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EfficientNet-based Expert System for Personalized Facial Skincare Recommendations

Akshya J
Department of Computational Intelligence
SRM Institute of Science and Technology, Chennai
akshyaj@srmist.edu.in

Vinit Mehra
Department of Computational Intelligence
SRM Institute of Science and Technology, Chennai
vm4739@srmist.edu.in

*M.Sundarrajan**
Department of Computer Science and Engineering
SRM Institute of Science and Technology,Chennai
sundarrm@srmist.edu.in

Pattapu Teja Sri
Department of Computational Intelligence
SRM Institute of Science and Technology Chennai
pt2549@srmist.edu.in

Mani Deepak Choudhry
Department of Information Technology,
KGiSL Institute of Technology,
Coimbatore
manideepak.c@kgkite.ac.in

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***Abstract*— In recent years, recommender systems have gained a lot of traction in both the commercial world and the academic research community. The term "recommendation system for facial skin care" refers to an automated system that gives consumers advice on which facial skin care products to use based on their specific skin type, skin issues, and preferences. Product recommendation systems analyze user data using a variety of methods, including collaborative filtering, content-based filtering, and machine learning algorithms. Better skincare results may be achieved through the usage of a suggestion system in which consumers receive advice related to their own skin issues. The problem with current models is that they don't adequately address users' issues and concerns while being based on collaborative or content-based filtering. In order to create an effective face skincare model, the authors of this study suggest a hybrid approach that integrates several existing methods (including KNN, CNN, Transfer Learning of Efficient Net B0, and a content-based filtering recommendation engine). The user's skin tone, skin type, and acne severity are all inputs into the algorithm, which then outputs a recommendation for the most suitable product. The results of a comparison between the suggested model and other models prove its superiority. Using a hybrid model that takes into account a number of different methodologies and user inputs, the article aspires to deliver a more all-encompassing and individualized solution for facial skincare recommendations. The proposed model has the potential to enhance the precision and efficiency of current skincare recommendation systems. The implementation of EfficientNet B0 improves the model's accuracy, which now has a validation accuracy of 80% and a training accuracy of 87.10%.**

Keywords: Deep Learning, Recommendation System, Skin Tone, Skin Type, Acne, Transfer Learning, EfficicentNet

I. INTRODUCTION

Facial skin care is essential for many reasons. First, it helps maintain the skin's health, which is particularly important because of the natural shedding of skin cells throughout the day. How well your face skin care will be affected by the items, you use. Investing in high-quality cosmetics may enhance your skin's current and future beauty. Keeping your face skin in good condition is essential for more than simply its appearance. It boosts your confidence and, in some instances, your sense of worth. An effective routine may help you prevent acne, reduce the appearance of fine lines, and reveal your finest skin. Acne is a common skin condition caused by the blockage of oil glands in the skin's hair follicles. Lesions known as pimples or zits result from a buildup of sebum, an oil that prevents skin from drying out, and dead skin cells in the pores.

An application that analyses a selfie for skin metrics using computer vision algorithms recommends a treatment regimen for the user's face [1]. Image processing and CNN models made extensions of skin tone, skin type, and acne concern level [2]. Using these points in time, goods with a high cosine similarity might be suggested in order of importance. A web application was built using the React-Flask framework.

Beneficial recommender systems let customers learn about new products and services they would not have otherwise discovered. When an AI algorithm, often associated with machine learning, uses data to offer more items to clients, it is known as a recommendation system [3]. Past purchases, browser history, demographic information, and other factors may all be used to identify these [4]. Many different recommender algorithms and approaches exist. However, they may often be broken down into one of three categories: collaborative filtering, content filtering, or context filtering.

Content and commerce providers widely use recommender systems when it comes to predicting customer interests and wants on a highly individualized level. Whether it's books, movies, fitness programs, or clothing, they may point buyers in the right direction [5]. Recommender systems learn about things and people's preferences, prior choices, and traits via their interactions. Actions like buying something or clicking a link fall within this category. Proposed application's architecture is shown in Fig 1, where a user's face is taken at launch, and product recommendations are made in response to the user's expressed interests and preferences [6].

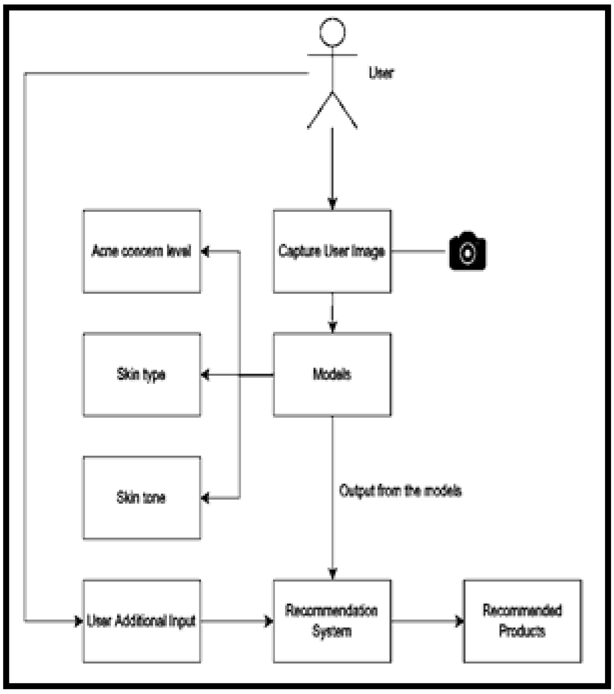

Fig. 1. Architecture Diagram for the Proposed Model

The software engineering stance of the application informs the particulars of the design. User experience design is an integral part of developing any software. Users are more likely to be pleased with a GUI if they can trust it. The fact that it is a web-based system means it can be accessed from anywhere, anytime. Our work aims to help users choose the finest skincare products for their needs by considering ingredients, brands, categories, ratings, and reviews. Models for identifying skin tone, skin type, and acne; content-based filtering; and a hybrid method are the three distinct manifestations of this. Initial segmentation, skin pixel prediction, and k-means clustering are the three primary steps in skin detection. Initial segmentation is performed using the threshold value. Thresholding, clustering, transform, and texturing algorithms are some methods that may be used to segment an image. Use of a Histogram was done for histogram-based thresholding, the most straightforward approach for picture segmentation. Methods such as the correlation matrix, clustering, and decision trees are used in collaborative filtering. Our suggested method's approach and the experimental findings are discussed in the remainder of the study.

II. LITERATURE SURVEY

Several internet applications, including e-commerce, social networks, and entertainment platforms, now include recommendation algorithms as an essential component. By examining their previous actions and behaviours, they attempt to forecast the preferences and interests of users, and then recommend pertinent products or information to improve their experience. The section initially discusses on the primary methods and methods utilised in recommendation systems in this literature study. First, the section would discuss upon the already existing in the literature. Most researchers have used the two primary filtering methods for recommendation systems in the existing literature. The first is content-based filtering, and the next is collaborative-based filtering. Because scalp issues are often complicated and it is challenging to gather photos with particular criteria to extract essential information, [7] concludes that machine learning approaches are required. The skin texture, acne severity, and skin tone are used as a model. In this work, the machine detects acne severity and skin texture in real-time utilizing OpenCV libraries developed in this application. Similar models are also available for deployment. The module analyses the user's picture following the criteria stated in [8] to identify the user's texture, skin tone, and level. Not only is [9] used to approve acceptable products, but also to label those with potentially harmful side effects; it may not be very accurate or appropriate for the end user. Therefore, it may not be able to provide them with exceptional items. In addition, Text Analysis of Product Reviews is used.

In this context, colour segmentation of an image utilizing histograms and k-means clustering was modified. According to [10], the results of this study suggest that the procedure might be helpful as a preprocessing step for any ineffective preprocessing in the segmentation and detection method. Recommendation Using Machine Learning from work [11] may provide recommenders who want to buy this article online with appropriate, reliable options. In [12], the model simply provides suggestions to the user based on their current interests. Enhanced K-Means Clustering Approach for Acne Kinds Diagnosis, based on [13] results of the performance of the K-means model, would give four output categories for acne types based on acne severity. These output categories include no, mild, moderate, and severe acne. Based on the concept of unmanned stores, [14] provides a hybrid system architecture for establishing a rapid and contactless finger-vein identification system. In addition to diagnosing acne and assessing the kind of skin on the face, this tool also gives suggestions for facial skincare items, which has included in our application since they will be helpful.

According to the study, results reported [15], the accuracy of the assessments was generally good. Compared to the items advised by this strategy, several products were excluded from the category of influential products. The concept proposed in [16] advocates for developing a system that recommends skin care products depending on the user's skin type and the composition of the product's ingredients. The chemical components of its users are detected using content-based filtering, which also identifies items with related constituent compositions. If they lack enough product expertise or have not yet identified a product they love using, users of this approach may alternatively enter their desired beauty effect rather than a product name. Modern recommender systems have several challenges, such as noise in user selection, scalability, the cold-start problem, the availability of several alternatives, and the handling of sparse data [17]. This article proposes multistage collaborative filtering as a solution to the issues of user choice noise and the availability of many choices. The filtering is performed in two stages: in the first stage, the Pearson coefficient is used as a similarity measure, and in the second stage, the longest common subsequence, also known as LCS, is used [18]. When the results are further compared with filtering conducted in a single site, it is discovered that the performance of multistage collaborative filtering is significantly improved across the datasets used [19]. From the review, a lot of limitations are identified from the existing systems. Several current models make use of general classifications of skin kinds and diseases, which might not accurately reflect the particular requirements of different users. Due to the absence of personalization, some users may not receive the best recommendations. Users may find it challenging to comprehend why particular products are recommended because many recommendation systems utilize complicated algorithms to produce recommendations. The recommendations may become less trusted and credible as a result of this lack of transparency. This paper tries to solve some of the problems in the existing research works.

III. METHODOLOGY

The suggested model is used to assess the amount of acne and skin type and tone. Several well-known algorithms, such as K-Means and EfficientNet, in addition to a content-based recommendation model, are included in the model so that it may provide the desired results. The following models and approaches are broken down into individual modules and discussed in this section.

A. Recommendation for Skin Tone

The skin tone can only be obtained by first locating and isolating the pixels that make up the skin, after which the color values must be assigned to the category corresponding to the desired skin tone. The technique of skin detection consists of three basic operations: initial segmentation, skin pixel prediction, and k-means clustering. Each of these procedures is described below. In light of this research's outcomes, collecting skin pixels was carried out appropriately. In this proposed model, the use of a thresholding technique for image segmentation is performed. By choosing a threshold value that distinguishes the pixels of interest from the background, the grayscale or colour image is converted into a binary image using the thresholding technique, which is frequently used in image segmentation. The first segmentation is carried out following the threshold value, which is calculated by averaging the TOTSU and TMAX values. Image analysis and pattern recognition are generally involved in the initial phase of image segmentation. These values were retrieved from the image histogram of the grayscale picture. Image segmentation may be done using many techniques, such as thresholding, clustering, transform, and texturing algorithms. Among these techniques is also the possibility of using texture algorithms. Histogram-based thresholding is the method of image segmentation that is the simplest to comprehend, and this method was also the one that that was utilized. Adjusting the threshold's intensity values makes it possible to differentiate between the background and the item (or objects) of interest when utilizing a histogram-based thresholding strategy. This is accomplished by modifying the threshold's intensity value. If it is assumed that TOTSU and TMAX are two numbers that need to be averaged for a recommendation system, the equation for doing so can be written as in 1:

$$Average = (TOTSU + TMAX) / 2 \quad (1)$$

In this case, "Average" refers to the combined total of TOTSU and TMAX.

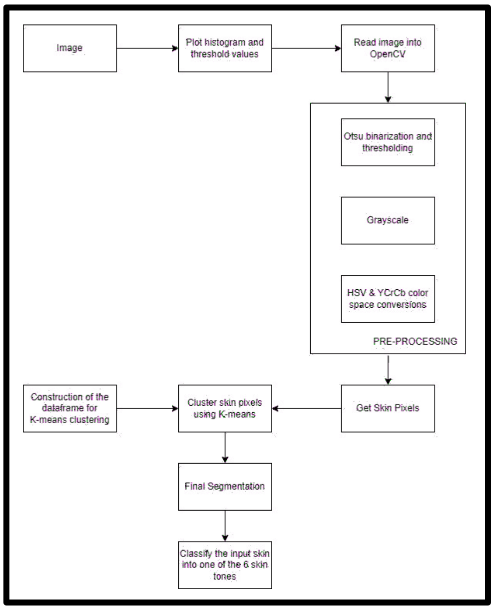

Fig. 2. Design Diagram – Skin Tone

The architectural model for determining skin tone is given in Fig. 2. First, a histogram is plotted. Then the image is preprocessed, all in preparation for the last step, which is the extraction of the preprocesses from the image. And with the assistance of K-means clustering, the final segmentation of the picture is obtained, and eventually able to categorize it as belonging to one of the six different skin tones. In recommendation systems, K-means clustering can be used to group comparable products or customers together based on their traits or preferences. Then, based on this grouping, consumers can receive recommendations. K-means clustering can be used in collaborative filtering-based recommendation systems to put users or products with similar traits or preferences together. Then, these groups can be utilized to create user suggestions based on the preferences of other group members.

To create recommendations for a specific user, collaborative filtering examines the actions and interests of a group of similar users. By analysing the behaviour and preferences of other users with comparable skin types, concerns, and preferences, this technique can be utilised to provide recommendations. The algorithm might suggest a certain skin care product to a user, for instance, if their skin type and concerns match those of other users who have expressed interest in that product. In order to produce recommendations that are likely to be successful for a specific person based on their skin type, concerns, and preferences, skin care product recommendation systems generally make predictions about user behaviour and preferences as well as the characteristics of skin care products.

B. Recommendation for Skin Type

The image is analyzed and classified using convolutional neural networks (CNN), dividing face skin types into standard, oily, and dry. With a training accuracy of 87.10% and a validation accuracy of 80%, transfer learning (EfficientNet B0) is being used to increase the model's accuracy, which currently has a training accuracy of 87.10%. EfficientNet is an approach for the building and scaling of convolutional neural networks. It uses a compound coefficient to consistently scale all depth, breadth, and resolution parameters. Table I, displays the total number of layers included in the EfficientNet-B0 architecture. Images with a resolution of 224 by 224 pixels may be uploaded to the network without issue. The term "MBConv" refers to a depth-wise separable convolution layer with an inverted linear bottleneck. When x is the input picture, $f1$ through $f7$ are the layers of the neural network, and y is the output classification label or probability distribution over the classes, the equation that represents the EfficientNet-B0 design is given in 2.

$$y = f7(f6(f5(f4(f3(f2(f1(x))))))) \tag{2}$$

TABLE I. LAYERS OF EFFICIENTNET- B0

Stage i	Operator F_i	Resolution H_i x W_i	#Channels C_i	#Layers L_i
1	Conv 3x3	224x224	32	1
2	MBConv1,k3x3	112x112	16	1
3	MBConv6,k3x3	112x112	24	2
4	MBConv6,k5x5	56x56	40	2
5	MBConv6,k3x3	28x28	80	3
6	MBConv6,k5x5	14x14	112	3
7	MBConv6,k5x5	14x14	192	4
8	MBConv6,k3x3	7x7	320	1
9	Conv 1x1 and Pooling & FC	7x7	1280	1

C. Acne Severity

One of the metrics about the skin is called the acne concern level, broken down into three levels: Low, Moderate, and Severe. The model has achieved an accuracy of 68% across both the training and validation image sets by using transfer learning in the model's design. This model's architecture is analogous to the Skin Types CNN model. The design diagram for determining skin tone and the severity of acne using EfficientNet is shown in Fig. 3, The primary EfficientNet-B0 network is constructed around the MobileNetV2 inverted bottleneck residual blocks in addition to the squeeze-and-excitation blocks.

D. Working of Proposed Recommender 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. This can be seen in Fig. 4, 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 may be used to convey this likeness.

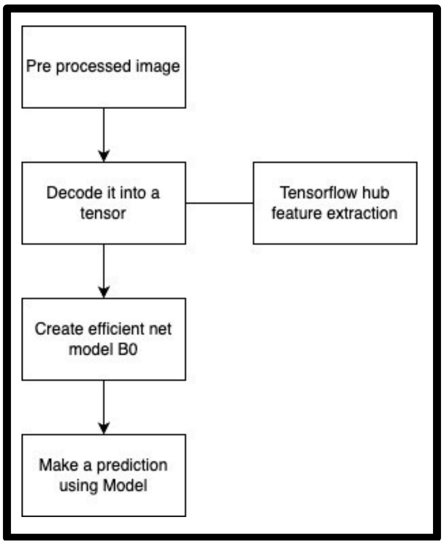

Fig. 3. Working of Recommendation System – Acne and Skin Type

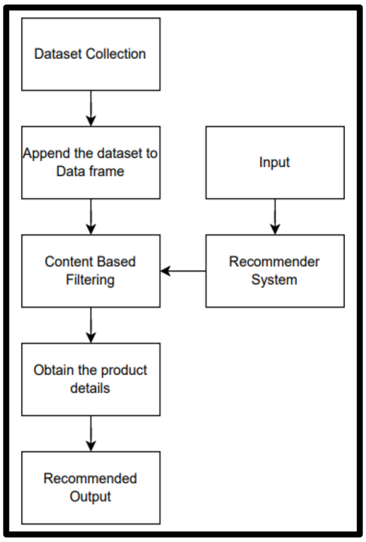

Fig. 4. Working of User's Recommender System

IV. EXPERIMENTAL RESULTS

The data training is done using the Python programming language and Tensorflow. Library (number 8) Plotting and other data processing tasks are accomplished using Matlab. Performance of numerous measurements at the exact location while gently moving the sensor head around the region. After that, the model has used to Determine the skin type of the individual whose skin was measured. The total number of spectra included in our database of skin spectra is. 216. All of the spectra that were measured from the same source are labeled by hand. Skin types of the same individual must be shared throughout the same body area. The layer of skin The type is determined by the skin types that make up most of the spectra taken from the same region of the same person's body and comparing them to the planned approach. The ratio of the number of samples obtained for each skin type is shown in Fig. 5. The information regarding the considered skin types is represented in the bar diagram. Below are six categorized lists of skin tones: Fair skin is described as having light eyes and hair, is easily burned, and rarely tans. Brown or hazel eyes, light brown hair, and skin that is light to medium in tone with occasional burning but potential for gradual tanning. Brown eyes and dark brown hair are complemented by skin that is medium to olive in tone, rarely burns, and tans easily. Brown eyes and black hair complement dark brown complexion, which rarely burns and tans quickly. Black eyes and black hair complement the deeply pigmented brown complexion, which never burns and tans easily. Black skin: Skin that tans readily, never burns, and has black hair and eyes.

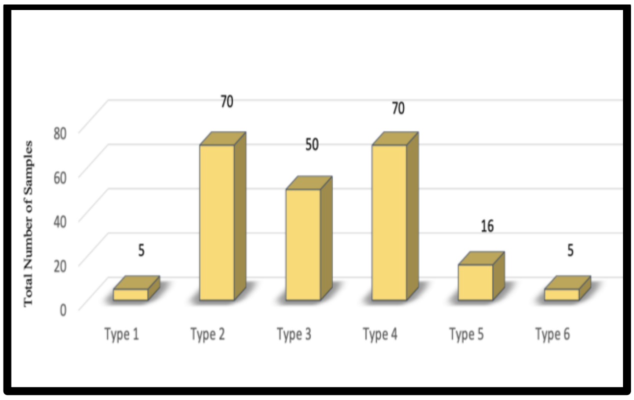

Fig. 5. Samples for each skin type

Convolutional Neural Network (CNN) analysis is used to determine the face skin type, which divides the picture into three categories: standard, oily, and dry. Transfer learning (EfficientNet B0) improves the model's accuracy, which currently has an accuracy of 87.10% compared to a validation accuracy of 80%. The capabilities of EfficientNet are shown in Table II, and they make it an ideal categorization of the skin spectrum that is exact is achievable. To demonstrate that the suggested model is superior to other methods already in use, a comparison is made between it and other methods.

TABLE II. OVERALL CLASSIFICATION ACCURACY

ACCURACY CLASSIFICATION			
	Conventional ITA Approach	ANN Approach	EfficientNet B0
Overall Accuracy	82.97%	85.56%	87.10%

One of the metrics pertaining to the skin is called the acne concern level, broken down into three levels: Low, Moderate, and Severe. Even though the acne severity level is categorized, it is appropriate to utilize conventional numeric values for them: 0 - No Acne, 1 - Clear, 2 - almost clear, 3-Mild, 4-Moderate, and 5-Severe. Fig 6, depicts the breakdown of the total number of images categorized into many groups based on their degree. There is an uneven distribution of image classes. The acne is mainly of Class 3 Mild kind. Both the training and the testing images have different severity levels. This effort was complicated because picture labels from dermatologists were noisy. It was observed that the training image collection included numerous identical (or nearly identical) images. They were categorized differently by several dermatologists.

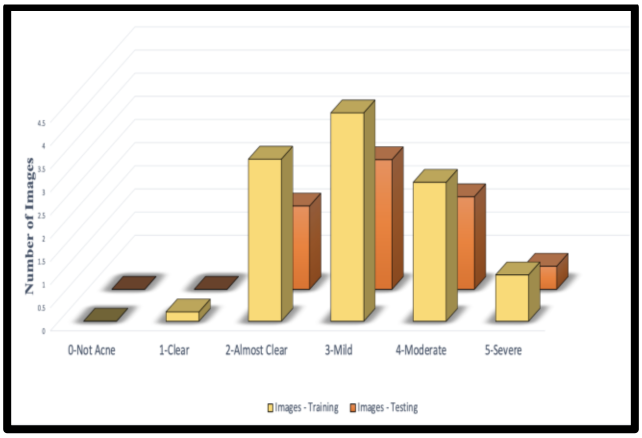

Fig. 6. Acne Severity

Transfer learning is using knowledge from one domain to address issues in another. Utilization of a pre-trained model to collect information from the lower levels before training a bespoke neural network model to tackle our issue. Use of pre-trained deep learning model was done to extract characteristics from the skin patch training images. Experiments demonstrated that, in terms of both performance and computing economy, on these variables, next training was done to a 3-layer fully connected regression neural network model (with 1024, 512, and 256 hidden neurons) to create the complete deep learning model acne-specific. Through the use of transfer learning, the structure of the model has been designed to be comparable to that of the Skin types CNN model. As a result, an accuracy of around 68% across the training and validation picture sets were obtained. Fig. 7 shows the snapshot of the recommendation systempresented in this study.

Fig. 7. Application – Recommender System

Once the user has provided the concerns they are experiencing, the recommendation system will open a new page and provide them with several product suggestions tailored to their skin type and tone. The recommendations given by the recommendation system are shown in Fig. 8. Now, the user can choose the product that has been suggested explicitly for them. Because the dataset that was utilized comprises data from the Myntra Beauty Section, each product is associated with a skin tone and one or more skin concerns (acne, blemishes, redness, etc.). As a consequence of this, every product that has been recommended to you is branded and certified.

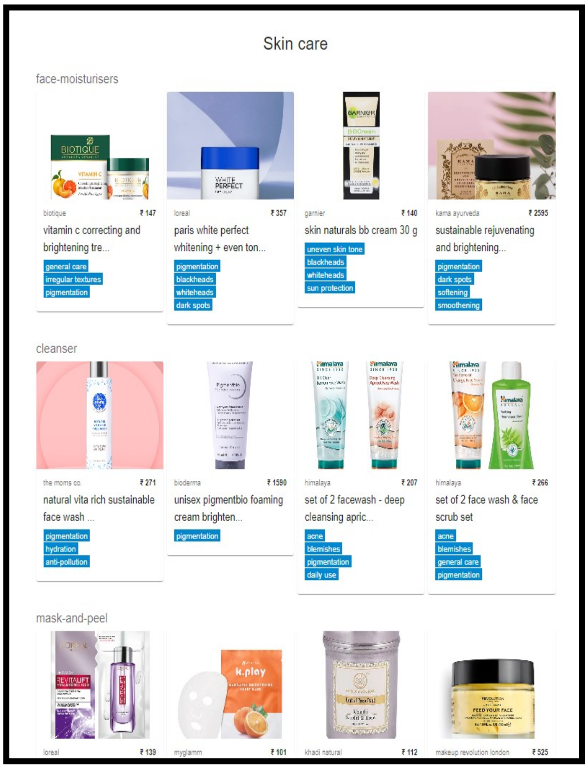

Fig. 8. User recommendations in real-time

V. CONCLUSION

Collaborative filtering-based recommendation systems for facial skin care have the ability to offer users individualised and useful recommendations in real-time. These systems can offer recommendations that are specifically suited to each user's needs by assessing user data such as skin type, concerns, and product usage. These technologies can be implemented in real-time through a variety of channels, including social media platforms, e-commerce websites, mobile apps, and virtual consultations, giving users rapid advice and improving their overall skin health.

In this study, it could be concluded that the application that is developed is capable of automatically detecting the severity of acne, the user's skin tone, and the user's skin texture by using the OpenCV libraries. Additionally, with the assistance of the developed recommender system, the application will give facial skincare product recommendations from the websites of mantra and Sephora. EfficientNet is a methodology for the construction of convolutional neural networks as well as their scalability. It applies a compound coefficient to the scaling process, ensuring that depth, breadth, and resolution are all uniformly sized. Several elements, like the user's skin tone, type, and the severity of their acne, go into choosing which product will give the consumer the most substantial benefit. With the help of this model, a hybrid model advantageous to the skincare of one's face will be constructed. The implementation of EfficientNet B0 improves the model's accuracy, which now has a validation accuracy of 80% and a training accuracy of 87.10%. Even more thorough and precise recommendations could result from additional study and development of these systems, which would ultimately be advantageous to both users and the skin care sector as a whole.

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