Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 3s (2025)

Facial Skincare Product Recommendation Using Deep Learning Techniques

Dr.S.Nithyadevi[1], Biji Rose[2], S.Senthil Kumar[3], Dr.A.Vijayalakshmi[4], Dr.A.Kingsly Jabakumar[5], Dr.V.Velmurugan[6]

[1]Assistant Professor, Department of Electronics and Communication Engineering, Sri Krishna College of Technology Coimbatore, ndsnithya88@gmail.com

[2]Assistant Professor (SG), Department of Electronics and Communication Engineering, Dr. N. G. P Institute of Technology, Coimbatore, bijirose@drngpit.ac.in

[3]Assistant Professor, Department of Artificial intelligence and Data Science, Sri Krishna College of Engineering and Technology, Coimbatore, sentengg@gmail.com

[4]Associate Professor, Department of Electronics and Communication Engineering, Hindusthan College of engineering and technology, Coimbatore, vijayalakshmi.adhi@gmail.com

[5]Associate Professor & Head, Department of ECE, Christ the King Engineering College, Coimbatore, kingslyjkumar@gmail.com

[6]Associate Professor, Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of science and Technology, Chennai, drvelmuruganv@veltech.edu.in

Article History:

***Received**: 20-09-2024*

***Revised**: 01-11-2024*

***Accepted**: 19-11-2024*

Abstract:

Skincare products are essential cosmetics, particularly in this day and age. Numerous online retailers offer a wide range of skincare products in their inventory. One issue with online skincare product purchases is that consumers are unable to test the product and must rely on reviews and ratings from other customers. To make this 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. It also takes a meticulous approach to assess skin tones. Users can effortlessly engage with this system through a user- friendly web interface, where they upload facial images. In return, they receive intricate recommendations tailored not only to their specific skin types but also to address 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. The system says the routine to the user. By offering personalized recommendations and valuable skincare routine with an overall accuracy of 92.34%.

Keywords: Skincare products, e-commerce, personalized recommendations, deep learning.

1. INTRODUCTION

In the domain of personalized skincare, the integrated system utilizes cutting-edge technology, like Convolutional Neural Networks and Efficient-net B0 transfer learning. This 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. CNN is a type of deep learning algorithm, excel at image classification tasks by detecting patterns and features within images. In the context of skincare, CNNs analyze facial images to accurately classify skin types such as Dry, Oily, Normal, Sensitive, or combination. They also identify specific concerns like dark circles and acne by recognizing unique visual cues indicative of these conditions.

Efficient Net B0 transfer learning maximizes the effectiveness of the skin type classification model by using pre-trained models. Using this pre-existing knowledge allows the model to quickly grasp intricate visual patterns related to skin types and concerns. During the transfer learning process, the model adjusts its parameters using a smaller, domain-specific dataset consisting of skincare images. By fine-tuning these parameters, the model specializes its representations to better suit the nuances of skincare images. This approach enhances the model's robustness and generalization capabilities enabling it to accurately classify skin types and concerns across diverse scenarios. Even in challenging conditions like variations in lighting, angles and image quality, the fine-tuned model can discern relevant features and make accurate predictions. To enhance its capabilities, the system employs a region-based skin detection method within the HSV and YCbCr color spaces [1]. This innovative approach categorizes skin tones using the six Fitzpatrick scale categories, now extended to include detailed information on dark circles and acne. Acne classification is seamlessly integrated into the system, utilizing a Convolutional Neural Network (CNN) structure with transfer learning powered by a specialized dataset, the recommender system employs cosine similarity to provide tailored product suggestions. These suggestions are intricately aligned with diverse skin metrics encompassing considerations for dark circles and acne [2].

Before the introduction of this advanced model, selecting skincare products online was often a challenging task for consumers. The lack of in-person testing meant individuals had to rely solely on product descriptions and reviews, which might not always accurately reflect how a product would perform on their unique skin type and concerns. This led to a trial-and-error approach that could be time- consuming, expensive and potentially ineffective [3].

The advantage of employing AI in skincare recommendation systems is significant. Firstly, AI algorithms can analyze vast amounts of data quickly and efficiently, allowing for more accurate classification of skin types and concerns. This reduces the guesswork involved in selecting products, saving consumers time and money. The AI-driven system is capable of maintaining high accuracy even when faced with challenges related to image quality. That users can confidently upload facial images taken in various lighting conditions and angles, without compromising the reliability of the recommendations they receive [4].

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 the advanced technology and personalized insights, the system aspires to redefine the skincare experience and empower users with targeted solutions for a radiant and healthy complexion [5].

2. RELATED RESEARCH

Experimental results conducted on the Multi-Type Skin Lesion Label Database (MSLD) demonstrate the efficacy of PWStE. Despite using 30% less labeled data compared to traditional supervised learning methods, PWStE achieves comparable segmentation performance. This highlights PWStE's potential to revolutionize skin lesion segmentation by enhancing efficiency and reducing the burden associated with acquiring large amounts of labeled data. In addition to its significant reduction in reliance on labeled data, PWStE showcases robustness across diverse skin lesion types and complexities. Its adaptability to various model architectures and backbones underscores its versatility and applicability in real-world scenarios. Moreover, the method's ability to maintain segmentation performance while scaling down labeled data usage signifies its potential to streamline the development of accurate and efficient skin lesion segmentation models [6].

Chaira Qalbyassalam et al. proposed a skincare recommender system employing Neural Collaborative Filtering (NCF) with implicit ratings offers a novel approach to personalized product suggestions based on user interactions. Unlike explicit ratings, which require users to provide feedback through stars or reviews, implicit ratings derive insights from user actions like product views, purchases or wishlist additions. These implicit interactions employs NCF, a deep learning technique, to analyze complex relationships between users and skincare products, uncovering hidden patterns and preferences [7].

The integration of Neural Collaborative Filtering (NCF) into skincare recommendation systems represents a significant advancement in personalization capabilities within the skincare industry. One of the primary advantages of this approach lies in its ability to analyze vast amounts of user interaction data to tailor recommendations to each individual's unique skincare needs and preferences. NCF's scalability is particularly noteworthy, as it enables the system to efficiently handle large datasets of user interactions. This scalability ensures that the system can accommodate the diverse preferences and behaviors of a broad user base, making it suitable for real-world applications with potentially millions of users. The integration of implicit feedback further enhances the system's effectiveness in generating personalized recommendations. By leveraging implicit interactions such as product views, purchases, or even time spent on specific product pages, the system gains valuable insights into user preferences without relying on explicit ratings. This approach not only reduces user burden but also enables the system to capture subtle nuances in user behavior that may not be reflected in explicit feedback [8].

The fusion of deep learning techniques with implicit user data represents a promising avenue for creating highly personalized skincare recommendations. Deep learning models, such as those employed in NCF, excel at capturing complex patterns and relationships within data, allowing the system to uncover hidden insights and make accurate predictions about user preferences. The integration of NCF and implicit feedback into skincare recommendation systems has the potential to revolutionize the industry's approach to product recommendations. By harnessing the power of deep learning and leveraging readily available user interactions, these systems can deliver highly personalized skincare recommendations that cater to the unique needs and preferences of each individual user, ultimately enhancing user satisfaction and driving business success in the skincare industry [9].

Central to the discussion would be the concept of virtual cosmetics recommendation, where the system analyzes the facial features of a user and suggests cosmetic products that would help achieve a desired appearance or look. Such a system holds immense potential, particularly in the context of e-commerce platforms or mobile applications, where users could virtually try on cosmetics before making a purchase decision. By harnessing the power of pre- trained computer vision models.

This system has the ability to provide personalized recommendations that align with the user's unique facial characteristics. This not only enhances the user experience by facilitating exploration of different cosmetic options but also assists users in finding products tailored to their individual preferences and needs. For those interested in delving deeper into the specifics of the proposed system or the research findings, exploring the full title of the paper online could offer further insights. The integration of natural language processing techniques enhances the comprehension of textual product descriptions, enabling a deeper understanding of skincare product attributes and benefits. This linguistic analysis augments the recommendation process by providing insights into ingredient efficacy and product suitability for specific skin concerns. Additionally, reinforcement learning algorithms are employed to optimize recommendation strategies over time, adapting to evolving user preferences and market trends. Such dynamic adaptation ensures that recommendations remain relevant and impactful in an ever-changing skincare landscape. The AI-assisted skincare recommendation systems integrated into extended reality platforms offer interactive experiences for users, leveraging convolutional neural networks for personalized product recommendations. Finally, an expert system incorporates various techniques such as K-nearest neighbors and transfer learning of Efficient Net B0, coupled with content-based filtering, to mimic the decision-making capabilities of human skincare experts.

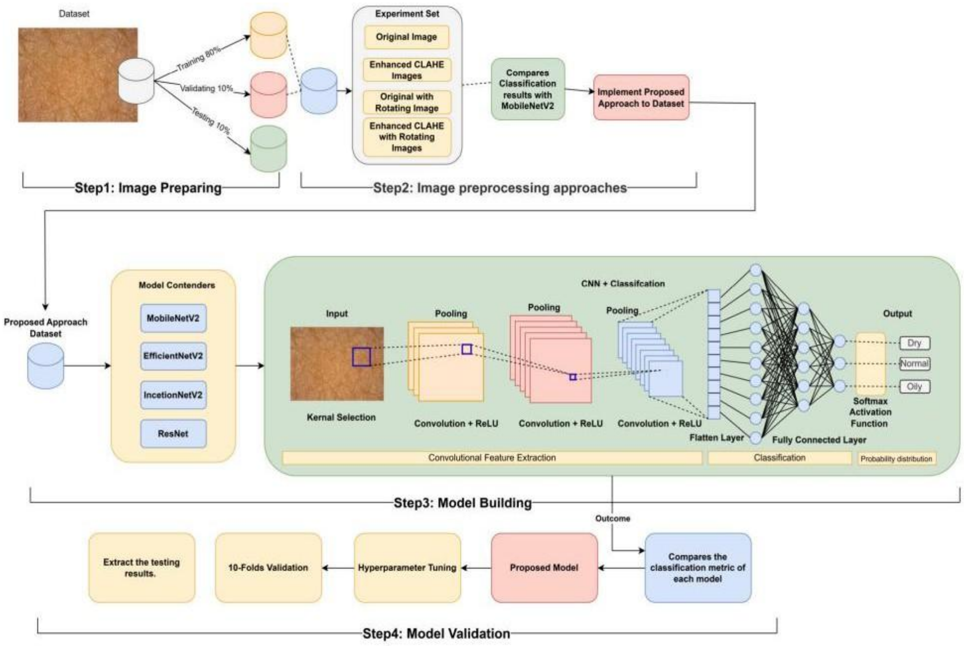

Figure 1: Architecture of the Existing framework

3. PROPOSED METHODOLOGY

In the modern era of skincare, there exists a need for personalized and effective skincare solutions that cater to individual skin types and concerns. Traditional skincare recommendations often lack accuracy and personalization, leading to sub-optimal results for users. To address this challenge, there is a demand for an innovative facial skincare recommendation system that leverages advanced image processing and deep learning techniques to accurately classify diverse skin types, identify specific skin concerns such as acne and pigmentation and provide tailored product recommendations and skincare routines. The goal is to revolutionize the skincare experience by offering personalized and comprehensive solutions that empower users to achieve healthier, glowing and confident skin.

The proposed system described about the facial skincare product recommendation system is a cutting-edge approach to personalized skincare guidance. By combining image processing and deep learning techniques, the system can accurately classify various skin types and address specific concerns such as acne, pigmentation, and dark circles. This advanced technology allows for precise identification of individual skincare needs, enabling the system to provide tailored product recommendations that cater to the unique requirements of each user. One of the key strengths of the system lies in its utilization of Convolutional Neural Networks (CNNs) and Efficient Net B0 for feature extraction and skin type classification. These neural network architectures excel in learning hierarchical features from visual data, making them well-suited for tasks related to facial skincare and skin type classification. These models makes the system that can extract essential features from facial images, including color, texture and statistical characteristics, to classify users into different skin types such as oily, normal, dry and sensitive.

The system incorporates region-based skin detection methods within the HSV and YCbCr color spaces to categorize skin tones and identify specific concerns like dark circles. By employing specialized datasets and techniques like cosine similarity and t-SNE, the system can provide personalized skincare recommendations that are aligned with users' skin attributes and concerns. This comprehensive approach ensures that users receive tailored product suggestions that address their individual skincare needs effectively.

The system not only offers product recommendations but also educates users on effective skincare routines and ingredient benefits. By empowering users with valuable skincare knowledge, the system becomes a trusted companion in helping them achieve healthier and more confident skin. Through its commitment to open-source principles and advanced technology, the system aims to redefine beauty routines and provide targeted solutions for achieving a radiant and healthy complexion.

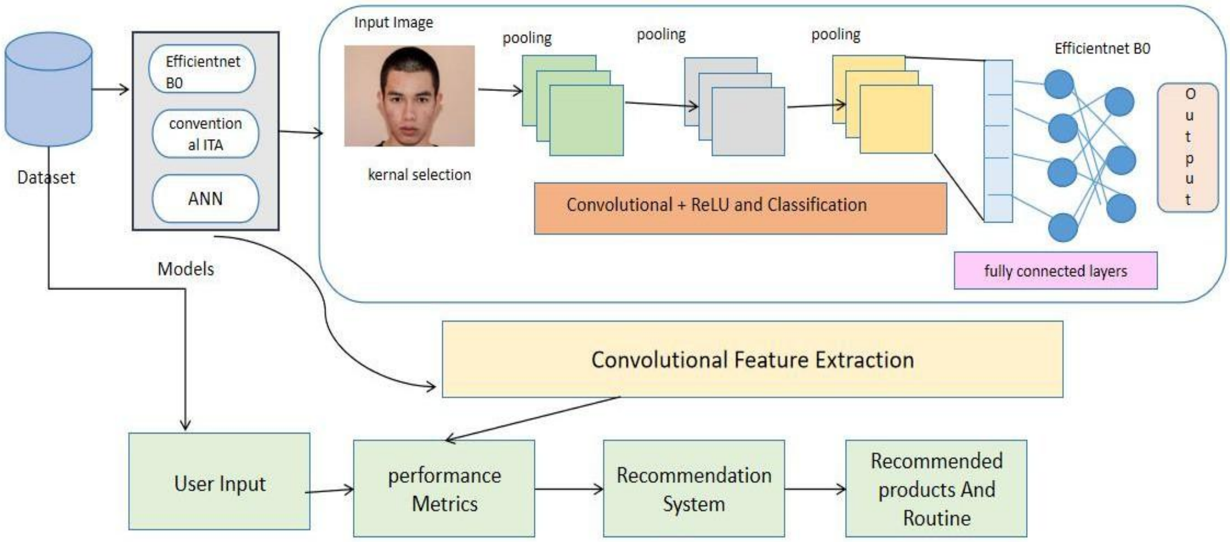

Figure 2: Architecture of the Proposed framework

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, dark circles and . 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, this 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, this holistic framework aims to redefine beauty routines, providing targeted solutions for a radiant and healthy complexion

The cutting-edge technology like Convolutional Neural Networks (CNNs) and Efficient-net B0 transfer learning, an integrated system accurately classifies facial images into categories such as Dry, Oily, Normal, Sensitive or combination, while identifying specific concerns like dark circles and acne. Using pre-trained models and fine-tuning with skincare-specific datasets, the system maintains heightened accuracy despite challenges in image quality, with a region-based skin detection method categorizing skin tones and seamlessly integrating acne classification. This advancement addresses challenges in online skincare product selection, offering the recommendations aligned with individual skin metrics and empowering users with targeted solutions for a radiant and healthy complexion

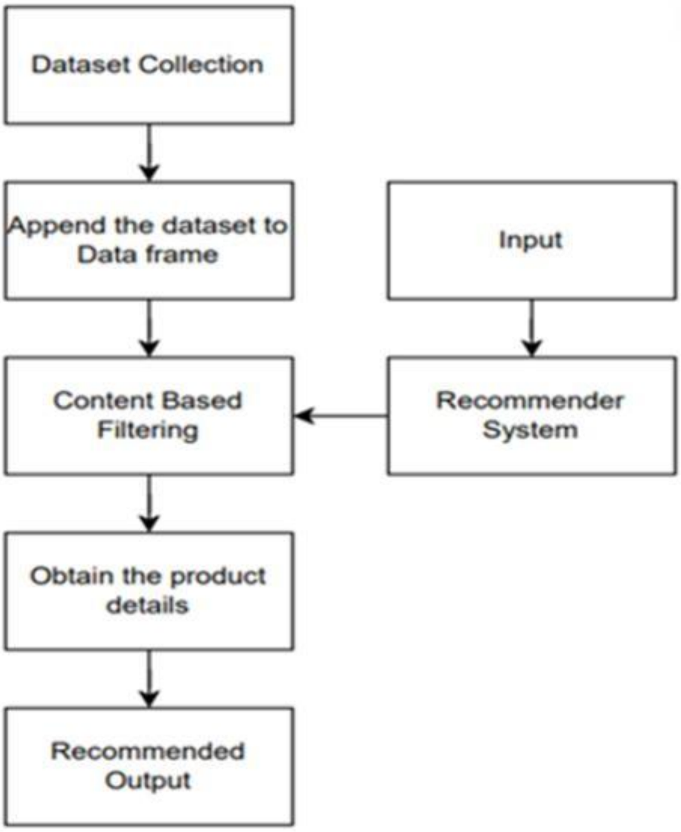

Figure 3: Flow diagram of Recommender system

The above model architecture describes 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 this architecture analyze the input image, identifying intricate facial features like the nose, eyes, mouth and the overall facial structure.

Once the features are extracted, a pooling stage follows to reduce the dimensionality of the data. This not only streamlines the system's computational efficiency but also helps prevent over-fitting, a common challenge in machine learning. The selection of kernels, or filters, in the convolutional layers is a critical step, as it determines which features the network focuses on during the analysis.

The next phase involves an Artificial Neural Network (ANN), likely working in tandem with the Efficient net BO network. The ANN is instrumental in classifying the extracted features or making predictions about the user's skin condition. The system's proficiency is honed through training on a substantial dataset comprising labeled facial images. Each image in the dataset is annotated with information about various skin conditions, such as acne, dark circle. Performance metrics are then employed to evaluate the system's accuracy in classifying these diverse skin conditions. The system suggests personalized skincare products. This intricate process underscores the system's capacity to analyze facial features, classify skin conditions and offer tailored skincare recommendations based on deep learning principles

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 3s (2025)

The system collects this interaction data to construct a user-item matrix, representing how users have engaged with different items. It creates user profiles, capturing individual preferences based on interaction history. This can be achieved using collaborative filtering techniques or matrix factorization. Cosine similarity can be utilized to measure the similarity between different skincare products based on their attributes, ingredients or effectiveness. By representing each product as a feature vector in a high-dimensional space, cosine similarity calculates the cosine of the angle between these vectors. Products with a smaller angle between their feature vectors are considered more similar, suggesting that users who like one product are likely to appreciate similar ones.

Then calculating the item similarities by analyzing how frequently users interact with similar items. This can be measured using cosine similarity, where items with a higher cosine similarity score are more similar. Based on user profiles and item similarities, the system generates personalized recommendations for each user. Matrix factorization methods decompose the user-item matrix into lower-dimensional representations, enabling more efficient computation of user preferences and item similarities. Deep learning architectures, including convolutional neural networks can extract intricate patterns and relationships from raw interaction data, leading to more nuanced and context-aware recommendations. Furthermore, incorporating contextual information such as user demographics, location, and temporal trends allows the system to adapt recommendations dynamically to changing user preferences and external factor and engagement in the skincare shopping experience.

4. SOFTWARE IMPLEMENTATION

The implementation of the skin type classification system involves a comprehensive series of steps to seamlessly integrate the trained model into a deploy able and user-friendly solution. Initially, the model is meticulously trained using the Efficient Net B0 architecture, leveraging a dataset enriched with color, texture and statistical features extracted from skin images. Following training, the model undergoes rigorous evaluation and fine-tuning to optimize its performance, ensuring it accurately classifies skin types across diverse datasets.

The model is trained and refined, it undergoes conversion and serialization to a deploy able format, enabling efficient storage and retrieval. The deployment infrastructure is established, encompassing the selection of a deployment platform or framework, configuration of servers and provisioning of necessary resources. Simultaneously, an API is developed to serve as the interface between the deployed model and external applications, allowing users to seamlessly submit skin images for classification.

Integration with the front-end or application follows, ensuring a smooth user experience. The skin type classification model is embedded into the user interface, allowing users to interact with the system intuitively. To address scalability and optimize performance, the deployment infrastructure is carefully configured, considering factors such as response time, resource utilization and concurrent user capacity.

Security measures are paramount throughout the implementation process. Encryption of communication channels, robust access control and mechanisms to prevent unauthorized access or data tampering are implemented to safeguard the model and user data. The system undergoes rigorous testing to ensure its resilience against potential security threats. To monitor the deployed model's real-time performance, monitoring tools are integrated, enabling proactive identification and resolution of issues such as model drift or changing data patterns. Regular maintenance routines are implemented to uphold the system's effectiveness and address any emerging challenges.

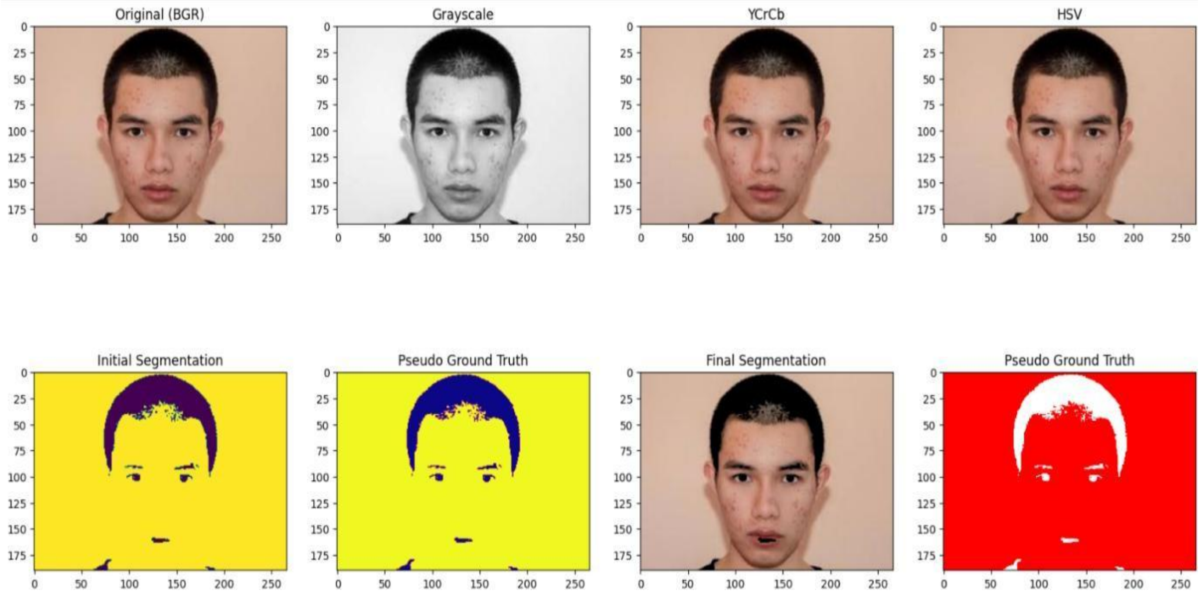

Figure 4: Data Augmentation

The Final Segmentation represents the refined outcome of the segmentation algorithm after adjustments based on the Pseudo Ground Truth. This 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.

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. This serves as a benchmark for evaluating the accuracy and effectiveness of the segmentation algorithms in capturing relevant skin attributes.

Table 1: Augmentation Parameters

PARAMETERS	VALUES
Original BCR	0.5
Grayscale	0.5
YCrCb	0.3
HSV	0.5
Initial Segmentation	0.2
Pseudo Ground Truth	0.2
Final Segmentation	20

To facilitate the clustering process, a special dataset is defined containing input features required for clustering. These features include components from both the HSV and YCrCb color spaces (Hue, Cr, Cb), as well as the positions of pixels on the image (Xp, Yp), and a rough estimation of skin pixels (I).All six components of the dataset (Cr, Cb, Hue, Xp, Yp, and I) are converted into appropriate vectors for further processing. Image pixels are then clustered into three groups background, foreground, and skin pixels using the k-means clustering algorithm. Square Euclidean measure is commonly used as the distance metric for clustering.The approximated skin pixels (I) obtained from the special dataset are used to determine which cluster represents skin pixels. This final step identifies and separates the skin pixels from other clusters, effectively detecting the skin regions within the image.

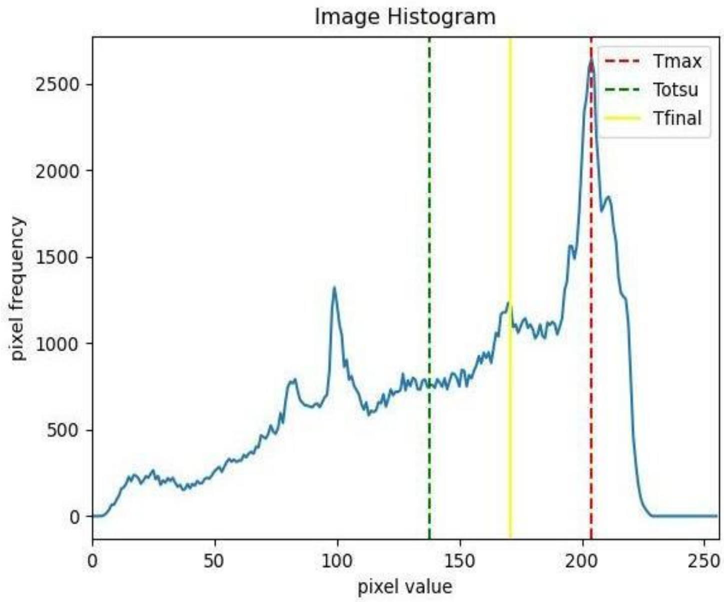

Figure 4: Data Augmentation

Data flow testing is crucial for identifying potential vulnerabilities or errors related to data handling within the system. By analyzing the flow of data, testers can uncover potential data leakage, unauthorized access or improper manipulation of sensitive information. This type of testing helps ensure the integrity and security of data as it moves through various components of the system. ultimately enhancing the reliability and trustworthiness of the software product. Additionally, data flow testing aids in validating the correctness of data transformations and processing logic, contributing to overall system robustness and quality assurance efforts.

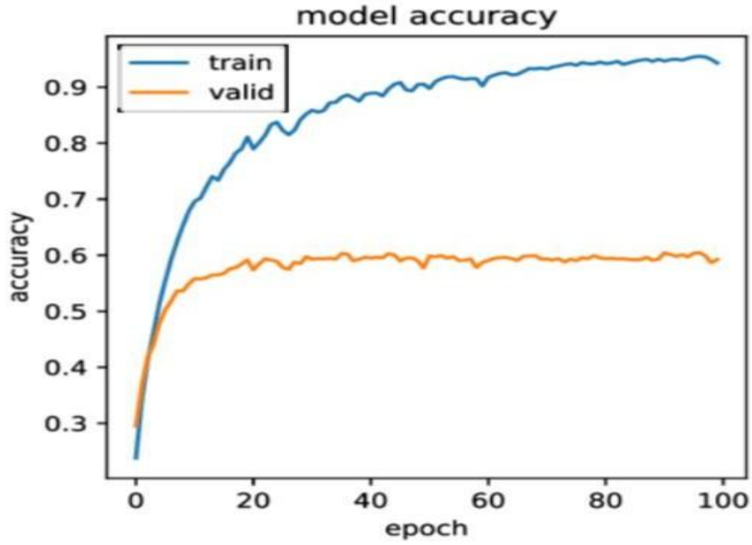

Figure 5: Model Accuracy

The scalability ensures its capacity to accommodate growing user demand and data volume. Finally, a comparative analysis against existing benchmarks or skincare recommendation systems helps identify performance improvements and advantages over traditional methods, guiding further enhancements for a more robust and reliable skincare solution. continual optimization of computational resources and algorithmic efficiency is essential for maintaining optimal performance and minimizing latency in real-time inference scenarios.

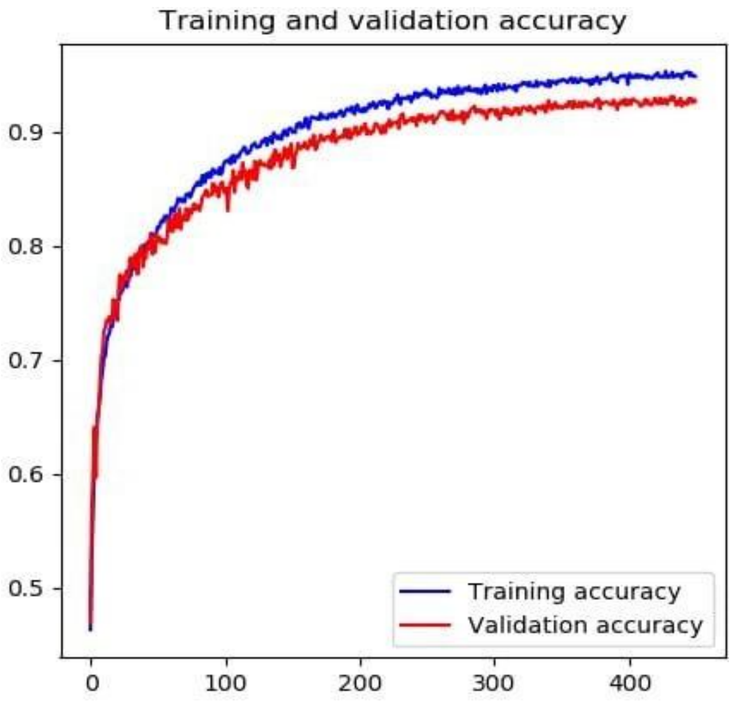

Figure 6 : Training And Validation Accuracy

The y-axis indicates accuracy, while the x- axis represents epochs, measuring the number of times the entire dataset has been passed through the training algorithm. Training accuracy reflects the model's performance on the skincare product recommendation training data, while validation accuracy assesses its performance on a separate dataset, ensuring generalization to unseen data. Additionally, a notable discrepancy emerges in the graph, where the training accuracy surpasses the validation accuracy and adjusting the model architecture may help balance training and validation performance, leading to improved overall accuracy and robustness of the model for the system.

5. CONCLUSION

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 with accuracy of 92.34% . 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. The Facial Skincare Recommendation System offers promising avenues for future development and enhancement. Some potential directions for future research and expansion include Implementation of features that allow users to provide real-time feedback on recommended products, creating a dynamic system that adapts to individual preferences over time and exploration of possibilities for integrating the system with wearable devices that continuously monitor skin health metrics, providing a continuous and proactive skincare advisory service.

References

[1] Dong x, Yan y, Ouyang w, (2021) "Style Aggregated Network For Facial Landmark Detection," Ieee Conference On Computer Vision And Pattern Recognition, Pp.379-388.

[2] Goindi, S., Thakur, K., & Kapoor, D. S (2023) "Skin Disease Classification and Detection by Deep Learning and Machine Learning Approaches."

[3] Iwabuchi, R., Nakajima, Y., et al. (2023) "Artificial Intelligence based Smart Cosmetics Suggestion System based on Skin Condition."

[4] Lee, Gyeongeun (2020) "A Content-based Skincare Product Recommendation System."

[5] Li, Yi, Song, Lingxiao, Wu, Xiang, He, Ran (2020) "AntiMakeup Learning A, B –Level Adversarial Network For Makeup Invariant Face Recognition," AAAI Conference, pp.79-388.

[6] Liu, Xudong, Taoli, Iris Chuoying Ouyang, and Ruizhe Wang (2023) "Understanding Beauty via Deep Facial Features," IEEE Conference, volume- 246-256.

[7] Ma, X., Lu, J., Liu, X., & Kuang, H. (2022) "Skincare Recommender System Using Neural Collaborative Filtering with Implicit Rating."

[8] Rathgeb, Christian, Dantcheva, Antitza, Busch, Christoph (2022) "Impact Of Facial Beautification On Face Recognition," IEEE Access 2021,7,152667- 152678.

[9] Saiwaeo, S., Arwatchananukul, S., Mungmai, L., Preedalikit, W., & Aunsri, N. (2023) "Human Skin Type Classification Using Image Processing and Deep Learning Approaches."