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Dermavision: Transforming Skincare, One Recommendation at a Time

Bhakthi Shetty[1], Nikita Shetty[2], Saloni Suvarna[3], Prof. Rajesh Kolte[4]
Department of Information Technology Usha Mittal Institute of Technology SNDT Women's University Mumbai, India

Abstract: DermavisionisanAI-drivenskincarerecommenda- tion system that integrates deep learning, computer vision, and augmentedreality(AR)toprovidepreciseandreal-timeskincare solutions. Traditional skincare recommendation systems often rely on sentiment analysis, quizzes, or static image processing, leading to subjective and less accurate results. Dermavision enhancespersonalizationthroughmachinelearningmodels,clus- tering in YCbCr and HSV color spaces for accurate skin classifi- cation, and AI-driven allergy detection. The system incorporates a virtual ARbased skincare application, an AI chatbot for real- time skincare guidance, and a community-driven platform for userengagement.Thispaperdetailsthemethodology,implemen- tation, and technological advancements that make Dermavisiona 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, DeepLearning,SkinAnalysis,PersonalizedSkincare,Augmented Reality, CNN, Allergy Detection.

I. INTRODUCTION

Theskincareindustryhasevolvedwithartificialintelligence (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 leadingtoinaccuraciesandoverlookingreal-timevariationsin skin health, tone, and conditions. Additionally, these systems frequently lack essential features like allergy detection, skin disease classification, and AR-based visualization, limiting theireffectiveness.Dermavisionaddressesthesechallengesby integrating advanced AI models, clustering techniques, and augmented reality to provide precise, science-backed skincare recommendations. Through real-time image analysis, CNN-basedskinclassification,andingredientsafetyassessments, Dermavision enhances the accuracy of skincare suggestions while ensuring user safety. Furthermore, it incorporates a so- cial community platform for user engagement and discussion, making it a comprehensive and interactive skincare assistant. DespiteadvancementsinAI-drivenskincare,existingsolutions remain limited by subjective inputs, lack of real-time adapt- ability, and insufficient allergy detection. Users often receive generalized recommendations that do not account for diverse skintypes,environmentalfactors,orevolvingskinconditions. Theselimitationshighlighttheneedforamoredata-drivenand adaptive solution, which Dermavision addresses through AI- powered real-time skin analysis, ingredient safety assessment, and personalized recommendations.

II. LITERATURE SURVEY

AI-drivenskincarerecommendationsystemshaveadvanced significantly with the integration of machine learning, com- puter vision, and augmented reality (AR). Studies have ex- plored methods such as CNN-based skin analysis, sentiment- driven recommendations, and AR-based virtual try-ons to enhanceuserengagement.Apersonalizedskincarerecommen- dation system utilize ing OpenCV and CNN emphasizes real- time skin analysis but relieson sentiment analysis, which may introduce subjectivity [1]. Similarly, another study on smart skincareproductsleveragescomputervisionforacnedetection 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].AcomparativestudyonCNNmodelsforskindisease detection identified Inception-ResNet-v2 as the most efficient (77%accuracy),highlightingtheneedforspecializeddatasets[4].Dermavision enhances this by integrating EfficientNetB0 withdata aug mentationtechniquestoimproveaccuracy.Trans- ferlearninganddata augmentati onhavealso beenapplied in AI-based skincare systems[5],but Dermavision optimizes real-timeprocessingwithalightweightmodelforwideracces- sibility. Recent research highlights the effectiveness of AI in dermatology and skincare through deep learning-driven anal- ysis and real-time monitoring. AI-based systemsleveragingCNNs have significantly improved the accuracy of skincare recommendations and dermatological diagnoses [18].

Deeplearning-basedclusteringtechniqueshavebeenwidely used in medical image segmentation, enhancing accuracy in skinanalysisandclassification.K-Meansclustering,combined with HSV and YCbCr-based segmentation, has been demon- strated to effectively improve classification in AI-powered dermatologyapplications[19].Otherstudieshighlighttherole 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 withAI-driven skin improvement tracking for a more functional and user-centric approach. AI-based chatbot systems havealso been explored for beauty recommendations, but existing implementationsarelimitedtobasicproductsuggestions[17]. Dermavision enhances chatbot interactions by providing sci- entificallybackedskincareadvicebasedonimageanalysisand user history.

Whilemachinelearninghasbeenappliedindermatologyfor diseasedetection[12], Dermavisionextendsbeyonddiagnosis by incorporating ingredient safety, allergy tracking, and per- sonalized 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 factorsinAI-drivenskincaresolutions.Recentstudiesindicate that integrating AI-powered ingredient analysis can enhance product safety recommendations by identifying potential al- lergens and adverse interactions based on user skin profiles [20]. With its integration of clustering techniques, AI-driven analysis,andreal-timepersonalization,Dermavisionbuildson 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 Sys- tem employs OpenCV and CNNs for skin type classification but relies on sentiment analysis, making it subjective and dependentonuserfeedbackratherthanreal-timeskinanalysisnificant computational resources. Dermavision optimizes effi- ciency 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 skincareanalysis[4].Otherskincaresystemsrelyheavily on manual input for recommendation refinement [5], while Dermavision automates this process using deep learning, min- imizing user dependency. Additionally, existing ML-based dermatology models lack clinical validation [6], an issue Der- mavision addresses by training on dermatologically validated datasets.

While Augmented Reality (AR) in beauty applications enhances virtual product try-ons, most implementations lack scientificaccuracy.DermavisionintegratesARwithAI-driven skin improvement predictions, offering both visualization and data-backed recommendations [7]. Research on Online Com- munitiesandAIChatbotsinSkincarehighlightstheirrole 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 rec- ommendations, leveraging deep learning to detect allergens and identify ingredient interactions in real time [20]. By mergingcomputervision,deeplearning,ARvisualization,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 pro- cess 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 ac- curate face detection. Subsequently, the quality of the imageis 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 com- putedbasedonacombinationofthemaximumhistogrampeak $T_{\max}$andthe Otsu'sthreshold value T_{otsu},asshownbelow:

$$T_{\text{final}} = \frac{T_{\max} + T_{\text{otsu}}}{2} \tag{1}$$

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

$$T_{\text{final}} = \frac{T_{\max} + T_{\text{otsu}}}{4} \tag{2}$$

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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:

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

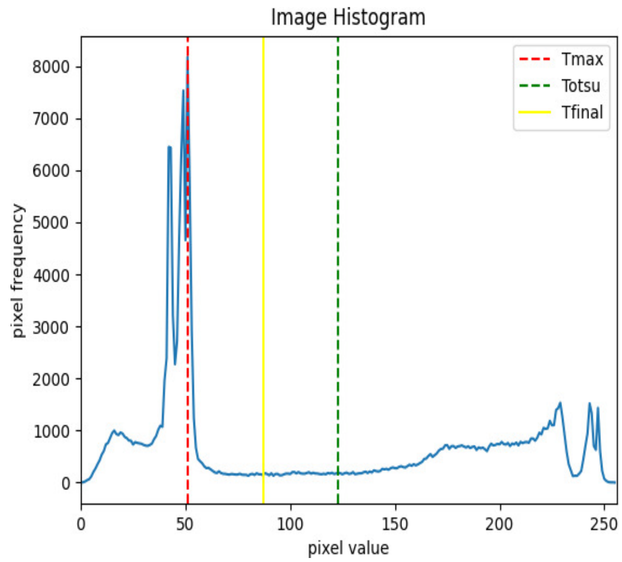

Fig.1:ImageHistogramforSkinPixelExtraction

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:

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

These segmented skin regions are then passed to Efficient- NetB0, a highly efficient CNN model which classifies theskin type (dry, oily, combination) and acne severity based on features extracted from the image (fig. 2). For accurate skin tonemapping,atwo-steptechniqueisimplemented—first,the image is transformed into YCbCr and HSV spaces, and then clustering is used to map the extracted tones onto the Fitz- patrick scale. To finalize classification, the K-Nearest Neigh- bors (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 simi- larity 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:

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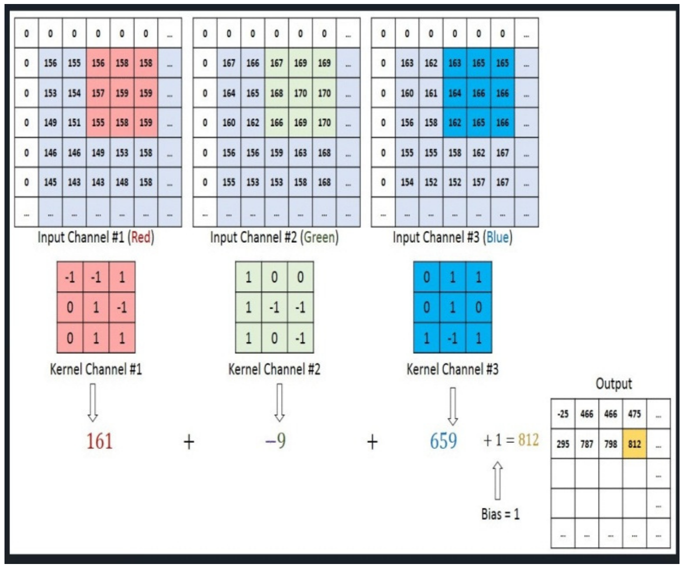

Fig.2:FacialSkinTypeClassificationwithCNN

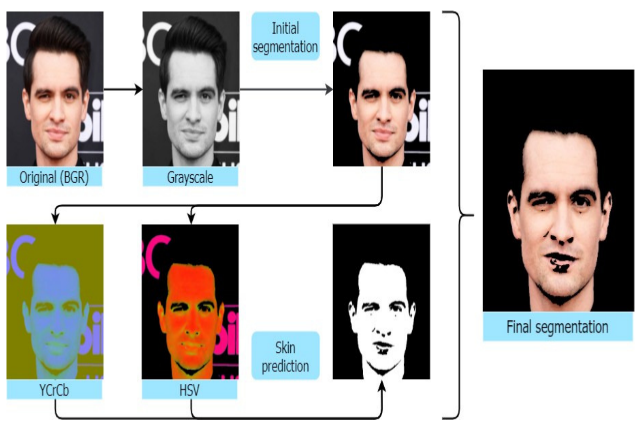

Fig.3:SkinDetectionUsingK-MeansClustering

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

AllpredictionsarebackedbydatafromtheKaggleAcne Grading Classification dataset [21], and although the dataset lacks dermatological ground truth labels and diverse skin tones, data augmentation techniques are employed to im- prove generalization. (TABLE I) compares commonly used CNN architectures with Dermavision's EfficientNetB0-based approach, highlighting its suitability for real-time and person- alizedskincarerecommendations.Infutureiterations,Dermav- isionwillincorporateclinicallyvalidateddermatologydatasets 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 systemthatconsistsofbothfrontendandbackendcomponents, eachintegratedtosupportreal-timeskinanalysis,recommen-dations,ARvisualization,anduserengagement.Thefrontend, built with React.js, is responsible for the user interface, in- cludingreal-timewebcam-basedARinteractions,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 onfacialregionsintheARMakeupandARSkincaremod- ules. User interactions are managed via React Router, and MaterialUIcomponentsprovideanelegantandresponsive

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TABLEI:ComparisonofDeepLearningModelsforSkincareAnalysis

Model	Features	Advantages	Disadvantages
ResNet-50	Uses skip connections (shortcuts) tobypass layers, allowing very deep net-works without vanishing gradients.	Helpsdeepnetworkslearneffici ently,reduces vanishing gradient problem.	Requiresmorecomputationalp owerdue to deep architecture.
Inception-v3	Uses Inception Blocks with multiplekernel sizes to capture different featurescales.	Efficient at extracting multi-scale fea-tures,goodaccuracywithfewer param-eters.	More complex structure, requires care-ful tuning.
DenseNet-121	Uses dense connections where eachlayer gets inputs from all previous lay-ers.	Improvesgradientflow,reduce soverfit-ting, and increases feature reuse.	Requiressignificantmemorydu etodense connections.
Xception	Uses depthwise separable convolutionsfor improved efficiency and perfor-mance.	Faster and more efficient than standardconvolutions, improves accuracy.	Needsmoretrainingtimeandtun ing.
Inception-ResNet-v2	Combines Inception Blocks withResNet skip connections for deepfeature extraction.	Benefits from both ResNet and Incep-tion,retainsefficiencywhileim provinglearning in deep networks.	Computationallyexpensive,re quiresmore memory.
Dermavision(EfficientNetB0+Clustering)	Uses EfficientNetB0 with YCbCr &HSV-based clustering for real-timeskincare classification.	Balances speed &accuracy,lightweight, enhances real-timeanalysis with clustering techniques.	May require further optimization fordarker skin tones in extreme lightingconditions.

design. The backend is built using Firebase and Node.js, andit handles core logic for user authentication, image process- ing, allergy-based product filtering, and personalized skincare recommendationengines.Alluploadedimagesarenormalized before being passed to neural networks, and the normalization function ensures that pixel values range between 0 and 1, defined as:

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

Once normalized, image features are extracted using con- volutional 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:

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

Duringtraining,thenetworkisoptimizedusingthecategor- icalcross-entropylossfunction,whichcomparesthepredicted probability distribution $y\hat{}$ to the true distribution y:

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

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 recommenda- tions. The chatbot is built using a hybrid NLP model that combinesretrievalandgenerativeresponsestoassistusersin detectionaccuracy, and recommendationprecision. 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 tosimulaterealisticimprovements,likechangesinbright- ness,blur,andsaturation evelsbasedons kinconditionand productcategory.Moreover,askindiseasedetectionfeature ness,blur , andsaturationlevelsbasedonskinconditionand productcategory.Moreover,askindiseasedetectionfeature 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 approxi- mately87.67%.Theentiresystemisdesignedtobeextensible, withfutureplansforoptimizingmodelinference,integrating userfeedbackforactivelearning,anddeployinglightweight mobileversionsforbroaderaccessibility.

VI. RESULTS AND DISCUSSION

TheDermavisionsystemwasevaluatedusingkeyperformancemetrics,includingauthenticationspeed,imageprocessingaccuracy,skinclassificationeffectiveness,skindisease

User Authentication and Profile Management achieved a 100% success rate, with an average authentication time of under two seconds, ensuring seamless user access. Profile up- dates, 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-timeperformance.Thethresholdingprocessbasedonthe image histogram significantly improved skin pixel extraction, reducing false detections.

Skin Analysis and Classification achieved 80% accuracy in categorizingskintypesandacneseverityusingEfficientNetB0. YCbCr and HSV clustering techniques improved skin tone representation, ensuring diverse and inclusive analysis. K- Means clustering optimized skin pixel segmentation, enhanc- ing classification performance. The recommendation engine generatedskincareproductsuggestionsinunderthreeseconds, 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 usingtheEfficientNetV2Smodel, whichwastrainedonthe HAM10000dataset.Themodelachievedanaccuracy of approximately 87.67% in detecting skin lesions such as melanoma, keratosis, and benign nevi. This feature demon- strated 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 diverseandclinicallyvalidateddatasetstoenhancedetectionaccuracy 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.

UserSatisfactionSurveyResults:Toassesstheusabilityand 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, followedbyashortfeedbacksurvey.

Participantsratedthesys- tem based on usability, accuracy, recommendation relevance, allergydetection,skindiseasedetection,ARvisualization,and likelihood of future use, using a 5-point Likert scale (1 - StronglyDisagreeto5-StronglyAgree).Theresultsindicated that:87%ofusersratedtheiroverallexperienceas4orhigher. 80% agreed that the skin analysis was accurate. 78% foundthe 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 ARvisualizationhelpedthemunderstandproducteffects.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 longitu- dinaluserdataand dermatologist-verifiedprogresstrackingto enhance scientific credibility.

Feedback and Suggestions: Participants provided valuable feedback, praising the intuitive interface, real-time analysis, andthepotentialforearlydetectionofskindiseases.However, commonsuggestionsincludedimprovingimageprocessing under low-light conditions, expanding the allergy databasefor better personalization, and enhancing the skin disease detection module to include more diverse dermatological cases. This feedback highlights areas for enhancement andwill 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 detectioninpoorlightingconditionswas5%.Theskindisease 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,optimizingallergydetection,improvingskindisease detection, and integrating more diverse datasets to improve system reliability across a broader range of users and environ- ments.

VII. CONCLUSION

The development of Dermavision marks a significant ad- vancement 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 im- ageprocessing,augmentedreality-basedproductvisualization, an AI-powered chatbot, and a community-driven platform enhance user engagement and accessibility. While the sys-tem 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 predic- tions. 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 thegap between artificial intelligence and personalized beauty solutions.

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