CosmoAI – Autonomous AI-Driven Personalized Cosmetic Formulation System

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Abstract : The cosmetic industry mainly offers generalized products that do not address individual skin needs. Existing AI beauty platforms provide analysis or recommendations but do not create personalized cosmetic formulations. CosmoAI is an autonomous AI system that scans a user's face in real time using a camera to analyze skin type, tone, texture, and concerns. Computer vision and deep learning extract precise skin features. A generative AI model then creates fully customized cosmetic formulas, including ingredients and shades. The system adapts dynamically to environmental factors such as UV, humidity, and pollution. This project introduces a unique, end-to-end AI-driven beauty creation platform with no current commercial equivalent.

The proposed CosmoAI system integrates computer vision and deep learning to perform real-time skin analysis. A monitoring and feature extraction pipeline processes facial images, including skin texture, tone, and acne presence. A CNN-based model is employed to classify skin types based on extracted features. To improve personalization, a generative AI model creates customized cosmetic formulas tailored to individual users. An environmental analysis module dynamically adjusts recommendations based on UV, humidity, and pollution data.

The system is evaluated using a facial skin image dataset representing various skin types and conditions. Experimental results demonstrate improved personalization performance compared to traditional recommendation-based approaches. The proposed framework provides a scalable, intelligent, and adaptive solution for personalized cosmetic formulation in the modern beauty industry.

INTRODUCTION

The cosmetic and skincare industry has experienced rapid growth in recent years, with consumers increasingly seeking products that match their unique skin characteristics and personal beauty requirements. However, most commercially available cosmetic products are designed for generalized skin categories and often fail to address the individual differences in skin type, tone, texture, and specific skin concerns.

To address this limitation, this work introduces CosmoAI, an autonomous AI-driven cosmetic formulation system. The proposed system focuses on dynamically analyzing facial skin characteristics in real time, thereby generating personalized cosmetic recommendations
tailored to each individual user. Additionally, the system provides ingredient-based cosmetic formulas and estimated cost comparisons with commercial products.

NEED OF THE STUDY.

In modern beauty and skincare environments, most cosmetic products are designed for broad skin categories rather than individual users. While many AI-based beauty platforms exist, they focus on recommending pre-existing commercial products rather than generating personalized cosmetic formulations. These general-purpose solutions do not adequately address the unique skin characteristics of each individual. Therefore, there is a strong need for advanced AI systems that can intelligently analyze skin conditions and generate customized cosmetic formulations.

Traditional cosmetic recommendation systems rely on predefined product databases and rule-based approaches. These systems are limited in their ability to detect subtle skin variations or generate custom formulas. They often recommend already available products rather than creating formulations tailored to an individual's specific skin type, tone, and concerns. As a result, conventional methods fail to deliver truly personalized skincare solutions.

The advancement of Artificial Intelligence (AI) and deep learning provides new opportunities for improving cosmetic personalization. AI-driven skin analysis systems can analyze facial images and extract detailed skin features, allowing accurate classification of skin type, detection of skin conditions such as acne, pigmentation, and wrinkles, and generation of customized cosmetic formulas with specific ingredients and shades.

Another important need for this study is the complexity and diversity of skin characteristics. Different individuals have vastly different skin profiles influenced by genetics, lifestyle, and environment. A single centralized recommendation system may struggle to handle such variation efficiently. By using an autonomous AI-driven system, the CosmoAI platform can analyze multiple skin attributes simultaneously and generate highly personalized formulations for each user.

Furthermore, skin conditions are significantly influenced by environmental factors such as UV radiation, humidity, and pollution. Early identification of skin concerns and adaptive cosmetic recommendations based on environmental data can help users maintain healthier skin. Therefore, integrating AI-based skin analysis with environmental factor analysis can significantly enhance the personalization and effectiveness of cosmetic recommendations.

3.1Population and Sample

The population of the study consists of all individuals who use cosmetic and skincare products, particularly those seeking personalized beauty solutions. In modern society, people across different skin types, tones, and conditions interact with various skincare platforms and products daily. These users include individuals with oily skin, dry skin, combination skin, sensitive skin, and normal skin. The facial image data generated from these users, including information about skin texture, pigmentation, acne, and moisture levels, forms the universe of the study.

3.2 Data and Sources of Data

The success of a personalized cosmetic formulation system largely depends on the quality and reliability of the data used for skin analysis. In this study, the data mainly consists of facial skin images and skin feature information collected from publicly available dermatology and skincare datasets. These data sources help in understanding normal and abnormal skin conditions, as well as identifying the most suitable cosmetic ingredients for different skin types.

The dataset used in this research includes different types of skin and cosmetic data, such as facial images with labeled skin conditions, skin type classification data, ingredient compatibility information, and environmental condition records.

3.3 Theoretical framework

In modern skincare environments, individuals experience varied skin conditions based on genetic, environmental, and lifestyle factors. Traditional cosmetic recommendation systems mainly rely on rule-based methods, which are not efficient in identifying complex skin variations. Therefore, this study is based on the integration of Artificial Intelligence, Machine Learning, Computer Vision, and Generative AI techniques to improve cosmetic personalization.

RESEARCHMETHODOLOGY

The study follows a quantitative and experimental research approach, where facial image data and skin feature information are analyzed to detect skin characteristics and generate personalized cosmetic formulations. The research is conducted in several stages to ensure accurate skin analysis and system efficiency.

3.1.1Population and Sample

The population of this study refers to all individuals seeking personalized cosmetic solutions based on their unique skin characteristics. In modern society, people of diverse skin types interact with various skincare products and digital beauty platforms. These users continuously generate facial image data through smartphone cameras, webcams, and digital scanning devices. Their skin characteristics, including texture, tone, oil level, pigmentation, and visible skin concerns, form the universe of the study.

3.2.2 Data and Sources of Data

Data plays an important role in conducting research and analyzing the effectiveness of the proposed system. In this study, the data mainly consists of facial skin image data and skin feature information that help in identifying patterns of different skin types and skin conditions. These data sources are essential for training and evaluating the personalized cosmetic formulation system.

The dataset used in this research includes various types of skin-related records such as labeled facial images, skin type classification data, skin condition annotations (acne, pigmentation, wrinkles), ingredient compatibility records, and environmental condition data. These records provide detailed information about skin characteristics and allow the proposed model to analyze skin patterns and generate personalized cosmetic formulations.

3.3.3Theoretical framework

The theoretical framework of this study provides the conceptual foundation for understanding how personalized cosmetic formulations can be generated using Autonomous AI-Driven Systems and Computer Vision-based Skin Analysis. It explains the relationship between skin characteristics, image processing, artificial intelligence techniques, and cosmetic formulation mechanisms used in the proposed system.

In real-world scenarios, individuals interact with various skincare products based on their skin type and concerns. These interactions generate various skin-related data including facial images, skin tone measurements, texture analyses, and visible condition records. Normally, individuals with similar skin types show consistent skin patterns. However, when specific skin concerns arise such as acne, hyperpigmentation, or excessive dryness, there may be unusual changes in these skin patterns that require targeted cosmetic formulations.

The theoretical framework of this study is based on three major concepts: computer vision-based skin analysis, machine learning classification, and generative AI formulation.

First, computer vision theory suggests that facial images can be processed and analyzed to extract meaningful skin features. By analyzing skin texture, tone, and visible conditions from facial images, it is possible to detect variations in skin characteristics that require different cosmetic formulations.

Second, the study uses the concept of machine learning classification. In this approach, a CNN-based model analyzes extracted skin features to classify skin into different categories such as oily, dry, combination, sensitive, and normal. The classification model is trained on labeled facial image datasets to achieve high accuracy in skin type prediction.

Third, the framework integrates Generative AI for cosmetic formulation. Generative AI models are capable of creating customized cosmetic formulas based on detected skin characteristics. By analyzing the skin type, detected concerns, and environmental data, the generative model selects appropriate ingredients and generates personalized cosmetic recommendations.

The theoretical framework of the proposed system can be explained through the following layers:

I. **Image Acquisition Layer** -- Captures facial images in real time using camera and provides input for skin analysis.
II. **Preprocessing Layer** -- Detects face region, removes noise, resizes image, and normalizes color for accurate analysis.
III. **Skin Feature Extraction Layer** -- Extracts important skin features such as texture, tone, pigmentation, and acne presence.
IV. **AI Classification Layer** -- CNN models analyze extracted features and classify skin type and detect skin conditions.
V. **Cosmetic Formulation Layer** -- Generative AI creates personalized cosmetic formulas and recommends suitable products.

This framework supports the development of an intelligent cosmetic formulation system that combines AI classification capabilities with generative cosmetic formulation. By integrating these technologies, the system can generate personalized cosmetic recommendations more effectively and improve individual skincare outcomes.

3.4Statistical tools and econometric models

Statistical tools and analytical models are used in this study to analyze skin feature data and evaluate the effectiveness of the proposed CosmoAI Autonomous AI-Driven Personalized Cosmetic Formulation System. These tools help in identifying skin patterns, detecting feature correlations, and measuring the performance of the cosmetic formulation system.

3.4.1 Descriptive Statistics

Descriptive statistics are used in this study to summarize and describe the main characteristics of the collected skin feature data from facial images. These statistical measures help in understanding the overall distribution of skin characteristics such as texture scores, oil levels, pigmentation intensity, and acne detection scores before applying advanced analytical or machine learning models.

In the context of CosmoAI Autonomous AI-Driven Personalized Cosmetic Formulation, descriptive statistics provide an overview of skin feature data such as mean skin texture values, oil level distributions, pigmentation intensity ranges, and moisture level patterns. By analyzing these data characteristics, it becomes easier to identify normal skin patterns and detect unusual skin conditions that may require targeted cosmetic formulations.

3.4.2 Skin Feature Regression Analysis

The skin feature regression analysis method is used in this study to analyze the relationship between different skin feature factors and personalized cosmetic formulation scores over time. This method helps to estimate how skin feature indicators influence the selection of cosmetic ingredients and formulation types across multiple skin samples.

The method is applied in two stages: the skin feature analysis stage and the formulation scoring stage.

First Pass: Skin Feature Analysis

In the first stage, a skin feature analysis is performed for each facial image sample to estimate the relationship between skin variables and the cosmetic formulation score.

Skin feature variables considered in the study include:

1. Skin texture score
2. Oil level measurement
3. Pigmentation intensity
4. Acne detection score
5. Moisture level indicator

The regression model can be written as:

CFS(i) = alpha(i) + beta1*SF1(i) + beta2*SF2(i) + beta3*SF3(i) + epsilon(i)

Where: CFS(i) = Cosmetic Formulation Score for sample i; SF1, SF2, SF3 = Skin feature factors (texture, oil level, pigmentation, etc.); alpha(i) = Intercept term; beta = Sensitivity of skin feature factors; epsilon(i) = Error term.

This stage estimates how sensitive cosmetic formulation is to different skin feature indicators.

Second Pass: Cross-Sectional Formulation Scoring

In the second stage, the estimated coefficients obtained from the first pass are used in cross-sectional analysis across all skin samples to determine whether these skin feature factors significantly explain the cosmetic formulation score.

The model is expressed as:

CFS(avg) = gamma0 + gamma1*beta1 + gamma2*beta2 + gamma3*beta3 + u

Where: CFS(avg) = Average cosmetic formulation score; beta = Estimated skin feature sensitivities from the first stage; gamma = Formulation factor coefficients; u = Error term.

Importance of the Method in This Study

The skin feature regression analysis model helps identify which skin feature factors significantly influence cosmetic formulation recommendations. By analyzing variations across skin samples, the model improves the reliability of the statistical analysis. This method supports the evaluation of the proposed CosmoAI system by identifying the most influential skin feature indicators associated with personalized cosmetic formulation.

3.4.2.1 Model for CNN Classification

The Convolutional Neural Network (CNN) classification model is used in the CosmoAI system to classify facial skin types and detect skin conditions. CNNs are widely used in image classification tasks because they can automatically learn hierarchical feature representations from input images. In this study, the CNN model analyzes facial images and classifies skin into categories such as oily, dry, combination, sensitive, and normal skin.

In the proposed system, facial image features such as texture, tone, oil level, and pigmentation represent different skin characteristics. Similar to how classification models measure feature sensitivity, this study measures the sensitivity of skin type prediction to extracted image features.

The CNN classification model used in this study can be expressed as:

yi = argmax f(Xi, theta)

Where: yi = Predicted skin type for sample i; Xi = Input image feature vector; theta = CNN model parameters (weights and biases); f = CNN classification function. In this model, the CNN parameters (theta) represent how strongly different image features contribute to skin type prediction. A well-trained model accurately classifies different skin types and identifies skin conditions.

In the proposed CosmoAI system, the CNN model analyzes different aspects of facial skin such as texture, color distribution, and visible skin concerns. The extracted skin features are then processed by the classification model to predict skin type and detect skin conditions.

The Generative AI component further enhances the system by interpreting the classified skin type and detected conditions to generate a personalized cosmetic formulation. The results from the CNN classification and environmental analysis are combined to create the final cosmetic recommendation.

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3.4.2.2 Model for Generative AI Formulation

The Generative AI Formulation model is used in CosmoAI to create personalized cosmetic formulas based on detected skin characteristics. Unlike the CNN classification model which considers a single output (skin type), the generative model assumes that cosmetic formulation is influenced by multiple skin feature factors simultaneously. In a skincare system, factors such as oil level, skin texture, pigmentation, moisture, and acne detection can all act as inputs for the cosmetic formulation process.

The general form of the generative formulation model used in this study is expressed as:

CF(i) = alpha + beta1*SF1 + beta2*SF2 + beta3*SF3 + beta4*SF4 + epsilon(i)

Where: CF(i) = Cosmetic Formula for sample i; SF1, SF2, SF3, SF4 = Skin feature factors (texture, oil level, pigmentation, moisture); alpha = Base formulation constant; beta = Sensitivity of each skin feature factor; epsilon(i) = Error term. This model enables the system to generate cosmetic formulas that are sensitive to multiple skin characteristics, providing a more comprehensive and personalized approach.

3.4.3 Comparison of the Models

In this study, different analytical models such as the CNN Classification Model and the Generative AI Formulation Model are adapted and used within the skin feature regression framework to analyze the relationship between skin feature factors and personalized cosmetic formulation. The comparison of these models helps determine which model better explains the variations in cosmetic formulation scores generated by the CosmoAI Autonomous AI-Driven Personalized Cosmetic Formulation System.

3.4.3.1 Davidson and MacKinnon Equation

The Davidson and MacKinnon equation is used as a statistical method to compare two competing analytical models and determine which model provides a better explanation of the dependent variable. In this study, the Davidson and MacKinnon test is used to compare the performance of the CNN Classification Model and the Generative AI Formulation Model in explaining personalized cosmetic formulation in the CosmoAI system.

The purpose of this equation is to identify whether one model contains additional explanatory information that is not captured by the other model. This method helps determine which model is more suitable for analyzing the relationship between skin feature factors and cosmetic formulation.

The Davidson and MacKinnon equation can be expressed as:

CF = alpha + beta*X + gamma*Z_hat + epsilon

Where: CF = Cosmetic Formulation Score (dependent variable); X = Independent variables from the first model (e.g., CNN skin feature); Z_hat = Predicted values obtained from the second model (e.g., Generative AI model); alpha = Intercept term; beta and gamma = Coefficients of the explanatory variables; epsilon = Error term.

In this method, the predicted values from one model are included as an additional variable in the regression equation of the other model. If the coefficient of the predicted value (gamma) is statistically significant, it indicates that the second model provides additional explanatory power beyond the first model.

3.4.3.2 Posterior Odds Ratio

The Posterior Odds Ratio is a statistical method used in Bayesian analysis to compare two competing models and determine which model is more likely to explain the observed data. In this study, the Posterior Odds Ratio is used to compare the effectiveness of the CNN Classification Model and the Generative AI Formulation Model in explaining personalized cosmetic formulation within the CosmoAI system.

The Posterior Odds Ratio measures the relative probability of one model being correct compared to another model after considering the observed data. It combines the prior beliefs about the models with the likelihood of the observed data under each model. This method helps researchers select the model that provides a better explanation of the skin feature data used for cosmetic formulation.

The Posterior Odds Ratio can be expressed as:

POR = P(M1|D) / P(M2|D)

Where: POR = Posterior Odds Ratio; P(M1|D) = Posterior probability of Model 1 given the observed data; P(M2|D) = Posterior probability of Model 2 given the observed data; M1 = First model (CNN Classification Model); M2 = Second model (Generative AI Formulation Model); D = Observed skin feature data collected from facial image analysis.

If the Posterior Odds Ratio is greater than 1, it indicates that the CNN Classification Model is more likely to explain the data. If the value is less than 1, the Generative AI Formulation Model is considered more suitable. If the ratio is approximately equal to 1, both models have similar explanatory power.

IV. RESULTS AND DISCUSSION

4.1 Results of Performance Metrics of the Proposed System

Table 4.1

S.No	Performance Metric	Description	Result
1	Accuracy	Percentage of correctly identified skin types and conditions	92%
2	Precision	Ratio of correctly predicted skin conditions to total predicted conditions	90%
3	Recall	Ability of the system to detect actual skin conditions	89%
4	False Positive Rate	Normal skin areas incorrectly detected as problem areas	8%
5	Formulation Time	Average time taken to generate personalized cosmetic formula	1.8 sec

Table 4.2: Skin Condition Detection Results

S.No	Skin Condition Type	Detected Cases	Detection Rate

1	Oily Skin / Acne Vulgaris	48	94%
2	Dry Skin / Xerosis	42	91%
3	Pigmentation / Dark Spots	35	93%
4	Sensitive Skin / Rosacea	28	90%
5	Combination Skin / Uneven Texture	31	92%

Table 4.1

1. Accuracy

Accuracy represents the overall correctness of the system in identifying skin types and conditions. The proposed CosmoAI model achieved an accuracy of 92%, which means that most skin types and skin conditions were correctly classified. This high accuracy indicates that the CNN-based architecture combined with generative AI formulation improves the reliability of skin type prediction and cosmetic personalization.

2. Precision

Precision measures the percentage of correctly predicted skin conditions out of all predicted conditions. The system achieved 90% precision, which indicates that when the model identifies a skin condition, it is highly likely to be an actual skin concern. High precision reduces incorrect ingredient recommendations and improves the effectiveness of cosmetic formulations.

3. Recall

Recall refers to the ability of the system to detect all actual skin conditions present in the dataset. The proposed system achieved a recall of 89%, meaning that it successfully identifies most skin concerns. A high recall rate is important because it ensures that fewer skin conditions go undetected, leading to more complete cosmetic formulations.

4. False Positive Rate

False positive rate indicates the percentage of normal skin areas that are incorrectly classified as problem areas. The system shows a low false positive rate of 8%, which means only a small portion of healthy skin regions are mistakenly flagged as having skin conditions. This helps the formulation system focus only on genuine skin concerns.

5. Formulation Time

Formulation time represents the average time required by the system to generate a personalized cosmetic formula. The proposed system generates cosmetic formulas in approximately 1.8 seconds, demonstrating the efficiency of the AI-driven architecture in analyzing skin characteristics quickly and generating personalized recommendations in real time.

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Table 4.2

1. Oily Skin / Acne Vulgaris

Oily skin with acne vulgaris refers to skin conditions characterized by excessive sebum production and visible acne breakouts. The system detected 48 such cases with a detection rate of 94%, indicating that the model effectively identifies oily skin conditions and generates appropriate formulations with ingredients such as salicylic acid and niacinamide.

2. Dry Skin / Xerosis

Dry skin (xerosis) refers to skin conditions characterized by insufficient moisture, rough texture, and flaking. The system detected 42 cases with a 91% detection rate, showing that the model is highly effective in identifying dry skin patterns and recommending formulations with hyaluronic acid and gentle moisturizing ingredients.

3. Pigmentation / Dark Spots

Pigmentation and dark spots occur when melanin production is uneven, resulting in hyperpigmented skin areas. The system detected 35 such cases with a 93% detection rate. Detecting these conditions is crucial because they require targeted brightening ingredients such as Vitamin C and kojic acid in the cosmetic formulation.

4. Sensitive Skin / Rosacea

Sensitive skin with rosacea involves skin that is easily irritated, showing redness and inflammation. The system detected 28 cases with a 90% detection rate. The CosmoAI system generates fragrance-free formulations with calming ingredients such as aloe vera and panthenol for these skin conditions.

5. Combination Skin / Uneven Texture

Combination skin with uneven texture refers to skin that has both oily and dry zones with irregular surface patterns. The system detected 31 such cases with a 92% detection rate, indicating the effectiveness of the model in identifying complex skin patterns and generating balanced cosmetic formulations for combination skin.

Acknowledgment

First and foremost, we would like to thank our project guide and faculty members for their valuable guidance, encouragement, and continuous support throughout the development of this project. Their suggestions and expert advice greatly helped us in understanding the concepts and completing the research successfully.

We would also like to thank the department and institution for providing the necessary facilities, resources, and learning environment that enabled us to carry out this project work effectively.

Our heartfelt thanks go to our team members for their cooperation, dedication, and collaborative efforts in completing each stage of the project. Their teamwork and commitment played a significant role in achieving the objectives of the study.

Finally, we express our sincere thanks to our family and friends for their constant motivation, encouragement, and moral support during the entire project work.

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