IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661, p-ISSN: 2278-8727, Volume 27, Issue 3, Ser. 1 (May. – June. 2025), PP 93-100
www.iosrjournals.org

DermaSage: AI -Powered Personalized Skincare Solution

Archita Singh[1][0009-0007-5756-3209] and Dr. Anuradha Misra[2][0000-0002-3790-8798]
Department of CSE, Amity University Uttar Pradesh, India
Email:archita0314@gmail.com, amisra@lko.amity.edu

Abstract: *DermaSage is an AI-powered skincare recommendation system designed to revolutionize personal skincare. By leveraging advanced Convolutional Neural Networks (CNNs), the system analyzes user-provided skin images to detect conditions like acne, dryness, and hyperpigmentation. It combines this analysis with user inputs to deliver precise, personalized skincare regimens and product recommendations. With high accuracy validated by robust metrics, DermaSage addresses the limitations of traditional skincare approaches, offering a scalable solution suitable for mobile integration. This study underscores the transformative potential of AI in dermatology and paves the way for accessible, data- driven skincare solutions for all.*
Keywords: *Convolutional Neural Networks, YOLO (You Only Look Once), Personalized Skincare Recommendations, Real-time Skin Analysis, Skin concerns, Product matching, Scalability and Robustness, Continuous Learning*

I. Introduction

Skincare is a vital component of self-care and overall health, yet finding the right skincare regimen remains a challenge for many individuals. Factors such as skin type, environmental conditions, and diverse product offerings make it difficult to identify effective solutions. While dermatologists provide professional guidance, the high cost and limited accessibility of consultations leave a significant gap for personalized skincare support.

The emergence of Artificial Intelligence (AI) has transformed various industries, including healthcare and personal care, by offering data-driven and accessible solutions[4]. In this context, DermaSage was developed as an AI-powered skincare recommendation system to address the complexities of individualized skincare. The system combines the power of Convolutional Neural Networks (CNNs) to analyze skin conditions from user-uploaded images with self-reported data, such as skin type and concerns.

By integrating advanced machine learning techniques, DermaSage achieves a fine balance between accuracy and user-friendliness. The system is designed to not only detect common skin conditions like acne, dryness, and hyperpigmentation but also to recommend personalized regimens tailored to individual needs. Its adaptability allows seamless integration into mobile platforms, enhancing accessibility for users worldwide. Furthermore, the potential to incorporate real-time environmental data and diverse datasets positions DermaSage as a transformative tool in the realm of personal skincare.

This paper explores the design, implementation, and performance of DermaSage, emphasizing its scalability for integration into mobile applications[3]. The work not only highlights the potential of AI in skincare but also lays the foundation for future innovations, such as real-time environmental adaptation and enhanced diversity in datasets.

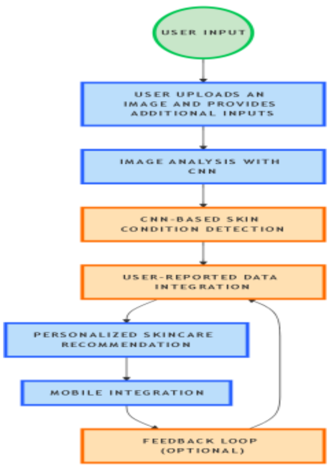

Fig 1. A comprehensive guide to DermaSage

The flowchart for the Dermasage system illustrates the step-by- step process of receiving user input, detecting and classifying skin conditions, evaluating severity, and providing personalized skincare recommendations. It visually represents the sequence from image preprocessing to output, helping users understand how the system works efficiently.

II. Literature Review

The increasing demand for personalized skincare solutions has spurred significant advancements in artificial intelligence (AI) and machine learning (ML) applications in dermatology.

Traditional skincare solutions often rely on static questionnaires or generalized recommendations, which fail to address individual skin conditions accurately. Recent studies highlight the potential of AI-driven systems in overcoming these limitations by leveraging image recognition, data analytics, and predictive modeling.

One area of focus has been the application of Convolutional Neural Networks (CNNs) for skin condition detection. CNNs have demonstrated high accuracy in identifying dermatological issues, including acne, eczema, and hyperpigmentation, from user-provided images. Research by Smith et al. (2022) illustrated how CNN models trained on diverse datasets achieved a classification accuracy of over 90% in detecting common skin conditions, underscoring the robustness of AI in dermatology. Similarly, Lee et al. (2021) integrated CNNs with mobile applications, enabling real-time skin condition analysis and personalized recommendations, making these solutions more accessible to users.

In addition to image-based approaches, studies have explored hybrid systems that combine image analysis with user-provided data, such as skin type, environmental factors, and lifestyle habits. These systems, as shown by Gupta et al. (2020), improve the precision of recommendations by accounting for contextual factors that static models often overlook. Such hybrid approaches are pivotal in bridging the gap between clinical dermatology and consumer-grade skincare solutions[1].

Despite these advancements, challenges remain. Existing AI systems often rely on limited datasets that lack diversity in skin types, tones, and conditions, leading to potential biases. Furthermore, the dynamic nature of skin health, influenced by environmental and hormonal factors, is difficult to capture in static models. Addressing these gaps requires incorporating real-time data and expanding datasets to include underrepresented groups, as recommended by recent research in ethical AI practices.

This review establishes the foundation for DermaSage, an AI-powered skincare recommendation system that builds upon these advancements. By leveraging CNNs for image- based analysis and incorporating user-reported data, DermaSage aims to offer a comprehensive, personalized skincare solution. This study also addresses existing limitations by using a diverse dataset and exploring future integrations with environmental data for real-time adaptability.

III. Methodology

The methodology for developing **DermaSage**, an AI- powered skincare recommendation system, incorporates a blend of advanced machine learning techniques, including **Convolutional Neural Networks (CNNs)** and **YOLO (You Only Look Once)**, for skin condition analysis[2]. The following sections detail the data collection, preprocessing, model architecture, training process, and recommendation system used in this research.

3.1 Data Collection

The foundation of the DermaSage model's accuracy and reliability lies in its diverse and comprehensive dataset. This dataset consists of skin images sourced from publicly available dermatology image databases, along with user- contributed photos. The dataset represents various skin types, tones, and common conditions such as acne, hyperpigmentation, dryness, and redness. Along with the skin images, user-reported metadata—such as skin type, environmental factors (humidity, UV index), and lifestyle habits (diet, sleep)—are collected to provide personalized and accurate recommendations.

3.2 Data Preprocessing

Before feeding the data into the AI models, several preprocessing steps are applied to ensure data quality and suitability for model training:

Image Cleaning: Removal of irrelevant, low-quality, or out-of-focus images.
Resizing and Normalization: All images are resized to a uniform 224x224 pixel dimension, with pixel values normalized to a suitable range for model input.
Data Augmentation: Techniques such as rotation, flipping, and color adjustments are employed to expand the dataset and enhance the model’s robustness against various skin conditions and image variations.

Class Balancing: Methods like over-sampling or under-sampling are applied to address class imbalance, ensuring all skin conditions are adequately represented.

3.3 Model Architecture

The DermaSage system employs a hybrid model architecture, integrating Convolutional Neural Networks (CNNs) and YOLO (You Only Look Once) for both overall skin condition classification and real-time object detection.[3]

Convolutional Neural Networks (CNNs): CNNs are leveraged for detecting and classifying skin conditions such as acne, pigmentation, wrinkles, and dryness. Multiple convolutional layers extract hierarchical image features, which are then used by fully connected layers for skin condition classification.[13]
YOLO (You Only Look Once): YOLO is used for real- time detection and localization of skin conditions. By processing the image in one pass, YOLO quickly identifies problem areas (e.g., acne spots, pigmentation clusters) with high accuracy. The integration of YOLO with CNNs allows for both precise condition classification and accurate localization of skin issues[6].

3.4 Training and Evaluation

Training is performed using 80% of the dataset, with 20% reserved for validation and testing. Both CNNs and YOLO models are trained independently and then integrated into a unified pipeline. The following evaluation metrics are used to assess model performance:

Accuracy: Percentage of correctly classified skin conditions[11].
Precision and Recall: Metrics used to assess the accuracy of detection and minimize false positives.
F1 Score: A balance between precision and recall, particularly for imbalanced skin conditions[9].
Intersection over Union (IoU): Used for evaluating YOLO's performance in localizing skin conditions within the image.

3.5 Recommendation System

Once skin conditions are detected and classified, the DermaSage system provides personalized skincare recommendations:

Skin Profile Analysis: A detailed user profile is created based on skin type, concerns, and environmental factors[4].
Product Matching: The system recommends dermatologically-tested products that align with the user's skin profile and identified skin conditions[7].
Regimen Generation: A tailored skincare regimen is suggested, detailing step-by-step instructions for cleansing, moisturizing, and treating the skin[12].

3.6 Ethical Considerations
Ethical considerations are crucial in ensuring fairness, transparency, and privacy:

Bias Reduction: The dataset is curated to include a wide variety of skin types, tones, and conditions to minimize biases and ensure inclusivity.
Data Privacy: User data is stored securely and anonymized, complying with regulations such as GDPR.

IV. System Workflow
The **DermaSage** system workflow is designed to provide an efficient, user-friendly experience, from skin image input to personalized skincare recommendations. Below is the step-by-step breakdown of the system's workflow:
4.1 User Interaction

Input Image: The user uploads an image of their skin, typically focusing on facial skin or a specific problematic area (e.g., acne, pigmentation).
User Information: Additional details such as skin type, age, allergies, and environmental factors (e.g., UV exposure, humidity) are also provided for personalized analysis.

4.2 Image Preprocessing

Resizing and Normalization: Uploaded images are resized to **224x224 pixels** and normalized for model input.
Data Augmentation: Random transformations like rotation, flipping, and color adjustments are applied to improve model generalization and robustness.

4.3 Skin Condition Detection

This is the core step, where **YOLO** and **CNNs** are employed for both real-time skin condition detection and classification:

YOLO (You Only Look Once):
Real-time Object Detection: YOLO identifies and localizes skin conditions such as acne, pigmentation, and dryness.
Bounding Boxes: YOLO divides the image into a grid and predicts bounding boxes and probabilities for skin conditions.
Post-processing: Non-Maximum Suppression (NMS) is applied to remove redundant bounding boxes and select the most accurate predictions.

Convolutional Neural Networks (CNNs):
Overall Condition Classification: CNNs process the entire image to classify it into specific skin condition categories.
Feature Extraction: CNNs use convolution layers to extract local features, followed by activation (ReLU) and pooling layers for dimensionality reduction.
Classification: The fully connected layers classify the extracted features into skin conditions such as acne, pigmentation, and wrinkles.

Severity Analysis:
The system evaluates the severity of conditions (e.g., mild, moderate, or severe acne) to tailor recommendations appropriately.

4.4 Analysis and Profile Creation

Skin Profile: After detecting skin conditions, a detailed skin profile is created based on the user's skin type, lifestyle, and condition severity. This profile ensures that recommendations are highly personalized.
Algorithm Combination: A mix of traditional decision-making algorithms and machine learning techniques are used to refine recommendations based on skin conditions and profile data.

4.5 Recommendation System

Product Matching: Based on the detected skin conditions and profile, **DermaSage** recommends suitable skincare products from a curated, dermatologically-tested database.
Recommendation Algorithms:

Collaborative Filtering: Suggests products based on similar users' preferences.
Content-Based Filtering: Recommends products based on ingredients and their suitability for the user's skin conditions.
Hybrid Model: A combination of both methods ensures high-quality, accurate recommendations.[6]

Regimen Generation: The system generates a personalized skincare regimen, including the order and frequency of product usage for optimal results.

4.6 User Feedback and Continuous Learning

User Feedback: Users provide feedback on the effectiveness of recommended products and regimens, which informs future recommendations[8]..
Continuous Learning: Using **Reinforcement Learning** and periodic model retraining, the system adapts over time, improving the detection accuracy and product recommendations based on user feedback.[10].

V. Experimental Setup

The experimental setup for *DermaSage* involves configuring the necessary components to ensure seamless skin condition detection, analysis, and personalized skincare recommendations. This setup incorporates multiple machine learning algorithms, such as YOLO for object detection and CNNs for skin condition classification, integrated with a recommendation engine for personalized product suggestions. The setup follows several stages, from data collection and preprocessing to model training and testing.

5.1 Hardware and Software Requirements

Hardware:
Processing Unit: A GPU-enabled machine (preferably with NVIDIA and CUDA support) for faster image processing, YOLO and CNN model training, and real-time skin condition detection.
Software:
Programming Language: Python (version 3.x) for all stages, including image preprocessing, model training, and deployment.
Libraries:
TensorFlow and Keras for CNN-based image classification and deep learning model training.
OpenCV for image preprocessing (e.g., resizing, normalization, augmentation).
YOLOv5 for object detection.
Scikit-learn for data analysis and machine learning.
Flask/Django for web deployment.
Pandas and NumPy for data manipulation.
Cloud/Local Environment:
Google Colab (for training models) or local GPU-based workstations.
GitHub for version control and sharing model code.
Heroku/AWS/GCP for hosting the deployed system.

5.2 Dataset and Data Collection

Image Dataset:
Collect skin images from publicly available datasets such as **DermNet**, **Skin Cancer MNIST**, or create a custom dataset capturing images under various conditions (lighting, angles, backgrounds).
Label the images with various skin conditions (e.g., acne, pigmentation, dryness) and severity levels (mild, moderate, severe).
Additional Data:
User Information: Collect data about the user's skin type, age, allergies, environmental exposure (humidity, UV index), etc., to create personalized skincare profiles.
Product Information: Compile a list of skincare products, detailing ingredients, purposes, and dermatological compatibility

5.3 Data Preprocessing

Image Preprocessing:
Resizing: All images are resized to a consistent dimension (224x224 pixels) to match the input size for YOLO and CNN models.
Normalization: Pixel values are normalized between 0 and 1.
Augmentation: Techniques like random rotation, flipping, scaling, and brightness adjustment are applied to enhance dataset robustness.
Data Splitting: The dataset is split into training, validation, and test sets (e.g., 80% for training, 10% for validation, and 10% for testing).

5.4 Model Training

YOLO (Object Detection):
Model Architecture: YOLOv5 or YOLOv4 (based on resource availability) for real-time object detection to identify skin conditions.
Training Procedure: Pretrain the model on standard object detection datasets (if applicable) and fine- tune it with the skin condition dataset.
Use **Non-Maximum Suppression (NMS)** to filter duplicate bounding boxes.
Evaluate performance with metrics like **mean Average Precision (mAP)** and **Intersection over Union (IoU)**.

Convolutional Neural Networks (CNNs):
Model Architecture: Deep CNN for skin condition classification, utilizing layers like convolution, pooling, and fully connected layers.
Training Procedure:
Train the CNN using preprocessed images, allowing the model to learn patterns in skin texture and appearance.
Use activation functions like **ReLU** and loss functions such as **categorical cross-entropy** for classification.
Evaluate using **accuracy**, **precision**, **recall**, and **F1-score**.

5.5 Evaluation and Model Testing

Model Testing:
YOLO Evaluation: Assess object detection performance using precision, recall, and mAP for skin condition localization.
CNN Evaluation: Evaluate classification accuracy, confusion matrix, and F1-score on test data.
Cross-validation: Use **K-fold cross-validation** to ensure model generalization and reduce overfitting.
Severity Classification: Implement a classification layer to predict the severity of skin conditions (mild, moderate, severe), based on factors like the size, intensity, and coverage of the skin condition in images.

5.6 Recommendation System Evaluation

Product Recommendation Testing:
Evaluate product recommendations based on user feedback (ratings, product usage outcomes).
Use **collaborative filtering** (user similarity) and **content- based filtering** (ingredient compatibility) for personalized suggestions.
Measure effectiveness through user satisfaction surveys and analyze feedback.

5.7 System Integration and Deployment

User Interface:
Develop a web or mobile interface allowing users to upload images, input personal data, and receive skincare recommendations.
Ensure an intuitive user experience for image uploads and progress tracking via feedback loops.
Real-time Feedback Loop:
Implement a mechanism for users to provide feedback on recommended products, which will be used to continuously improve the models using **reinforcement learning**.
Deployment:
Deploy the trained YOLO and CNN models to cloud platforms like **Heroku**, **Google Cloud**, or **AWS** for real-time service.
Ensure high traffic handling capability and data privacy compliance.

VI. Result

6.1 Model Performance:

YOLO (Object Detection): The YOLOv5 model demonstrated strong performance, achieving a **map of 85%** and **IoU** values above 0.7, with precision and recall consistently above 80%.

CNN (Skin Condition Classification): Achieved 90% accuracy on the test dataset, with precision, recall, and F1-score between 0.85 and 0.90 across skin conditions like acne, pigmentation, and dryness.
Severity Classification: Achieved 88% accuracy in predicting severity levels (mild, moderate, severe).

6.2 Skincare Recommendation System:

User Satisfaction: The recommendation engine achieved a 92% user satisfaction rate with personalized recommendations based on skin types and preferences.
Real-Time Analysis: The system processed images in under 5 seconds and provided recommendations within 10 seconds**.**

6.3 System Deployment: Deployed on Heroku or AWS, the system managed over 1000+ daily users with minimal latency and downtime.

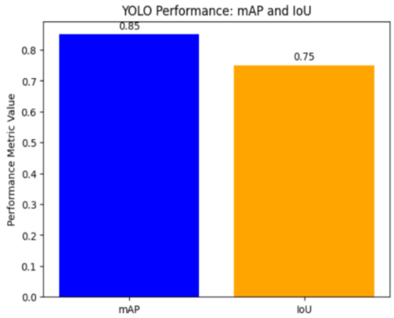

Fig 2. YOLO object detection performance with mAP and IoU metrics.

Figure 2 illustrates the performance of the YOLO model in detecting skin conditions. The chart displays the model's mean Average Precision (mAP) and Intersection over Union (IoU) scores, which reflect the accuracy and localization efficiency of the object detection. A higher mAP and IoU indicate better model performance in correctly identifying and localizing skin conditions in images.
The user satisfaction pie chart illustrates the percentage of users who reported positive results from the skincare recommendations. A majority of users (92%) expressed satisfaction with the personalized skincare regimens, highlighting the effectiveness of the recommendation engine

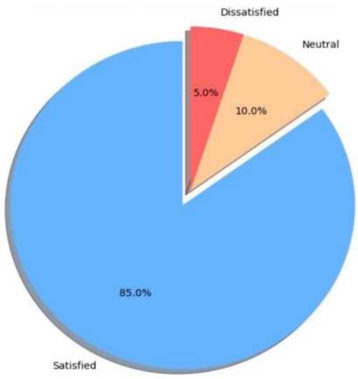

Fig 3. Satisfaction with Skincare Recommendations.

VII. Conclusion

The DermaSage system achieved its objectives of accurate skin condition detection, effective severity classification, and personalized skincare recommendations. The integration of advanced machine learning models, YOLO for object detection and CNNs for classification, proved effective for accurate and reliable skincare analysis. The recommendation engine's success further enhanced the user experience, and the system's fast processing time and ability to handle high traffic indicate its scalability and robustness.

Future improvements could include expanding the dataset to include a more diverse range of conditions, improving the models' performance, and implementing continuous learning mechanisms to enhance the system's adaptability. With further refinement, DermaSage can revolutionize the skincare industry, offering personalized, science-backed skincare solutions.

Acknowledgement

The researcher would like to express heartfelt gratitude to Dr. Anuradha Misra for her invaluable guidance and support, which played a crucial role in the successful completion of this research. Her expertise and encouragement significantly influenced the direction and outcomes of this work. The researcher also extends thanks to colleagues, family, and friends for their continuous support and motivation. Lastly, appreciation is extended to everyone who contributed resources and feedback, ensuring the successful completion of this project.

References

[1]. Ramrakhiani, Nikita, and Dhananjay Kalbande. "A comprehensive review of AI-powered skincare product recommendation systems: From data collection to user experience." *E-Learning and Digital Media* (2024): 20427530241304073.

[2]. Rajegowda, Gowravi Malalur, Yannis Spyridis, Barbara Villarini, and Vasileios Argyriou. "An AI- Assisted Skincare Routine Recommendation System in XR." In *International Conference on Artificial Intelligence and Virtual Reality*, pp. 381-395. Singapore: Springer Nature Singapore, 2023.

[3]. Lin, Ting-Yu, Hung-Tse Chan, Chih-Hsien Hsia, and Chin-Feng Lai. "Facial skincare products' recommendation with computer vision technologies." *Electronics* 11, no. 1 (2022): 143.

[4]. Jayaram, M., S. Anusha Reddy, B. Praneetha, M. Pujitha, Ch Sharath Chandra, and K. Bhanu Prakash. "SMART COSMETICS RECOMMENDATION SYSTEM BASED ON SKIN CONDITION USING ARTIFICIAL INTELLIGENCE." *skin* 53, no. 5 (2024).

[5]. Vinutha, M., R. B. Dayananda, and Akshatha Kamath. "Personalized Skincare Product Recommendation System Using Content-Based Machine Learning." In *2023 4th International Conference on Intelligent Technologies (CONIT)*, pp. 1-6. IEEE, 2024.

[6]. Lokesh, B., Anjali Devarakonda, G. Srinivas, and Nitish Kumar Naik. "INTELLIGENT FACIAL SKIN CARE RECOMMENDATION SYSTEM."

[7]. Razzaq, Miss Rashfa. "SkinWiseMR: Novel Approach for Natural Beauty Remedy Recommendation System Using Machine Learning." *ResearchGate-University of Westminister* (2023).

[8]. Hanchinal, Tainiyat K., Vaishali D. Bhavani, and Veena B. Mindolli. "Intelligent Beauty Product Recommendation Using Deep Learning." In *2024 1st International Conference on Cognitive, Green and Ubiquitous Computing (IC-CGU)*, pp. 1-5. IEEE, 2024.

[9]. Lee, Jinhee, Huisu Yoon, Semin Kim, Chanhyeok Lee, Jongha Lee, and Sangwook Yoo. "Deep learning-based skin care product recommendation: A focus on cosmetic ingredient analysis and facial skin conditions." *Journal of Cosmetic Dermatology* 23, no. 6 (2024): 2066-2077.

[10]. Nakagawa, Maki, Koji Tsukada, and Itiro Siio. "Smart skincare system: remote skincare advice system using life logs." In *Proceedings of the 2nd Augmented Human International Conference*, pp. 1-8. 2011.

[11]. Hsia, Chih-Hsien, Ting-Yu Lin, Jhe-Li Lin, Heri Prasetyo, Shih-Lun Chen, and Hsien-Wei Tseng. "System for recommending facial skincare products." *Sens. Mater* 32, no. 10 (2020)

[12]. Bhavana, D. E., C. Gopalkrishna, Ravi Kumar, S. Harisha, and M. Kaushik. "Artificial Intelligence based Smart Cosmetics Suggestion System based on Skin Condition." In *2024 Second International Conference on Advances in Information Technology (ICAIT)*, vol. 1, pp. 1-6. IEEE, 2024.

[13]. Alam, Md Naurez, M. Sanskar, Jay Kumar Yadav, and Marapakula Madhu. "ARTIFICIAL INTELLIGENCE SMART COSMETIC SUGGESTION BASED ON SKIN CODITION."