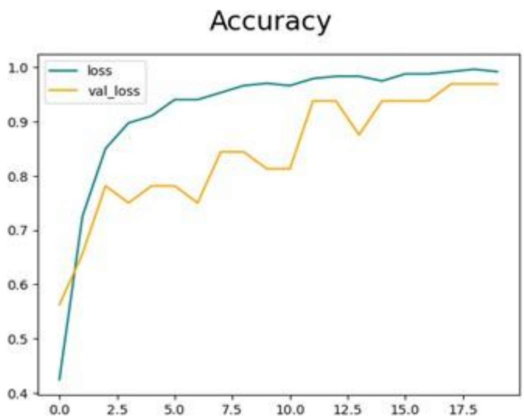

Figure 4: Training Accuracy vs Validation accuracy

The graph depicted in Figure 3 shows an inverse relationship between the loss and the number of epochs. As the number of epochs increases, the loss decreases whereas the graph in Figure 4 presents a clear correlation between the number of epochs and the accuracy of the model. As the number of epochs increases, the accuracy of the model also increases. This pattern suggests that the model is learning and improving with each epoch, making it more accurate and effective.

V. Conclusion

The proposed system captures a real-time facial image and processes it through a skin detection model to identify the skin using color space conversion and histogram analysis. The skin analyzer then determines various skin metrics, converts them into concern vectors, and recommends products that specifically target the user's skin concerns by calculating the cosine similarity between the existing product vectors and concern vectors. This system provides a comprehensive solution for identifying and addressing individual skin concerns.

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