Intelligent Skincare and Makeup Personalized Recommendation System using Image Processing

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***Abstract*—The skin condition, type, and colour of a person may also influence the usage of cosmetic and skincare products. Typically basing itself on subjective observations, traditional recommendation programs generate unsuitable and biased product recommendations. This work discusses an Intelligent Makeup and Skincare Recommendation System which is able to identify acne and infer skin colour through the means of image processing. The system evaluates the user photographs through Python machine vision to infer valuable skin attributes and deliver customized skincare and makeup advice. For further analysis and fine-tuning, the results are saved in a CSV file. This methodology combines dermatology principles with technology to provide more accurate and information-based skincare and beauty recommendations.**

***Index Terms*—Convolutional Neural Networks (CNN), Deep Learning, Skincare, Makeup, Product Recommendation, Image Analysis, Personalized Beauty, Feature Extraction**

I. INTRODUCTION

In recent years, artificial intelligence (AI) and data mining technologies have brought about a significant shift in the beauty and skincare industry. As people today become more aware of the needs that their own skin or hair care product has to meet for themselves alone, they require intelligent technologies that can observe reality and analyze personal characteristics. These requirements offer one official siding solution However, traditional beauty consultations are often held face to face and have their constraints. They may be subject to a fault at times if one consultant says you have an oval face shape whereas another claims that your features look square shaped, who will you believe? And often these consultations can be very time consuming indeed for both re- porter and receiver alike as well inaccessible to the mass man. This gap in the market illustrates a need for an automated, intelligent system providing recommendations which assures accuracy yet is personally relevant and easy for people to find. Advances in artificial intelligence (AI), machine learning (ML), and data analytics are rapidly transforming the beauty and skincare industry. Today's consumers expect more than just high-quality products—they seek deeply personalized experiences that consider their unique skin type, color tone, lifestyle habits, and even environmental factors. However, find- ing the right skincare product or makeup combination often involves trial and error. This process can result in skin damage, wasted time, and unnecessary expenses. Modern consumers aren't just seeking quality skincare they want solutions that feel made for them. Everything from their skin type and tone to daily habits and the environment can influence what works best. But figuring out the right products often comes down to guesswork. That trial-and-error approach can irritate the skin, waste money, and leave people feeling frustrated.

With so much of the beauty experience moving online, there's a real need for smarter tools that can offer the kind of guidance once only available through in-person consultations. Personalized beauty is no longer a trend—it's an expectation. People want technology that listens, learns, and makes thoughtful suggestions based on who they are and what they need. A step towards realizing that objective is an Intelligent Makeup and Skincare Recommendation System. Such a system can analyze user data, including skin type (oily, dry, sensitive, etc.), skin tone, facial features, age, gender, climate, and specific concerns (like acne, pigmentation, or dark circles), and provide precise, real-time product and routine suggestions by fusing AI and machine learning with dermato- logical insights and cosmetic science. To improve accuracy in skin assessment, certain systems may additionally make use of computer vision and face image processing techniques.

The system's capacity to continuously learn from user comments and product performance to enhance future recommendations is what defines it as innovative. In addition, incorporating component research, user evaluations, and compatibility with current goods may significantly improve user trust and confidence.

The goal of this research is to create a recommendation engine that is intelligent, simple to use, and effective while personalizing skincare and makeup recommendations. The suggested system aims to enhance skincare results through intelligent automation by utilizing user-centric design and sophisticated algorithms to address major problems in existing recommendation platforms.

II. RELATED WORK

The creation of intelligent recommender systems specifically for cosmetics and skin care has been the subject of numerous studies. In order provide personalised recommendations, these systems use machine learning, computer vision, and deep learning algorithms to evaluate skin tone, skin type, and skin problems. This section provides a quick overview of the body of research on the variety of approaches and methods used in skincare and cosmetic recommendation systems. According to the authors, study suggest a deep learning- based system for personalised cosmetic options based on skin type and concerns (e.g., dry, oily, sensitive) in order to overcome the increasing difficulty of skincare decision- making. By categorising products using complex algorithms, the system minimises mismatches. A online application offers product recommendations along with links for purchase and validates user knowledge. [1]

In order to design a new business model for skincare goods for the face, this study presents a computer vision-based method. It offers an innovative solution built for unattended retail settings. In addition to identifying acne and classifying skin types using facial picture analysis, the system addition- ally recommends appropriate skincare items. Comparing it to previous techniques, experimental data indicate that it delivers the highest accuracy in skin type classification.[2]

The challenge that customers have picking appropriate beauty stores in the face of a growing number of possibilities is discussed in the study. With the Collaborative Filtering technique, the authors created an online application that uses user ratings to suggest beauty parlours in Bandar Lampung. By matching recommendations to customer preferences, this technique seeks for better user happiness.[3]

Study presents a system that identifies the severity of acne from facial images via deep learning. The model applies semantic segmentation to target spots affected by acne after being trained on a re-annotated dataset. When it came to discriminating among areas affected by acne versus those that were not, the DenseNet121 architecture scored a high F1 score of 60.84%. This technology delivers an effective means for diagnosis acne remotely, minimising the necessity for in- person dermatologist sessions and offering rapid treatment.[4]

Shows a system for suggesting personalised skincare prod- ucts based on content. For choosing relevant skincare products, the system considers user preferences, skin type reliability, and product attributes like ingredients. The approach aims to enhance skincare routine efficacy and customer satisfaction by applying machine learning strategies. By providing an a data- driven option to match shoppers with ideal skin care products based on their specific requirements and tastes, work promotes the area of customised dermatology.[5]

For the purpose to classify different types of acne, the research study presents a deep learning model which makes use of convolutional neural networks, or CNN. By computing the classification of acne variants with image analysis, the initiative intends to support dermatological diagnosis. By effectively collecting information from skin images and precisely distinguishing between acne types, AcneNet shows positive outcomes. Applying AI-based tools, this approach could improve dermatology's detection and treatment plan- ning.[6]

The study suggests a technique based on deep learning to produce skin-type-specific advice for skincare items. This study classifies skin types and assesses facial features through image processing and neural networks, then suggests tailored skincare products. This driven by AI solution aims to enhance customer satisfaction in the beauty industry by providing ex- act, data-driven solutions that tackle individual dermatological requirements.[7]

The application of AI to recommend cosmetics based on a person's skin type is studied in this research. The suggested method uses machine learning and image processing techniques to evaluate facial photos and identify different skin conditions including pigmentation, dryness, or acne. According to the study, it promotes appropriate skincare based on the user's skin type. This study focuses the expanding use of AI in customized skincare and makeup with the objective of enhancing customer satisfaction and product choices.[8]

In this research study, a content-based filtering-based customised skincare recommendation system is provided. Users no longer need to provide particular product labels since the system analyses their skin types and preferred beauty goals to suggest goods with equivalent ingredient concentrations. In the beauty sector, this strategy intends to improve buyer satisfaction and speed the selection process by highlighting ingredient suitability and user preferences.[9]

The study presents a system that improves recommendations for products by exploiting face sentiment analysis. The system captures and examines users' facial expressions to figure out their emotional states via the Microsoft Azure Face API. These findings are then used to supply real-time, specific suggested products. By fitting recommendations to the user's visible emotional surroundings, the method aims to improve user satisfaction and involvement.[10]

Suggest using algorithms trained with machine learning for generating a customised skincare suggestion system. To provide individualised product suggestions, the system evaluates user data, covering skin type, illnesses and preferences.

The model increases the effectiveness and importance of recommendations by employing classification and prediction methods, with the goal of maximising consumer satisfaction while acquiring skincare products.[11]

A technique that uses deep learning to generate skin-type- specific cosmetic suggestions is presented in the paper. The system leverages Convolutional Neural Networks (CNNs) to classify skin types (e.g., dry, oily, or neutral) through facial image analysis and suggest suitable beauty products. Model training employing a dataset of different skin types, feature extraction with an emphasis on skin texture and colour, and data preprocessing are all included in the methodology. The proposed algorithm proved its success in enhancing personalised skincare choice by achieving a high accuracy rate of 97.38% in offering appropriate cosmetics.[12]

III. METHODOLOGY

The methodology adopted for the *Intelligent Skincare and Makeup Recommendation System* integrates image processing, machine learning, and personalized recommendation techniques through a modular pipeline. The system is implemented as a web application using Django and Python, ensuring accessibility and usability.

A. Data Collection and Datasets

Two datasets are utilized:

- Skincare Dataset: Contains product names, ingredients, and suitability for different skin types (oily, dry, combi- nation, normal) and acne conditions.
- Makeup Dataset: Includes foundation shades, lipsticks, and concealers mapped to skin tones (fair, medium, dark) for compatibility-based recommendations.

B. Image Upload and Preprocessing

Users upload facial images through the web interface. The uploaded image undergoes the following preprocessing steps:

- Resizing to 224 × 224 pixels
- Pixel normalization
- RGB conversion
- Data augmentation for training (e.g., rotation, flipping)

Fig. 1. Skin Type

C. Face Detection and Landmark Localization

Face detection and feature localization are performed using pre-trained models from `face-api.js`:

- Tiny Face Detector: Detects the face bounding box.
- 68-Point Landmark Detector: Identifies key facial re- gions such as cheeks, forehead, and jawline.

D. Skin Tone Classification

The extracted cheek region undergoes classification:

- Convert RGB to Lab color space:

$$L = 0.2126R + 0.7152G + 0.0722B \qquad (1)$$

- Calculate average Lab values to classify as fair, medium, or dark.
- CNN model (e.g., MobileNet or ResNet) used for training and prediction.

TABLE I: SKIN TONE CLASSIFICATION BASED ON LAB VALUES

Tone	L (Lightness) Range
Fair	70–100
Medium	40–69
Dark	0–39

E. Acne and Spot Detection

The acne detection module includes:

- Grayscale conversion
- Gaussian blur:
- Thresholding and contour detection for acne localization

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (2)$$

F. Recommendation Engine

The engine uses rule-based filtering to suggest skincare and makeup products:

- Skincare: Matches skin type and acne status to suitable products from `skincare.csv`
- Makeup: Uses cosine similarity for matching foundation shades

$$\cos(\vartheta) = \frac{A \cdot B}{\|A\|\|B\|} \qquad (3)$$

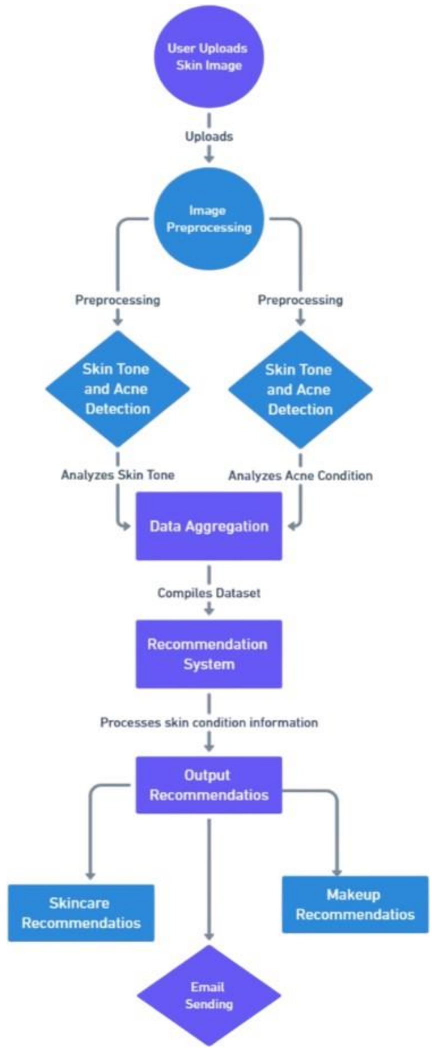

Fig. 2. Skin Type and Acne Detection Flow

G. Email Notification System

Results are:

- Displayed via the Django frontend
- Sent to the user via SMTP using Python's `smtplib`:

```
import smtplib
from email.mime.text import
MIMEText
msg = MIMEText("Your␣personalized␣
recommendations␣are␣ready.")
server =
smtplib.SMTP('smtp.gmail.com', 587)
server.starttls()
server.login(sender_email,
password)
server.sendmail(sender_email,
receiver_email,
msg.as_string()) server.quit()
```

H. System Architecture

Figure 3 illustrates the overall architecture of the

Intelligent Skincare and Makeup Recommendation System. The system is composed of several interconnected modules that work together to collect input, analyze facial features, and generate personalized product recommendations for users.

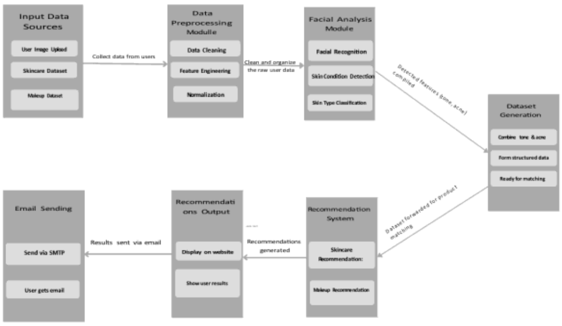

Fig. 3. System Architecture of the Recommendation System

The architecture consists of the following modules:

- Input Data Sources: This module collects inputs from the user in the form of uploaded facial images, and also accesses skincare and makeup datasets for recommendation matching.
- Data Preprocessing Module: The collected data is cleaned, normalized, and processed through feature engineering techniques. This ensures that only structured and meaningful data is used in further analysis.
- Facial Analysis Module: This component performs facial recognition and detects skin-related features such as acne presence and skin tone. It uses image processing and machine learning techniques such as CNNs and color space analysis.
- Dataset Generation: Based on the features detected from the facial analysis module, this block compiles a structured dataset, which includes details like acne severity and skin tone. This data is then forwarded for recommendation processing.
- Recommendation System: The core recommendation engine uses techniques like TF-IDF and cosine similarity to match detected features with suitable products. It generates skincare and makeup recommendations tailored to the individual.
- Recommendations Output: The results are displayed through the web interface using Django and frontend technologies such as HTML/CSS. The user can view their analysis and recommended products.
- Email Sending: In addition to displaying results on the website, the system also sends recommendations to the user's email via SMTP, providing a convenient way to access results offline.

This modular design ensures scalability, accuracy, and a user-friendly experience while enabling real-time intelligent recommendations.

IV. EVALUATION AND RESULTS

To evaluate the effectiveness of the proposed Intelligent Skincare and Makeup Recommendation System, various performance metrics were computed using a labeled validation dataset. These metrics include accuracy, precision, recall, F1-score, and a confusion matrix.

A. Model Accuracy

The overall accuracy is computed as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Model 2 achieved the highest accuracy of 89.25% compared to Model 1 (80.19%) and manual calculation (82.67%). This shows significant improvement in prediction capability.

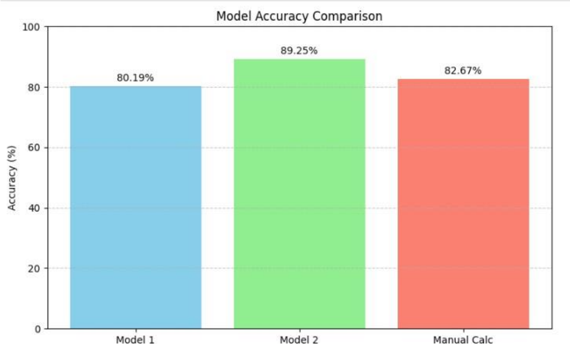

Fig. 4. Model Accuracy Comparison

B. Confusion Matrix Analysis

The confusion matrix evaluates classification performance for each skin type. The matrix highlights the true classification rates and misclassifications.

From Fig. 5, we observe:

- Oily skin was correctly classified 79% of the time.
- Dry skin was misclassified as Oily in 39% of cases.
- Combination skin had the highest classification accuracy at 84%.

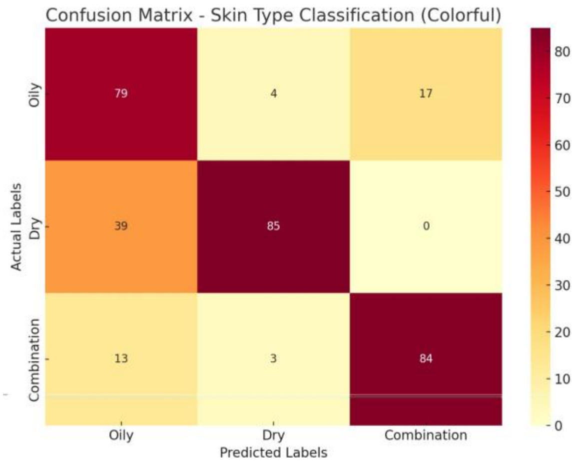

Fig. 5. Confusion Matrix - Skin Type Classification

C. Precision, Recall, and F1 Score

To further understand model reliability across classes, we computed precision, recall, and F1-score:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{6}$$

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{7}$$

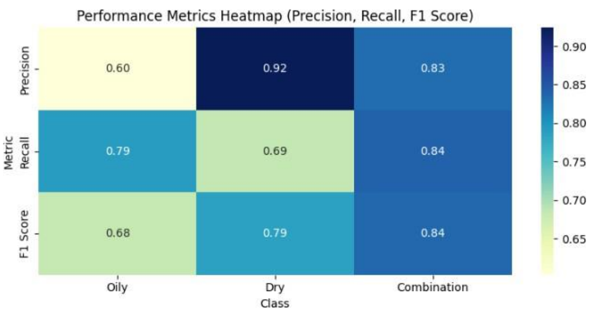

Fig. 6. Performance Metrics Heatmap (Precision, Recall, F1 Score)

As shown in Fig. 6, the model demonstrates strong predic- tive capabilities:

- Highest precision was achieved for Dry skin (0.92).
- Highest recall and F1 score were observed for Combina- tion skin (0.84 each).
- Oily skin showed the lowest precision (0.60), indicating potential class imbalance or similarity in visual traits with other classes.

D. Web-Based System Output and UI Integration

The system offers real-time recommendations for users based on classified skin type and selected concerns. Below are the screenshots showing:

1) User selecting their skin type
2) Product recommendation results based on virtual analy- sis

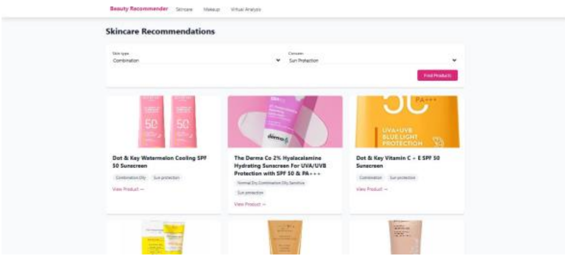

Fig. 7. User Skin Type Input Interface

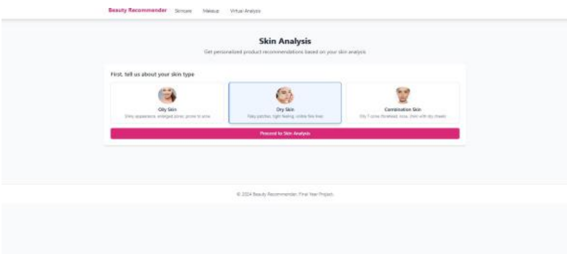

Fig. 8. Skincare Product Recommendations

E. System Performance Summary

The complete system achieved high levels of performance across various metrics, particularly excelling in recommending suitable products for combination skin types.

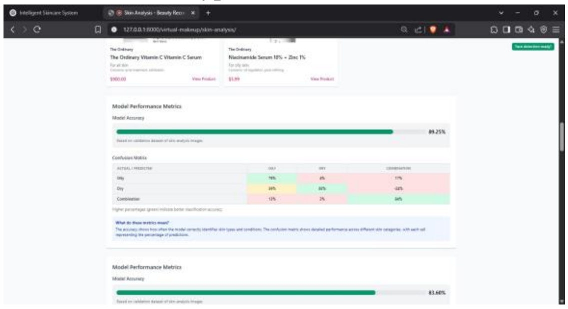

Fig. 9. Backend Model Metrics Display - Web UI

V. FUTURE SCOPE

The structure of this cosmetics and skincare proposal frame- work clears out a parcel of room for future advancement. One potential way to take after with usually including outside variables, like contamination or nearby climate, that have a tendency to influence the skin. By integrating these real- world conditions, the framework would be able to offer more accurate and targeted proposals that are way better custom fitted to each person user's every day needs. A webcam- based real-time investigation can moreover be given, giving quick input and intuitively comes about. Besides, sharing their encounters and comes about by clients will give a criticism circle through which the system learns and progresses its proposals. Within the future, employments such as expanded reality (AR) can moreover be utilized to provide virtual try- ons, advertising shoppers a practical implies of seeing how things seem see earlier to buy.

VI. CONCLUSION

In this work, we have introduced a deep learning-based skincare and makeup product recommendation system that leverages Convolutional Neural Networks (CNNs) to evaluate facial image data and offer personalized product suggestions. The proposed system demonstrates how CNNs can effectively extract and interpret key skin characteristics such as texture, tone, and imperfections, enabling tailored recommendations that enhance users' makeup and skincare routines.

By utilizing advanced computer vision algorithms to address specific skin concerns, our method represents a significant improvement over traditional recommendation systems, offering more efficient and personalized results. CNNs allow the system to adapt to various user profiles and continue improving as more data is collected.

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