

SKIN TYPE DETECTION AND COSMETIC SUGGESTIONS USING XCEPTION MODEL AND COSMETIC RECOMMENDATION SYSTEM

N. Nagaveni¹, G. Saidulu², D. Seshu Reddy³, E. Vaishnavi⁴

^{1,2}Associate Professor, Department of CSE, CMR College of Engineering & Technology, Hyderabad, Telangana, India

^{3,4}B. Tech Student, Department of CSE, CMR College of Engineering & Technology, Hyderabad, Telangana, India

Corresponding author mails: neelamnagaveni2@gmail.com, golla.siddu79@gmail.com,

Co-author mails: seshureddydevireddy@gmail.com, vaishnaviettedi27@gmail.com

Abstract—The fast development of the cosmetic industry provides many choices to consumers based on the various skin issues, and thus the selection of the product becomes more complicated. Traditional skincare advice is normally based on personal view and subjective judgment that can result in poor selection of products, misinformation. The study proposes a deep learning-based application that will automatically recognize the types of skin based on the pictures of the face and will provide a recommendation of cosmetic products. The given solution involved the Xception convolutional neural network to categorize facial images as oily, dry, and normal skin types. The system uses preprocessing methods like image normalization to improve features extraction and improve classification. Moreover, it identifies individual problems with the skin such as acne, blackheads, dark spots, pores and wrinkles to give customized advice. A cosmetic product recommendation system is a rule-based mechanism that matches the detected skin characteristics with the correct cosmetic products. The model was trained against a dataset of about 5613 facial images and attained an overall classification accuracy of 89.3 percent. The suggested solution enhances the practice of skin care, decision-making, and confidence of the user in choosing cosmetic products.

Keywords: Rule-Based Inference, Xception Architecture, Computer vision, Skin Type Classification, Cosmetic Recommendation System, Dermatological Image Analysis.

I. INTRODUCTION

The cosmetic industry has experienced a rapid growth that has led to the development of various types of skincare products that will deal with number of skin problems. Although this gives more options to the consumers, it confuses about the suitability of the products. There is still a serious problem with choosing the right cosmetic product due to people use personal judgment or trial-and-error

approach. However, skincare products have not provided equal effects since the skin attributes differ among different individuals, oily, dry and normal skin. Inappropriate products could cause ineffective treatment, cause different reactions, and loss customer trust. Artificial intelligence, computer vision, and machine learning have grown by a large margin to enhance personalized recommendation systems in various fields. A number of studies have come up with recommendation systems that can be used in the cosmetic industry to help users make the right choice of products. As an example, Lee et al. has created a content-based recommendation system that uses content and preferences given by the user to create suggestions. Likewise, the content-based style was improved by Vinutha et al. with the help of machine learning to make the visualization and accuracy better. Other scientists have also taken into consideration the aspect of skin and have made mobile-based applications that can expand its features by analyzing images and environmental conditions like the weather. These systems enhance the user user-friendliness and interaction via interactive interfaces.

Even in these developments, the current methods have a number of limitations. A significant number of recommendation systems are mainly depend on user feedback, preference information or historical data, which can be biased, incomplete. This makes it less reliable particularly with new users who do not already have data. Moreover, some systems do not use direct skin analysis based on the computer vision pipelines, which restricts their capacity to offer personalized and accurate suggestions. The standard convolutional neural network employed in previous methods might also fail at finer grained texture and color patterns of the facial images, which makes accurate detection of the skin type and skin problems. To overcome these constraints, this paper presents an AI-powered skin type detection and cosmetic products recommendations system with a pre-trained Xception deep convolutional neural network. Xception architecture is helpful in extracting features efficiently by

using fine-grained texture and color patterns on face images. Image resizing and image normalization are also included in the proposed system as preprocessing steps that help to improve the performance of a model and its classification accuracy. This system is a combination of skin analysis and product recommendation processes, unlike before these processes were treated as individual processes.

The proposed model will categorize the skin type as oily, dry, and normal, as well as define the skin problems, including acne, blackheads, dark spots, pores, and wrinkles. According to the identified features, a recommendation engine that is based on rules pairs skin conditions with suitable cosmetic products. It is implemented through a web interface based on Streamlit, which offers more accessible interaction and real-time access along with an easy-to-use experience.

Recent researches show that many people use subjective trial-and-error techniques to choose skincare products, which can have a detrimental effect in terms of effective treatment and skin-related problems. Due to the development of artificial intelligence, deep-learning algorithms like convolutional neural networks (CNNs) have demonstrated a high level of performance in medical and dermatological analysis of images.

The Xception model is especially efficient because it utilizes depthwise separable convolutions that enhance the effectiveness of extracting the features and the lowering of computational complexity among other CNN models. This renders it to be extremely appropriate in identifying fine-grained skin-textures and delicate dermatological patterns

II. RELATED WORK

A number of papers have investigated the methods of artificial intelligence and machine learning to analyze skin and recommend cosmetic products. Initial studies were mainly concerned with the methods of content-based recommendation and the latest ones involve deep learning and computer vision in automated skin analysis. Which helps in complete analysis of the skin and customized suggestions.

Lee et al. (2023) built a content-based product recommendation skincare system that suggests the contents of a skincare product using manually entered user information. The system mostly used data that was inputted by the user and did not involve facial image datasets to conduct automatic analysis. The lack of skin type and skin issue classification restricted the level of personalization and precision which incorporates automated deep learning-based analysis.

Vinutha et al. (2024) proposed an individualized skincare recommendation algorithm based on the visualization of its content with the help of the machine learning algorithm. Although the system enhanced user interaction and accuracy of recommendation, the skin properties were typed and the architecture relied on traditional

convolutional neural networks. and did not utilize advanced deep learning architectures.

Sharma et al. (2023) presented the AI-based skincare recommendation model based on the content filtering and skin attributes by manually inputting. Although the system was successful in matching the products with the user preferences, it depended on the subjective input of the user and omitted facial image analysis. This reliance decreased the fidelity and the scalability of the recommendation process.

Kim et al. (2023) suggested a deep learning framework of facial skin analysis using convolutional neural network to

identify skin diseases such as acne, dryness, and pigmentation. Even though the model had a high accuracy in classification, it did not include an integrated recommendation component, thus being less applicable in the real-life cosmetic product recommendations

A facial skin condition detection system, created by Chen et al. (2023) with the help of deep learning, was used to recognize the problems of acne, wrinkles, and pigmentation. Even though the system had high classification results, it was not able to give individualized cosmetic advice, making it less useful to the end-users with actionable skincare advice.

Kumar et al. (2024) summarized a skincare recommendation system, that is, a questionnaire-driven system, and a rule-based system. Although the system was able to give personalized suggestions, it relied on manual input and did not have automated skin analysis. This diminished their accuracy particularly where the users did not know exactly their skin condition.

Ali et al. (2022) provided a system on convolutional neural networks that are utilized in advising cosmetic products on the basis of a facial skin examination code. The analyzed system scans faces and determines skin conditions; general recommendations were made. However, it also did not contain advanced feature-finding algorithms and did not contain detailed categorization of skin issues and made it less accurate and more versatile.

A machine learning-based AI system of detecting and recommending skin conditions presented by Das et al. (2023) involves application of image processing and machine learning. The system carried out the mapping of the skin conditions and gave product suggestions. It was however founded on the previous models and not predicated on the utilization of improved deep learning structure in which the minute skin details are addressed.

In a work by Lin (2022), the author presented a skincare recommendation system that is a computer vision model, which processes funnels of image processing and analyzes a face to give a recommendation on the products. Although automated analysis was done by the system, it did not feature extract using deep learning and provided no

detailed classification of skin problems, which limited the quality of the recommendations.

Hemantha et al. (2022) developed a machine-learned personalized application of skincare recommendation system, but the system functions based on the input of the customer and the known conditions. The recommendations were proposed in the system on the basis of the information collected without the analysis of the facial images. Absence of automated skin detection also reduced its efficiency in providing specific and accurate recommendations.

Title	Problem Statement	Key Features /Methodology	Limitations
Content-Based Skincare Recommendation System (Lee et al., 2023)	Lack of automated skin type and skin issue detection; dependence on manual user input.	Content-based filtering using manually entered user preferences and product attributes.	No facial image analysis; no automated classification; lower personalization accuracy.
Personalized Skincare Recommendation using ML (Vinutha et al., 2024)	Manual entry of skin attributes reduces automation and scalability.	Content visualization with machine learning; conventional CNN for analysis.	Skin issues entered manually; uses basic CNN; limited deep feature extraction.
AI-Based Skincare Recommendation Model (Sharma et al., 2023)	Heavy dependence on manually filled skin attributes.	Content-based filtering; questionnaire-based skin analysis.	No automated image processing; subjective user input reduces accuracy.
Deep Learning-Based Facial Skin Analysis (Kim et al., 2023)	Absence of cosmetic recommendation integration	CNN-based detection of acne, dryness, pigmentation from facial images.	No recommendation engine; limited to classification only.
AI-Assisted Rule-Based Skincare Advice System	Inaccuracy due to manual questionnaire	Rule-based recommendation using user responses; product	No automated skin type detection; dependent on user

(Kumar et al., 2024)	ire-based inputs.	matching logic.	awareness of skin condition
Facial Skin Analysis using CNN for Cosmetic Recommendation (Ali et al., 2022)	Poor accuracy because of inability to have advanced feature extraction.	CNN-based facial skin analysis for basic classification and product suggestion.	Omits in-depth detection of skin problems; does not have elaborate deep-learning models.
AI-Based Skin Condition Detection and Recommendation System (Das et al., 2023)	Lack of fine-grained skin features.	Image processing and machine learning of skin conditions and their recommendations.	Uses traditional models; lacks advanced deep learning architectures.
Computer Vision-Based Skincare Recommendation System (Lin, 2022)	Limited accuracy in identifying detailed skin issues.	Facial analysis and recommendation computer vision/image processing.	one of the deep learning-based feature extraction; poor classification.
Personalized Skincare Recommendation System using ML (Hemantha et al., 2022)	Reliance on manual analysis rather than computerized analysis.	Recommendation on the basis of machine learning based on the predetermined conditions and the user data.	There is no analysis related to faces; there is less personalization and accuracy.

Table 1: Comparative Summary of Existing Related Work

III. METHODOLOGY

A. SYSTEM ARCHITECTURE

1. It begins with Streamlit multi-page web interface which captures webcam feed through OpenCV where MediaPipe face detector provides real-time positioning feedback.

- It guides users to center and position faces correctly before analysis.

2.The image is sent for preprocessing. Here image is resized to 224x224 and normalized then processed through dual parallel xception -based models.

3.The first model classifies skin type(oily, normal, and dry).The second model identifies skin issue(acne, darkspots, blackheads, pores, and wrinkles).

4. Model results are integrated together. Feeding into a rule-based recommendation system. This maps skin type and skin issue combinations to personalized skin care advice. Personalized skin care advice involves-

- Cosmetic recommendations
- Food items that need to be added in to your existing diet.
- Cautions to be taken while using recommended cosmetic

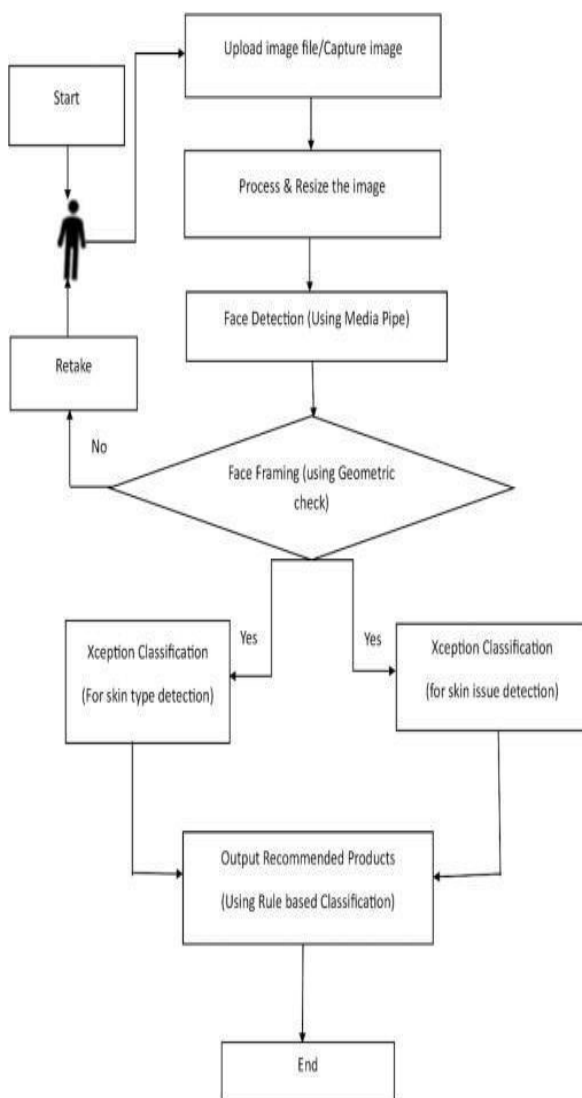


Fig 1: System Architecture

The suggested system workflow was configured to offer automatic skin scan and the cosmetic product suggestions with regards to individual preferences using a structured processing stream. The procedures have been triggered by a facial image being uploaded or taken via the interface of the

system. The input image was first resized and pre-processed to fit the demanded input size to be analyzed. MediaPipe was used in face detection and facial areas were correctly

identified which allowed the analysis of only relevant features. Geometric face framing check was also used to ensure that there was an appropriate facial alignment. In case of misalignment, the user was asked to recapture the image in order to ensure the accuracy of analysis.

After the adequate face alignment had been attained, the image was sent to the Xception deep learning model to be classified. The model did dual tasks, whereby skin type was categorized and skin problems detected, at the same time. As per the classification outcomes, customized cosmetic products as recommendations were created through a rule-based system with logical rules that were predefined. Lastly, the suggested products were presented to the user. The whole process was designed in such a way that the process of acquiring an image up to the generation of a recommendation was efficient.

A. FLOW CHART

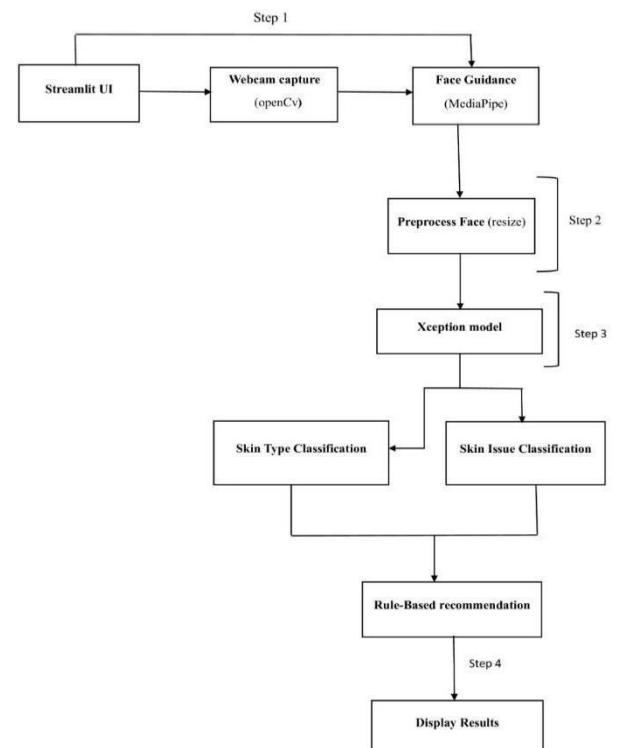


Fig 2: Flow Chart

B. MATHEMATICAL FORMULATION

3.3.1 Convolution Operation

The Xception network extracts spatial features from input skin images using convolution.

$$F(i, j) = \sum_{m=0}^M \sum_{n=0}^N I(i+m, j+n) \cdot K(m, n)$$

Where:

- I = input image
- K = convolution kernel
- F = feature map output

3.3.2 Depthwise Separable Convolution

Xception replaces traditional convolution with depthwise separable convolution to improve efficiency.

1. DEPTHWISE CONVOLUTION:

$$Y_k = X_k * K_k$$

Where:

- X_k = input channel
- K_k = channel-specific filter
- Y_k = output feature map

2. POINTWISE CONVOLUTION

$$Z = \sum_{k=1}^C Y_k \cdot W_k$$

Where:

C = number of channels

W_k = learned weights

3.3.3 SoftMax Function:

Used for multi-class skin type classification.

$$P_i = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}}$$

Where:

- P_i = probability of class i

3.3.1 Model Evaluation Metrics

Let:

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

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity)

$$Recall = \frac{TP}{TP + FN}$$

Specificity

$$Specificity = \frac{TN}{TN + FP}$$

F1 Score

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

C. DATASET DESCRIPTION

The dataset contains two primary subsets-skin types(oily, dry, and normal) and skin issues(acne, darkspots, blackheads, pores, and wrinkles).

Skin Type and Issue	Class	Number of Images
Skin Types	Oily	702
	Normal	702
	Dry	700
Skin Issues	Acne	700
	Black Heads	702
	Dark Spots	701
	pores	702
	Wrinkles	702

The data consisted of facial photographs based on the skin type and skin problems. There was a total of 5,613 images that were used to train and evaluate. To ensure that the models are generalized and that their evaluation is unbiased, the data was separated into the train, validation and testing sets in the 70:15:15 proportion. The distribution of classes was equal in various categories and this assisted

to enhance the performance of the model and minimize biasness in the classification.

Dataset Split	Percentage (%)	Number of Images
Training Set	70%	3929
Validation Set	15%	842
Testing Set	15%	842

D. EXPERIMENTAL SETUP

TensorFlow and Keras were used to implement the proposed model. Xception convolutional neural network was applied in terms of both skin type classification and skin issue detection. The hyperparameters used to train the model were:

Optimizer: Adam
Learning Rate: 0.0001
Batch Size: 32
Epochs: 25
Dropout Rate: 0.5
Input Image Size: 224 x 224
Loss: Categorical Cross-Entropy.
Activation Function: Softmax

A split of the dataset was performed in training, validation and testing set in proportion of 70:15:15. The model parameters were optimized during the training to reduce classification error and enhance performance of generalization. To provide adequate generalization of the model and the unbiased evaluation, the dataset was separated into training, validation, and testing groups: 70: 15: 15.

All the categories were balanced in terms of classes and this served to enhance better performance of the models and prevented bias in the classification process.

E. ALGORITHMS

The suggested system will combine deep learning and rule-based methods to conduct automatic analysis of the skin and recommendation of cosmetic products.

Facial Image Acquisition and Preprocessing

The preprocessing phase was used to prepare the facial images to be subjected to the deep learning analysis by taking or uploading images via the interface. Face detection and geometric framing were performed using mediapipe so that they were appropriately aligned. The face detected was resized and normalized to ensure similar dimensions of input and better the performance of the models.

Xception-Based Skin Type Classification

The classification of the skin types is achieved with the help of the Xception convolutional neural network which is a deep-learning model that is characterized by the high efficiency of feature extraction that is based on depthwise separable convolutions. The model examines images of faces to determine hidden patterns of texture and skin features. According to the features extracted, the system describes skin type as oily, dry, and normal. Xception model is suitable because it has the ability to perform better classification because it can capture finer visual nuances not captured by the conventional convolutional neural networks, making the process of skin analysis reliable.

Xception-Based Skin Issue Detection

Besides classifying skin types, the system identifies certain skin problems through Xception deep learning system. This model finds detailed face features and multi-classification is carried out to detect acne, blackheads, dark spots, pores, and wrinkles. Such a two-stage classification strategy allows to have an extensive study of the skin, analyzing both its overall type and specific problems. The ability to identify subtle changes on the skin texture or coloration patterns is made possible by the deep feature extraction ability of the Xception architecture.

Rule-Based Recommendation Algorithm

In the last phase of the system, the recommendation algorithm is a rule-based algorithm that suggests the personalized cosmetic products based on the individual preferences. Based on logical rules, the algorithm matches the forecasted skin type and identified skin problems with predetermined product categories. The system offers personalized recommendations based on the skin condition of a particular individual by integrating the results of the deep learning classification with rule-based reasoning. The outcomes are presented in the form of the Streamlit interface that allows a user to get real-time feedback and appropriate cosmetic recommendations.

The recommendation system uses predefined logical rules to suggest suitable cosmetic products based on detected skin type and skin issues.

Algorithm/Pseudocode:

Input: Skin_Type, Skin_Issue
Output: Recommended_Product

IF Skin_Type = Oily AND Skin_Issue = Acne
Recommend Salicylic Acid Cleanser

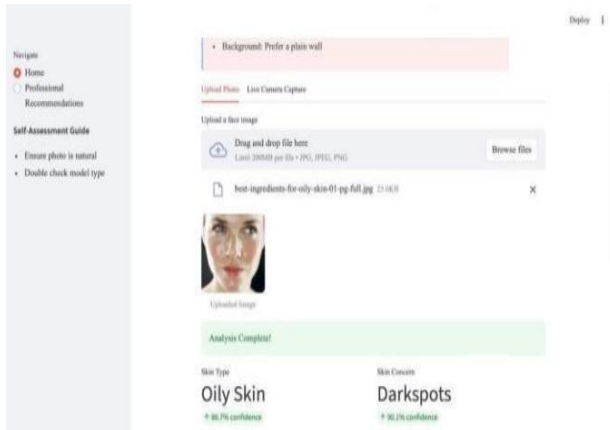
IF Skin_Type = Dry AND Skin_Issue = Wrinkles
Recommend Hyaluronic Acid Moisturizer

IF Skin_Type = Normal AND Skin_Issue = Dark Spots
Recommend Vitamin C Serum

RETURN Recommended_Product

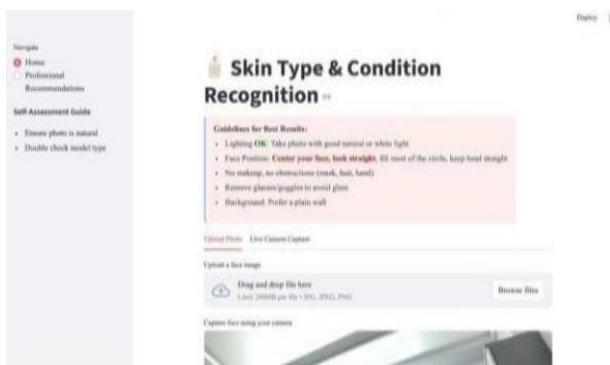
IV. RESULT ANALYSIS

STEP-1: User either uploads or captures the picture through the webcam



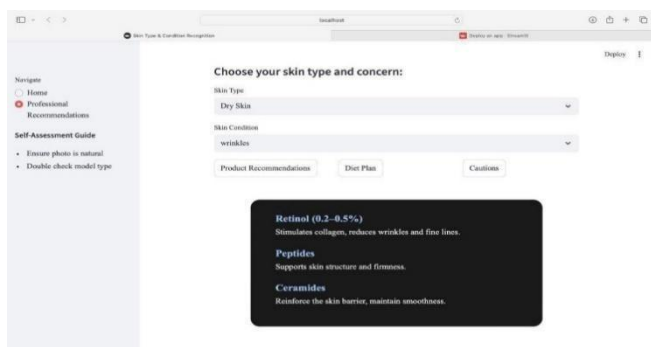
STEP-2: System displays the results:

1. Skin profile
2. Product recommendation
3. Confidence score



STEP-3: Product Recommendation page. This page displays:

1. Recommended Cosmetic products.
2. Food items to add in diet plan.
3. Cautions to be taken while using recommended products.



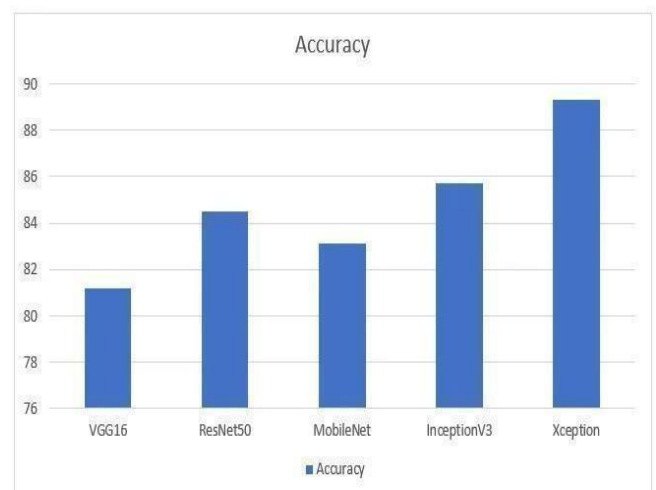
A. Performance Metrics of the Proposed Model

The table showed that Xception model was effective at identifying skin type and skin issue

Task	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Skin Type Classification	88.6	87.9	88.2	88.0
Skin Issue Detection	90.1	89.4	90.0	89.7
Overall System Performance	89.3	88.6	89.1	88.9

B. Accuracy Comparison with Existing Models

This graph depicts the accuracy of various Convolutional Neural Network models



C. Class-wise Performance Metrics

Precision, recall and F1-score were used to assess the performance of the proposed system to have a more holistic view of the classification performance. Precision is used to determine the accuracy of positive predictions and recall is used to determine how well the model can recognize all the relevant instances. F1-score is the harmonic mean of the precision and recall. The findings show that Xception model is able to perform consistently in all classes, which confirms that the model is effective in fine-grained skin features.

Class	Precision	Recall	F1-score
Oily	0.88	0.87	0.88

Normal	0.89	0.88	0.88
Dry	0.90	0.89	0.89
Acne	0.91	0.90	0.90
Blackheads	0.89	0.88	0.88
Dark Spots	0.90	0.89	0.89
Pores	0.88	0.87	0.87
Wrinkles	0.90	0.89	0.89

D. Confusion Matrix

1. Skin Type Classification

Actual	Predicted			
		Oily	Dry	Normal
	Oily	210	10	12
	Dry	15	205	12
	Normal	10	14	210

2. Skin Issue classification :

A c t u a l	Predicted					
		Acne	BlackHeads	Dark Spots	Pores	Wrinkles
	Acnes	180	5	6	4	5
	BlackHeads	6	175	7	5	4

	Dark Spots	5	6	178	6	6
	Pores	7	5	6	176	5
	Wrinkles	6	4	5	6	179

The confusion matrices illustrate the classification performance of the proposed model by comparing actual and predicted class labels. The diagonal elements represent correctly classified instances, while off-diagonal elements indicate misclassifications.

V. DISCUSSIONS

As demonstrated in this research, a deep learning-based system is effective to overcome the limitations of subjective and unreliable cosmetic products selection indicated in the abstract because the Xception model was able to outperform the convolutional neural networks because it incorporated the aspect of depthwise separable convolution, which allows easy extraction of fine-grained features of face images. This is especially required when pinpointing small skin features like pores, wrinkles and pigmentation. Contrary to most of the existing systems where the emphasis was on the skin tone analysis, or user input-based cosmetic recommendation system, this allows the system to integrate automated skin analysis with a rule-based cosmetic recommendation system. On the whole, this approach makes it possible to ensure that the system encourages people to practice better skin-cares, and gain more confidence with the choices they have to make with regards to cosmetic products.

Limitations

1. This can make the accuracy reduced in a dark environment.
2. The information sample is not diverse in terms of age, ethnicity and environment.
3. The system fails to take in account the external factors including lifestyle and weather.

Misclassification of some skin conditions of similar appearance might occur

VI. CONCLUSION

This research establishes a reliable and automated mechanism of identifying the skin type and skin issues with the help of deep learning algorithms. It has solved the shortcoming of traditional manual assessment ways, which

are subjective and may be inaccurate. The suggested system combines image processing, image classification based on Xception to detect the skin type and skin problems, and rule-based cosmetic recommendation framework into one system. The experimental assessment shows that the total classification accuracy is 89.3% which proves the efficiency of the method. The system offers real-time analysis based on a web-based interface and allows customized cosmetic suggestions based on analysis of detected skin characteristics.

VII. FUTURE WORK

1. The model will be trained on a larger and more varied dataset with differences in age, ethnicity, lighting, and environmental conditions in order to improve accuracy and generalization.
2. Other skin conditions such as sensitivity, pigmentation severity, and aging will be included to enable comprehensive skin analysis..
3. The app will be developed for mobile and real-time camera-based platforms, allowing for on-device analysis and greater accessibility for general skincare decision- making.

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