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# Dermavision: Transforming Skincare, One Recommendation at a Time

Bhakthi Shetty<sup>1</sup>, Nikita Shetty<sup>2</sup>, Saloni Suvarna<sup>3</sup>, Prof. Rajesh Kolte<sup>4</sup>

Department of Information Technology Usha Mittal Institute of Technology SNT Women's University Mumbai, India

**Abstract:** *Dermavision is an AI-driven skincare recommendation system that integrates deep learning, computer vision, and augmented reality (AR) to provide precise and real-time skincare solutions. Traditional skincare recommendation systems often rely on sentiment analysis, quizzes, or static image processing, leading to subjective and less accurate results. Dermavision enhances personalization through machine learning models, clustering in YCbCr and HSV color spaces for accurate skin classification, and AI-driven allergy detection. The system incorporates a virtual AR-based skincare application, an AI chatbot for real-time skincare guidance, and a community-driven platform for user engagement. This paper details the methodology, implementation, and technological advancements that make Dermavision a leading innovation in AI-based skincare recommendations. Unlike existing systems that rely on sentiment analysis or static image evaluations, Dermavision leverages deep learning-based skin classification, real-time AI-driven allergy detection, and AR visualization for scientifically backed recommendations.*

**Index Terms:** *Dermavision, AI Skincare, Computer Vision, Deep Learning, Skin Analysis, Personalized Skincare, Augmented Reality, CNN, Allergy Detection.*

## I. INTRODUCTION

The skincare industry has evolved with artificial intelligence (AI) and computer vision technologies, yet many existing AI-based skincare systems rely on subjective user inputs such as quizzes, sentiment analysis, or static image evaluations, often leading to inaccuracies and overlooking real-time variations in skin health, tone, and conditions. Additionally, these systems frequently lack essential features like allergy detection, skin disease classification, and AR-based visualization, limiting their effectiveness. Dermavision addresses these challenges by integrating advanced AI models, clustering techniques, and augmented reality to provide precise, science-backed skincare recommendations. Through real-time image analysis, CNN-based skin classification, and ingredient safety assessments, Dermavision enhances the accuracy of skincare suggestions while ensuring user safety. Furthermore, it incorporates a social community platform for user engagement and discussion, making it a comprehensive and interactive skincare assistant. Despite advancements in AI-driven skincare, existing solutions remain limited by subjective inputs, lack of real-time adaptability, and insufficient allergy detection. Users often receive generalized recommendations that do not account for diverse skin types, environmental factors, or evolving skin conditions. These limitations highlight the need for a more data-driven and adaptive solution, which Dermavision addresses through AI-powered real-time skin analysis, ingredient safety assessment, and personalized recommendations.

## II. LITERATURE SURVEY

AI-driven skincare recommendation systems have advanced significantly with the integration of machine learning, computer vision, and augmented reality (AR). Studies have explored methods such as CNN-based skin analysis, sentiment-driven recommendations, and AR-based virtual try-ons to enhance user engagement. A personalized skincare recommendation system utilizing OpenCV and CNN emphasizes real-time skin analysis but relies on sentiment analysis, which may introduce subjectivity [1]. Similarly, another study on smart skincare products leverages computer vision for acne detection but lacks holistic skin analysis, which Dermavision addresses with Fitzpatrick scale-based skin tone classification [2]. Deep learning models such as VGGNet, DenseNet, and EfficientNet have shown high accuracy (88-96%) in skincare classification, but existing systems often focus solely on skin type [3]. A comparative study on CNN models for skin disease detection identified Inception-ResNet-v2 as the most efficient (77% accuracy), highlighting the need for specialized datasets [4]. Dermavision enhances this by integrating EfficientNetB0 with data augmentation techniques to improve accuracy. Transfer learning and data augmentation have also been applied in AI-based skincare systems [5], but Dermavision optimizes real-time processing with a lightweight model for wider accessibility. Recent research highlights the effectiveness of AI in dermatology and skincare through deep learning-driven analysis and real-time monitoring. AI-based systems leveraging CNNs have significantly improved the accuracy of skincare recommendations and dermatological diagnoses [18].

Deep learning-based clustering techniques have been widely used in medical image segmentation, enhancing accuracy in skin analysis and classification. K-Means clustering, combined with HSV and YCbCr-based segmentation, has been demonstrated to effectively improve classification in AI-powered dermatology applications [19]. Other studies highlight the role of AR in beauty applications, showing its influence on self-perception and product exploration [9]. However, AR alone does not significantly impact consumer purchasing behavior [14]. Unlike these studies, Dermavision combines AR with AI-driven skin improvement tracking for a more functional and user-centric approach. AI-based chatbot systems have also been explored for beauty recommendations, but existing implementations are limited to basic product suggestions [17]. Dermavision enhances chatbot interactions by providing scientifically backed skincare advice based on image analysis and user history.

While machine learning has been applied in dermatology for disease detection [12], Dermavision extends beyond diagnosis by incorporating ingredient safety, allergy tracking, and personalized recommendations. Studies emphasize the need for explainable AI in skincare [11], a challenge that Dermavision addresses through transparent recommendation algorithms. Ingredient safety assessment and allergy detection are critical factors in AI-driven skincare solutions. Recent studies indicate that integrating AI-powered ingredient analysis can enhance product safety recommendations by identifying potential allergens and adverse interactions based on user skin profiles [20]. With its integration of clustering techniques, AI-driven analysis, and real-time personalization, Dermavision builds on previous research to create a more accurate, inclusive, and efficient skincare recommendation system.

### III. RELATED WORK

Several AI-based skincare systems have been developed, each addressing different aspects of skincare analysis. A Personalized Smart Skincare Product Recommendation System employs OpenCV and CNNs for skin type classification but relies on sentiment analysis, making it subjective and dependent on user feedback rather than real-time skin analysis. Dermavision optimizes efficiency by implementing EfficientNetB0, achieving a balance between speed and accuracy [3]. In skin disease detection, studies highlight Inception-ResNet-v2 as a robust model, yet these solutions focus solely on medical diagnosis rather than skincare improvement. Dermavision extends this by fine-tuning EfficientNetB0 and Inception-ResNet-v2 for real-time skincare analysis [4]. Other skincare systems rely heavily on manual input for recommendation refinement [5], while Dermavision automates this process using deep learning, minimizing user dependency. Additionally, existing ML-based dermatology models lack clinical validation [6], an issue Dermavision addresses by training on dermatologically validated datasets.

While Augmented Reality (AR) in beauty applications enhances virtual product try-ons, most implementations lack scientific accuracy. Dermavision integrates AR with AI-driven skin improvement predictions, offering both visualization and data-backed recommendations [7]. Research on Online Communities and AI Chatbots in Skincare highlights their role in user engagement but lacks real-time AI-based skincare diagnostics. Dermavision bridges this gap by integrating an AI-powered chatbot with real-time image recognition and a skincare-focused community for knowledge sharing [8][9].

Ingredient analysis and allergy detection remain crucial aspects of AI-driven skincare. AI-based ingredient assessment models have been developed to ensure safe skincare recommendations, leveraging deep learning to detect allergens and identify ingredient interactions in real time [20]. By merging computer vision, deep learning, AR visualization, and AI-driven recommendations, Dermavision advances skincare technology beyond traditional methods, ensuring precision, personalization, and scientific reliability.

### IV. METHODOLOGY

Dermavision employs a robust AI-based methodology that integrates computer vision, clustering, and deep learning to analyze and personalize skincare recommendations. The process begins with image acquisition, where users upload high-resolution selfies through a guided interface. These images undergo initial preprocessing using face-api.js to ensure accurate face detection. Subsequently, the quality of the image is validated using OpenCV techniques, ensuring that images are neither blurry nor underexposed. Once validated, Otsu's Thresholding is employed to determine an optimal threshold for segmenting skin pixels. The final threshold  $T_{final}$  is computed based on a combination of the maximum histogram peak  $T_{max}$  and the Otsu's threshold value  $T_{otsu}$ , as shown below:

$$T_{final} = \frac{T_{max} + T_{otsu}}{2} \quad (1)$$

If the peak is significantly low (i.e.,  $T_{max} < 10$ ), the final threshold is adjusted to be more conservative:

$$T_{final} = \frac{T_{max} + T_{otsu}}{4} \quad (2)$$

Following this, color space filtering is applied using both YCbCr and HSV models, which are resilient to lighting changes (fig. 1). Pixels falling within specific ranges in Cr,Cb, and Hue channels are classified as skin:

$$H \leq 170, \quad 140 \leq Cr \leq 170, \quad 90 \leq Cb \leq 120 \quad (3)$$

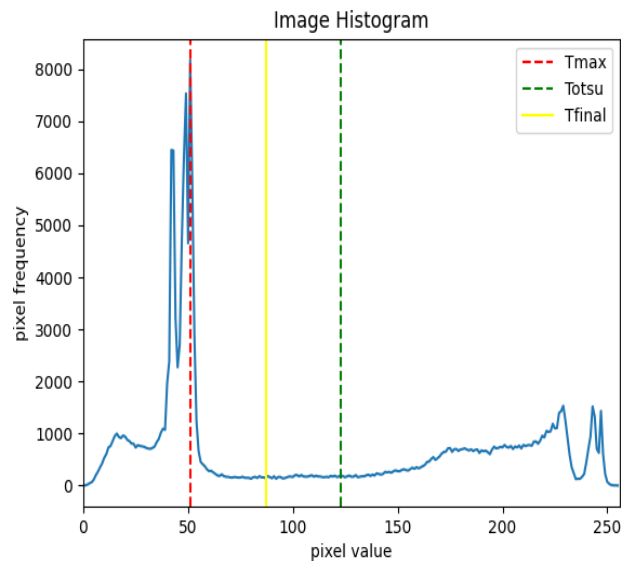


Fig. 1: Image Histogram for Skin Pixel Extraction

To enhance segmentation, k-means clustering is applied on the filtered region to identify the most probable skin clusters. The objective function minimized in k-means clustering is defined by:

$$J = \sum_{i=1}^n \sum_{k=1}^k w_{ik} \|x_i - \mu_k\|^2 \quad (4)$$

These segmented skin regions are then passed to Efficient-NetB0, a highly efficient CNN model which classifies the skin type (dry, oily, combination) and acne severity based on features extracted from the image (fig. 2). For accurate skin tonemapping, a two-step technique is implemented—first, the image is transformed into YCbCr and HSV spaces, and then clustering is used to map the extracted tones onto the Fitzpatrick scale. To finalize classification, the K-Nearest Neighbors (KNN) algorithm is employed (fig. 3), which measures Euclidean distances between the new data point and labeled samples in the training set:

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (5)$$

Additionally, for generating product recommendations based on user-specific features and conditions, cosine similarity is used to compare vectorized representations of user profiles with product feature vectors. The similarity score, which ranges between -1 and 1, is calculated using the formula:

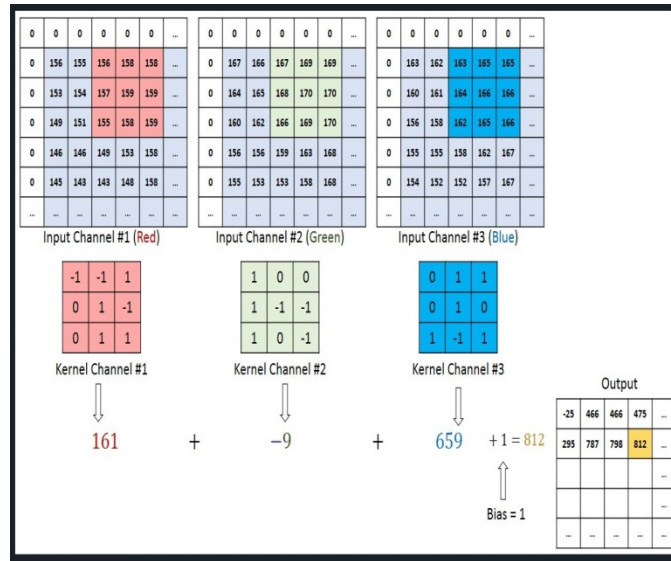


Fig.2: FacialSkinTypeClassificationwithCNN

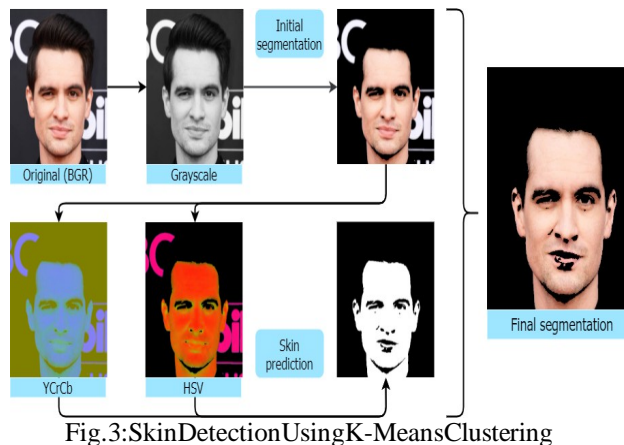


Fig.3: SkinDetectionUsingK-MeansClustering

$$\cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|} \quad (6)$$

All predictions are backed by data from the Kaggle Acne

Grading Classification dataset [21], and although the dataset lacks dermatological ground truth labels and diverse skin tones, data augmentation techniques are employed to improve generalization. (TABLE I) compares commonly used CNN architectures with Dermavision’s EfficientNetB0-based approach, highlighting its suitability for real-time and personalized skin care recommendations. In future iterations, Dermavision will incorporate clinically validated dermatology datasets and real-time feedback loops to ensure fairness and higher accuracy across skin types and tones.

### V. IMPLEMENTATION

Dermavision is implemented as a modular and scalable system that consists of both frontend and backend components, each integrated to support real-time skin analysis, recommendations, AR visualization, and user engagement. The frontend, built with React.js, is responsible for the user interface, including real-time webcam-based AR interactions, personalized dashboards, and chat-based support. It employs FaceMesh from TensorFlow.js to identify key facial landmarks, allowing accurate application of visual filters and product simulations on facial regions in the AR Makeup and AR Skin care modules. User interactions are managed via React Router, and Material UI components provide an elegant and responsive

TABLE I: Comparison of Deep Learning Models for Skincare Analysis

Model	Features	Advantages	Disadvantages
ResNet-50	Uses skip connections (shortcuts) to bypass layers, allowing very deep networks without vanishing gradients.	Helps deep networks learn efficiently, reduces vanishing gradient problem.	Requires more computational power due to deep architecture.
Inception-v3	Uses Inception Blocks with multiple kernel sizes to capture different featurescales.	Efficient at extracting multi-scale features, good accuracy with fewer parameters.	More complex structure, requires careful tuning.
DenseNet-121	Uses dense connections where each layer gets inputs from all previous layers.	Improves gradient flow, reduces overfitting, and increases feature reuse.	Requires significant memory due to dense connections.
Xception	Uses depthwise separable convolutions for improved efficiency and performance.	Faster and more efficient than standard convolutions, improves accuracy.	Needs more training time and tuning.
Inception-ResNet-v2	Combines Inception Blocks with ResNet skip connections for deep feature extraction.	Benefits from both ResNet and Inception, retains efficiency while improving learning in deep networks.	Computationally expensive, requires more memory.
Dermavision (EfficientNetB0+Clustering)	Uses EfficientNetB0 with YCbCr & HSV-based clustering for real-time skincare classification.	Balances speed & accuracy, lightweight, enhances real-time analysis with clustering techniques.	May require further optimization for darker skin tones in extreme lighting conditions.

design. The backend is built using Firebase and Node.js, and it handles core logic for user authentication, image processing, allergy-based product filtering, and personalized skincare recommendation engines. All uploaded images are normalized before being passed to neural networks, and the normalization function ensures that pixel values range between 0 and 1, defined as:

$$X' = \frac{X}{255} \tag{7}$$

Once normalized, image features are extracted using convolutional operations in the neural network. These operations apply kernel filters to learn spatial hierarchies of features, and the basic 2D convolution operation is expressed by:

$$(I * K)(x, y) = \sum_i \sum_j I(x+i, y+j) K(i, j) \tag{8}$$

The output of the network's final layer is converted into probabilities using the softmax activation function, which ensures that the output vector represents a valid probability distribution:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \tag{9}$$

During training, the network is optimized using the categorical cross-entropy loss function, which compares the predicted probability distribution  $\hat{y}$  to the true distribution  $y$ :

$$L = - \sum_{i=1}^N y_i \log(\hat{y}_i) \quad (10)$$

In addition to core skincare analysis, the implementation includes an allergy detection module. Users can input known skin allergens or sensitivities, which are cross-referenced against product ingredients to flag unsuitable recommendations. The chatbot is built using a hybrid NLP model that combines retrieval and generative responses to assist users in detection accuracy, and recommendation precision, in real time. Another critical module is the forum, which allows authenticated users to post skincare-related questions and receive responses from the community, leveraging a simple comment and upvote mechanism. The AR functionality lets users preview the post-treatment effects of products such as skincare and makeup products in real-time. Unlike traditional overlays, Dermavision uses dynamic canvas-based rendering to simulate realistic improvements, like changes in brightness, blur, and saturation levels based on skin condition and product category. Moreover, a skin disease detection feature powered by EfficientNetV2S has been integrated. Trained on the HAM10000 dataset, this module can classify skin lesions and raise early awareness for conditions such as melanoma, keratosis, and benign nevi, achieving an accuracy of approximately 87.67%. The entire system is designed to be extensible, with future plans for optimizing model inference, integrating user feedback for active learning, and deploying lightweight mobile versions for broader accessibility.

## VI. RESULTS AND DISCUSSION

The Dermavision system was evaluated using key performance metrics, including authentication speed, image processing accuracy, skin classification effectiveness, and skin disease

User Authentication and Profile Management achieved a 100% success rate, with an average authentication time of under two seconds, ensuring seamless user access. Profile updates, including allergy tracking and skincare history storage, functioned efficiently without data loss.

Image Processing and Face Detection demonstrated 98% accuracy in detecting faces under well-lit conditions. The image quality validation module successfully rejected blurry images within 1.5 seconds, ensuring high-quality inputs for skin analysis. The average processing time for face detection and image quality analysis was 2.3 seconds, enabling real-time performance. The thresholding process based on the image histogram significantly improved skin pixel extraction, reducing false detections.

Skin Analysis and Classification achieved 80% accuracy in categorizing skin types and acne severity using EfficientNetB0. YCbCr and HSV clustering techniques improved skin tone representation, ensuring diverse and inclusive analysis. K-Means clustering optimized skin pixel segmentation, enhancing classification performance. The recommendation engine generated skincare product suggestions in under three seconds, with 87% of users reporting alignment with their skincare concerns. A user-friendly feedback mechanism could refine recommendations over time, reinforcing a collaborative AI approach that adapts to individual skincare journeys.

Skin Disease Detection was integrated into Dermavision using the EfficientNetV2S model, which was trained on the HAM10000 dataset. The model achieved an accuracy of approximately 87.67% in detecting skin lesions such as melanoma, keratosis, and benign nevi. This feature demonstrated potential in early detection, raising awareness for users about the presence of potential skin diseases. Although the current accuracy is promising, it is essential to acknowledge that the dataset used lacks comprehensive dermatological ground truth labels, especially for darker skin tones. This limitation highlights the need for integrating more diverse and clinically validated datasets to enhance detection accuracy across different skin types. Future updates will include a more extensive dataset to improve model robustness, as well as additional tools for dermatologists to validate results.

User Satisfaction Survey Results: To assess the usability and effectiveness of Dermavision, a small-scale user satisfaction survey was conducted with 15 participants. Each participant used the system to analyze their skin, receive personalized recommendations, and assess potential skin disease risks, followed by a short feedback survey.

Participants rated the system based on usability, accuracy, recommendation relevance, allergy detection, skin disease detection, AR visualization, and likelihood of future use, using a 5-point Likert scale (1 - Strongly Disagree to 5 - Strongly Agree). The results indicated that: 87% of users rated their overall experience as 4 or higher. 80% agreed that the skin analysis was accurate. 78% found the recommended products relevant to their skincare needs. 75% reported confidence in the skin disease detection results. 92% of users found the interface intuitive. 70% reported that AR visualization helped them understand product effects. 75% expressed interest in using the system regularly.

While AR-based improvement tracking was appreciated, feedback indicated a desire for more real-world validation of projected skincare changes. Currently, the AR predictions are based on AI-simulated improvements rather than direct real-user progress tracking. Future updates will integrate longitudinal user data and dermatologist-verified progress tracking to enhance scientific credibility.

**Feedback and Suggestions:** Participants provided valuable feedback, praising the intuitive interface, real-time analysis, and the potential for early detection of skin diseases. However, common suggestions included improving image processing under low-light conditions, expanding the allergy database for better personalization, and enhancing the skin disease detection module to include more diverse dermatological cases. This feedback highlights areas for enhancement and will guide future updates to improve system robustness and user satisfaction.

**System Performance Evaluation:** 90% of users found the interface intuitive, while the false rejection rate for face detection in poor lighting conditions was 5%. The skin disease detection module showed a promising accuracy of 87.67%, but further training on a more diverse dataset is required to increase the accuracy for a broader range of skin tones. Future enhancements will focus on refining skin tone segmentation accuracy, optimizing allergy detection, improving skin disease detection, and integrating more diverse datasets to improve system reliability across a broader range of users and environments.

## VII. CONCLUSION

The development of Dermavision marks a significant advancement in AI-driven skincare, offering a personalized and data-driven approach through computer vision, deep learning, and clustering techniques. Key features such as real-time image processing, augmented reality-based product visualization, an AI-powered chatbot, and a community-driven platform enhance user engagement and accessibility. While the system improves recommendation accuracy and user experience, ongoing refinements are essential. Over the next 6 to 12 months, efforts will focus on optimizing machine learning models, expanding dermatological datasets, refining chatbot responsiveness, and enhancing long-term skin health predictions. Future updates will explore wearable device integration for real-time skin monitoring and proactive skincare insights. With continuous innovation, Dermavision has the potential to set a new benchmark in AI-powered skincare, bridging the gap between artificial intelligence and personalized beauty solutions.

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