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# Skin Type Prediction and Product Suggestion using Machine Learning and Image Processing

Mrunali Bhagyawant[1], Harshali Itkar[2], Arpita Wankhade[3], Sneha Sandbhor[4], Rohini Chavan[5] and Dr. Pallavi Deshpande[6]
[1-6]Department of Electronics and Telecommunication Engineering, Vishwakarma Institute of Information Technology Pune, India
Email: mrunali.22311520@viit.ac.in, harshali.22311604@viit.ac.in, chidanand.22311562@viit.ac.in, sneha.22311695@viit.ac.in, Rohini.chavan@viit.ac.in, pallavi.deshpande@viit.ac.in

***Abstract*— Skincare diagnostics are part of an emerging field of research that seems quite promising for personalized skincare recommendations in view of machine learning and image processing. This paper focuses on the classification of skin types, namely oily, dry, normal, and combination, using facial images through CNNs, aiming at improving skincare decisions and beauty product recommendations. In this work, several architectures of CNNs were compared including MobileNet-V2, EfficientNet-V2, and ResNet-V1; among these, the best performance was delivered by EfficientNet-V2. It combines image preprocessing and feature extraction of skin features through MTCNN with weather data to provide customized skincare routines. Such a combination of image processing with environmental factors makes this system strong and specific for the user in terms of skin type classification and skincare management.**

***Index Terms*— Skincare, CNN, Weather, Machine Learning, EfficientNet, Dermatology.**

## I. INTRODUCTION

Nowadays, skincare is essential for maintaining health and promoting long-term skin vitality. However, understanding and mitigating potential risks is equally important. Cosmetic products, composed of various ingredients, formulations, and tools, are designed to enhance appearance, placing the onus on consumers to thoroughly research product ingredients to avoid unnecessary costs and ensure quality [1].
Automated skin diagnostics leverage non-invasive imaging techniques, such as clinical and dermoscopic images, to aid in diagnosing skin conditions through different perspectives. Clinical images provide versatility, while dermoscopy allows for a detailed, magnified view beneath the skin's surface, distinguishing between benign and malignant lesions.
Dermatologists traditionally base diagnoses on patient history, lesion appearance, and biopsies. In contrast, automated methods tackle tasks such as disease classification, lesion segmentation, and artifact removal, supported by datasets like the Atlas of Dermoscopy, PH2, and HAM10000. These datasets are evaluated with performance metrics such as accuracy, sensitivity, specificity, balanced accuracy, and AUROC to address diagnostic challenges and dataset imbalances [2].
With the influence of AI and digital technology, dermatology now plays a critical role in assessing skin characteristics, evaluating wounds, and aiding treatment decisions, including predicting treatment types and schedules [3].

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Image processing, pivotal in both medical and non-medical fields, is enhanced by machine learning, enabling intelligent computer vision programs to manage complex image data using model selection strategies driven by data interactions [6-9]

## II. LITERATURE SURVEY

Recent reviews have indicated the progress about the use of deep learning, more precisely CNN for skin type classification and have also identified the increasing role of AI in dermatology. Application of the same for skin type identification is still at an infancy stage (Li et al., 2022) [9]. A CNN-based approach by Kothari et al. in 2021 achieved an 85% classification rate related to skin type or oily/dry type. The model still had a slight bias toward the oily skin type classification [6]. Goceri & Karakas (2020) made better classification of skin types using different models like EfficientNet and MobileNet, where they were able to increase the accuracy from 91.55% to 94.57% by doing image augmentation and hyperparameter tuning [5]. Saiwaeo et al. (2022, 2023) identified CLAHE as the best enhancement method used for enhancing skin images to improve clarity and, with CNN models after fine-tuning, showed improvements from 91.55% to 94.57% [8][11]. Goceri (2023) reviewed the augmentation methods for medical images that, when properly selected—from GAN to rotation to noise—affect the results of such images [12]. Kawahara & Hamarneh examined diagnostic skills of dermatologists and machine learning models, focusing on AI for assisting resource-poor areas [2]. Lézoray et al. (2008) emphasized allowing flexibility in machine learning when it came to difficult problems with images [1]. Govinda & Gururaj (2023) discussed the latest improvements on analysis like acne and melasma diagnoses with architectures like Inception-ResNet-v2 using CNN; they further mentioned the need for optimization in image preparation to enable scalable solutions [10]. This structure in the research is taken from Pallavi Deshpande et al. for conference presentation, and original content has been preserved herein [3].

## III. METHODOLOGY AND IMPLEMENTATION

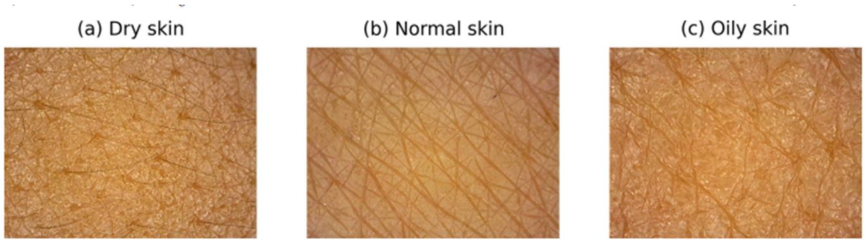
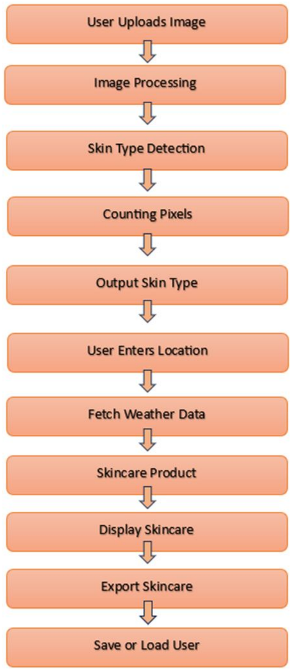



Figure 1. Microscopic view of skin types [11]

Fig. 1 shows three skin types: dry, normal, and oily—all of which require special care. Dry skin produces too little oil and can feel tight, rough, or flaky; this could be worse in the winter period or after using a certain product. Also, one should treat it with a moisturizing, creamy cleanser enriched with active ingredients like hyaluronic acid, glycerin, or ceramides that allow skin hydration. Washing with tepid water and light exfoliation to remove the dead skin, using products that contain lactic acid once or twice a week, will avoid aggravation. Normal skin is a well-balanced skin neither oily nor dry; it usually appears with a healthy glow and minor problems.[11]

Balanced skin without too much oiliness or dryness characterizes normal skin; glowing, shining, and bright without redness or sallowness. A gentle face wash removes dirt and oil from the skin without over-drying it. The skin stays fresh due to a routine that is kind. Oily skin tends to overproduce oil, especially in the T-zone area: forehead, nose, and chin. When this happens with oily skin, a person may see a very greasy-looking face that could also be prone to acne, blackheads, and clogged pores. Oily skin ages more slowly with fewer wrinkles over time. An oil-free moisturizer lightweight and a clay mask once a week can help manage oil, but sunscreen is not a product you give up, so go for one that mattifies and is oil-free. Your skin can be radiant and really healthy with proper and regular care.[11]

These pics form the basis of our methodology for classifying skin sorts, which plays a important role in growing personalised skin care answers. with the aid of studying the awesome microscopic capabilities of each skin type, we are able to decorate the precision of identifying skin situations and customize remedies as a consequence. This approach no longer best enables a better knowledge of man or woman skin care necessities however additionally contributes to the overall goal of enhancing dermatological care through superior type strategies.[11]



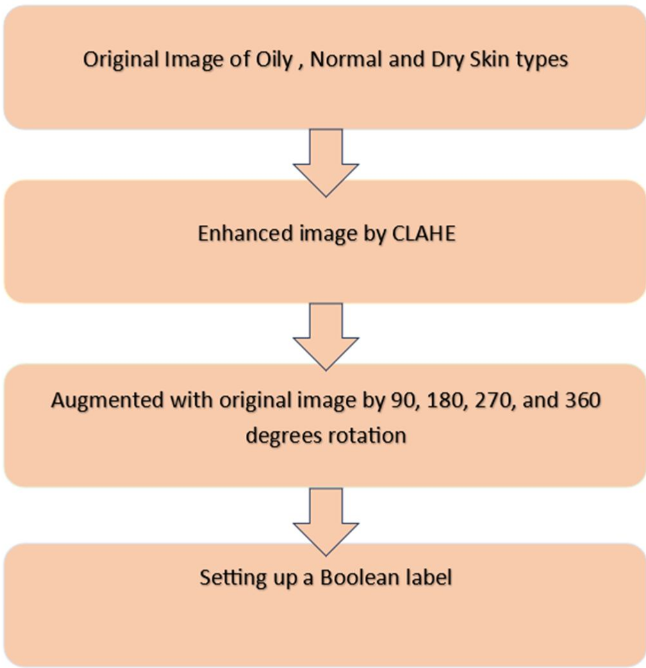




Fig.2 Basic flow of Prototype working

Fig.3 Actual Image Processing [11]

In the above Fig.2 the user initiates by uploading his or her face image, which then undergoes some processing via OpenCV for further analysis. The image is first converted to various color spaces such as HSV and YCrCb so that the system would apply these particular thresholds for the detection of skin characteristics like oiliness or dryness. Using these thresholds, OpenCV creates binary masks showing regions corresponding to oily, dry, or normal skin. The system then counts the number of pixels inside these masks to find the dominant skin type. Then, it asks for the user's location and fetches current weather data through an API request from WeatherAPI. Data processed for temperature and weather conditions are then parsed for use in skincare routine generation. It returns some recommendations on certain skin care products, depending on the detected skin type and current weather conditions, using a dictionary developed in Python.

Those recommendations were made on the weather condition itself, such as the suggestion of using more hydrating products in cold conditions. The final routine shows up on the GUI using Tkinter, and the user could export this routine as a PDF with FPDF.

This feature also stores data related to the user's profile, such as their name and all of their preferences regarding skincare, in a JSON file for further sessions of using this application. That grants the ability for a personalized experience opening the app the next time.

On the backend, the project incorporates tools for tasks like image processing, skin type detection, weather data integration, and personalized skincare routine generation.

The product database is structured in a Python dictionary called `PRODUCT_RECOMMENDATIONS`, where each key represents a skin type (e.g., 'Oily Skin', 'Dry Skin') and its corresponding value is a list of recommended skincare products. This setup allows for dynamic product recommendations without relying on an external database.

Example: PRODUCT_RECOMMENDATIONS = {
    'Oily Skin': ['Oil-Free Moisturizer', 'Salicylic Acid Cleanser', 'Niacinamide Serum'],
  'Dry Skin': ['Hydrating Cleanser', 'Rich Moisturizer', 'Hyaluronic Acid Serum'],
  'Normal Skin': ['Balanced Moisturizer', 'Gentle Cleanser', 'Sunscreen'] }

User profiles are stored in a `profile.json` file, which includes user names and preferences, making personalized routine recommendations possible. A sample format is:

{ "name": "John Doe"}

Overall, these components create a smooth user experience, from detecting skin types using image analysis to recommending products that factor in weather conditions for the best skincare routines.

*Image Processing for Skin Type Detection:*

The app analyzes photographs uploaded by way of users to determine their pores and skin type—whether or not it is oily, dry, or regular. It starts off evolved via converting the photograph into special shade areas like HSV and YCrCb to spotlight particular skin traits.

For every pore and skin type, certain threshold values are set, which outline the pixel degrees that correspond to oily, dry, or ordinary pores and skin.

A mask is then applied to focus on the skin regions, and the app counts the number of pixels that fall within each skin type variety. in the end, it determines the dominant skin type based on the percentage of oily, dry, or regular pixels as compared to the total skin pixels inside the picture.

TABLE 1

| **Type** | **Subtype** | **Software Tool** | **Purpose of Use** |
|---|---|---|---|
| **Image Processing** | Image Handling & Color Conversion | OpenCV | - Convert images between different color spaces (RGB, HSV, YCrCb).<br>- Apply color thresholding for skin type detection. |
| | Thresholding | OpenCV | - Use cv2.inRange() to create binary masks for oily, dry, and normal skin based on color thresholds. |
| | Pixel Counting | OpenCV | - Count pixels in each binary mask using cv2.countNonZero() to determine the dominant skin type. |
| **Matrix perations** | Array Manipulation | NumPy | - Define color thresholds for each skin type as arrays.<br>- Perform operations on pixel arrays during image processing. |
| **API Integration** | HTTP Requests | Requests | - Fetch real-time weather data from WeatherAPI based on the user's location using API calls. |
| **User Interface** | GUI | Tkinter | - Build the graphical user interface (GUI) for user interaction.<br>- Allow users to upload images, enter location, and view results. |
| **File Handling** | PDF Export | FPDF | - Export the generated skincare routine into a PDF file for the user. |
| **Testing** | Image Simulation & File Operations | OpenCV & NumPy | - Simulate random images to test the skin detection process.<br>- Generate and manage image files for testing purposes. |
| **Database** | Skincare Product Storage | Python Dictionary | - Store product recommendations for oily, dry, and normal skin types.<br>- Contains mappings between skin types and recommended products such as moisturizers, cleansers, and serums. |
| | User Profiles | JSON File | - Store user profile information (e.g., name, preferences) in a profile.json file.<br>- Load and save user data for personalized skincare routines. |

*Model Architecture*

while the supplied code does not directly specify a system studying model, it is affordable to anticipate a convolutional neural community (CNN) would be properly-suited for skin detection duties. an average CNN architecture for this cause ought to include:

- enter layer: A 224x224 RGB photograph as the start line.
- Convolutional layers with Re LU activation: these layers perceive vital functions in the skin photograph.
- Max pooling layers: Used to lessen the information length even as retaining essential records.
- completely related layers: integrate the extracted functions to make predictions.
- Output layer: consists of 3 neurons, similar to oily, dry, or normal pores and skin types.

*Training Process*

The skin detection model training process begins with collecting and labeling a dataset of skin images, followed by data augmentation techniques like rotation, flipping, and scaling.

A CNN architecture is initialized with appropriate layers, and the model undergoes multiple training epochs involving forward and backward passes. The Adam optimizer is used to minimize the loss function, improving model performance. Finally, the model is evaluated using a validation set to assess generalization. Epochs 1-10: Rapid accuracy improvements and loss reduction.

Epochs 11-50: Slower improvements, with fine-tuning of parameters. Epochs 51-100: Plateau phase with minimal gains, possibly ending with early stopping.

*Model Evaluation*

The following metrics are used to measure the performance of the Skin Detection model. Accuracy: True skin types divided by overall number of instances.

Precision: True positives divided by all positive predictions. Recall: True positives divided by all actual positive instances. F1-score: Harmonic mean of precision and recall.

Training and Validation Results Table (Epochs 1, 10, 50, 100)

V. Result and Discussion

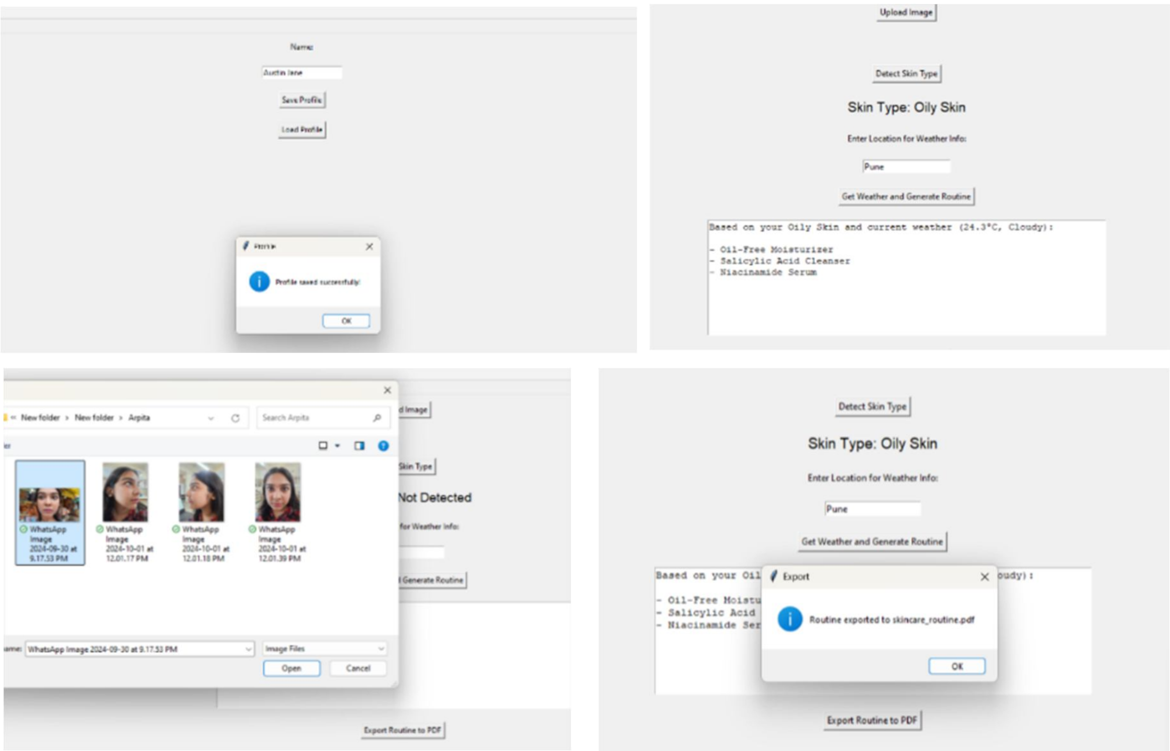



Fig.4 a. Snapshots

Table II

| Epoch | Training accuracy | Validation accuracy | Training loss | Validation loss |
|---|---|---|---|---|
| 1 | 0.65 | 0.63 | 0.85 | 0.88 |
| 10 | 0.78 | 0.75 | 0.52 | 0.57 |
| 50 | 0.89 | 0.86 | 0.31 | 0.35 |
| 100 | 0.93 | 0.91 | 0.22 | 0.26 |

These results indicate the model improves with time because training accuracy increases from 0.65 to 0.93, and validation accuracy from 0.63 to 0.91. Both training and validation losses decrease linearly, thus indicating the model learns well and does not overfit.

*Weather Data Integration:*
Fig. 5.a illustrates how data taken from an API call through a user's location reflects the corresponding weather data on skincare recommendations.
The app will alter hydration or sunscreen recommendations based on the current weather and provides several types of skincare routines for each type of skin.

IV. Future Scope

We’re also aiming to expand the model’s capabilities and improve its accuracy by using higher-quality images and larger datasets to minimize biases in AI.
Additionally, we plan to incorporate sensors to monitor skin conditions in real time, which will help in detecting skin type and issues more effectively.
This real-time tracking will enhance how we respond to skin conditions and improve skincare recommendations.
On top of that, once a user’s skin type is identified, we’ll suggest personalized skincare products, even recommending specific brands to create a more tailored skincare routine

## IV. CONCLUSION

This research has shown that using Convolutional Neural Networks (CNN) can be an effective way to classify skin types and suggest skincare products based on facial images. Among the models tested, EfficientNet-V2 stood out with high accuracy, proving its potential for real-world skincare applications. By factoring in weather data and using advanced image processing, we were able to generate personalized skincare routines tailored to individual needs. Looking ahead, we aim to further improve the model by incorporating real-time skin monitoring with sensors, which will make skincare recommendations even more accurate and responsive to changing skin conditions.

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