

# Facial Skin Classification by using Machine Learning Approach

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## ABSTRACT

**Background:** The classification of facial skin types accurately is crucial for dermatology and cosmetics, but traditional approaches depend on personal assessments that are capable of errors. An alternative which is more accurate and objective is machine-learning.

**Objective:** This research uses deep-learning and feature extraction techniques to create an automated machine learning-based method for classifying the various types of facial skin: normal/dry/oily.

**Methods:** We used 166 facial images as our dataset, which were manually collected. We used preprocessing-methods such as CLAHE for contrast enhancement and Gaussian-Blur and Bilateral-Filtering for noise reduction to prepare the data. MobileNetV2 and a HOG extracted features. We have used the Adam optimizer, categorical cross-entropy loss, and the deep-learning models ResNet50 and VGG16 to classify the images. 5-fold cross-validation was used to evaluate-performance.

**Results:** With an accuracy of 84.16%, ResNet50 beat VGG16. Combining texture-based and deep-learning features has greatly increased classification-effectiveness.

**Limitations:** The generalizability of the results is compromised by the small-dataset-size. Misclassifications also occurred mainly between dry-and-normal-skin-types.

**Conclusion:** Deep-learning is an efficient method for identifying the different-types of facial skin. To increase the application of this strategy in dermatology and skincare, future research should concentrate on larger-datasets, hybrid feature extraction techniques, and real-world validation.

**Keywords:** Facial skin type classification; machine learning; Deep Learning; Image preprocessing; Skincare; dermatology

## INTRODUCTION

Millions of people suffer from skin conditions, yet it is still difficult to classify them accurately using automation. Classifying facial skin types is essential in dermatology and cosmetics since it enables individualized treatment programs and skin care recommendations<sup>1,2</sup>. Usually classified as oily, dry, or normal, skin types are impacted by environmental factors, sebaceous gland activity, and hydration levels<sup>3</sup>. Existing categorization techniques frequently depend on subjective evaluations, which leads to errors and inconsistencies.

A potential replacement is machine learning. It classifies skin types with excellent accuracy and efficiency by analyzing facial skin images using computer models<sup>4,5</sup>. Recent developments in deep learning and computer vision have produced automated skin analysis systems<sup>6,7</sup>. These systems use deep learning classifiers and feature extraction methods to interpret images and deliver reliable and consistent outcomes.

The goal of this research is to develop a machine learning pipeline for facial skin type classification. It combines noise reduction, contrast improvement, and deep learning-based feature extraction techniques. The application of deep learning architectures such as ResNet50 and VGG16, which are well-known for their efficiency in learning hierarchical skin features<sup>8,9</sup> is the main emphasis of this study. Also, to improve model performance and image quality, preprocessing techniques such as Gaussian Blur, Bilateral Filtering, and Contrast Limited Adaptive Histogram Equalization (CLAHE) are used<sup>10,11,12</sup>.

The study suggests an innovative strategy that combines strong preprocessing approaches with advanced deep learning algorithms. It attempts to increase the accuracy and efficiency of facial skin type classification, helping the growing field of AI-driven dermatology applications<sup>13,14</sup>.

## METHODS

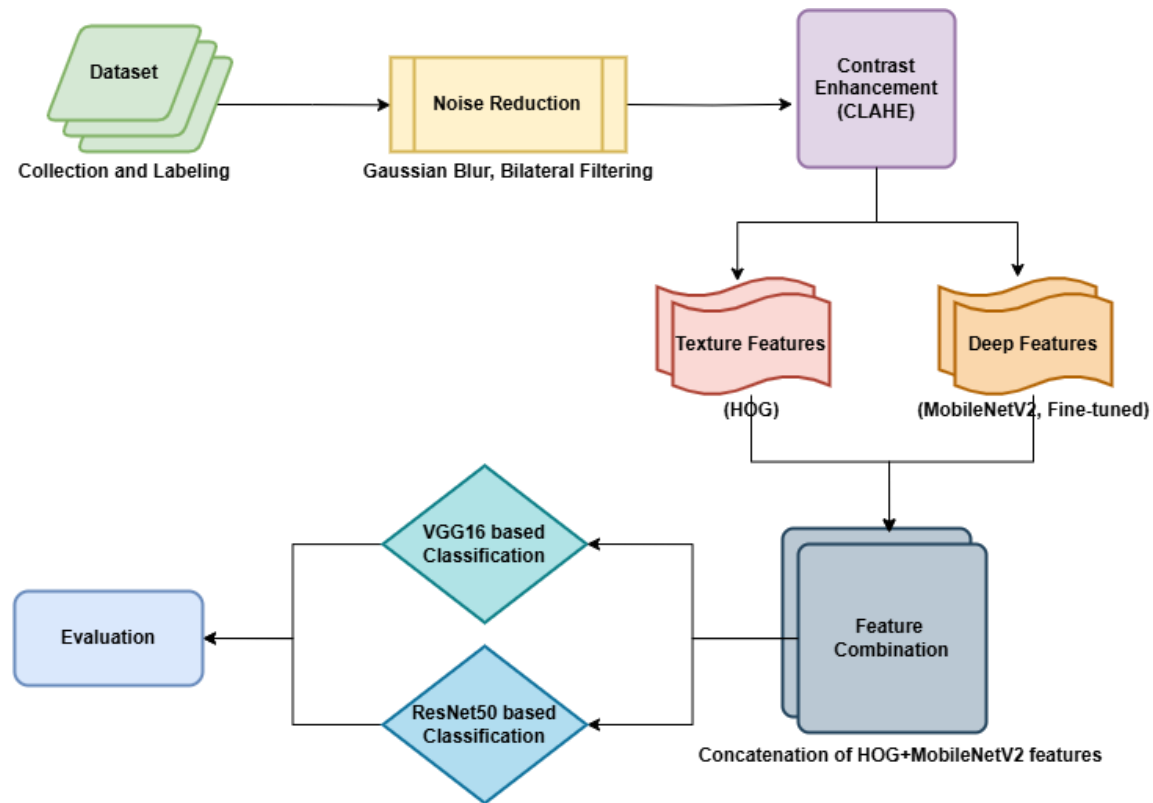
For data collection, preprocessing, feature extraction, and classification, the methodology uses a systematic workflow. Below is a list of the steps:

### **Dataset Description**

With the use of a 50 MP phone camera, the dataset was manually collected. Included in the sample are people ranging in age from 9 to 40. 166 photos were gathered and classified according to the skin type of individuals into three groups: normal (both dry and oily), dry, and oily. As usually common in dermatological datasets, manual annotation was used to guarantee accuracy<sup>15</sup>.

Feature extraction using VGG16 involves loading a pre-trained VGG16 model (without the top layers) to extract deep features from images<sup>8</sup>. Each image is resized to 224×224, preprocessed using standard normalization techniques, and passed through VGG16 to obtain a feature vector. These extracted deep features are then analyzed using K-Means clustering, a widely used unsupervised learning approach for image segmentation and grouping<sup>16</sup>.

In this study, brightness estimation is incorporated into the clustering process. The average pixel intensity of each image is computed as a heuristic to relate brightness levels to skin type, an approach explored in prior works on skin tone classification<sup>13</sup>. The extracted features are then clustered into three groups based on brightness levels, sorted from low to high, and labelled accordingly, as shown in [Table 1](#). This clustering procedure ensures the medical evaluation of skin tone variances, which can indicate unique skin types<sup>5,11</sup>. Low brightness indicates Oily skin, Medium brightness indicates Normal skin and High brightness indicates Dry skin.



**Figure 1:** Pipeline of Methodology

depicts the suggested methodology's ordered pipeline, which identifies the key stages from data preparation to categorization.

1. Darker images → Oily skin
2. Medium brightness → Normal skin
3. Brighter images → Dry skin

### Preprocessing

Combining methods for improving contrast and reducing noise improves picture quality for accurate skin type categorization. By removing background noise, Gaussian Blur and Bilateral Filtering preserve essential skin properties including texture and pore patterns. For accurate classification, these techniques efficiently smooth images without losing a substantial amount of structural information<sup>17</sup>.

Contrast Limited Adaptive Histogram Equalization (CLAHE) is employed to improve image contrast by enhancing the visibility of fine details, a widely used technique in medical and dermatological image processing<sup>3,10</sup>. Robust feature extraction can be

improved by this process, which makes small differences in skin texture easier to identify. Prior studies have demonstrated that CLAHE improves feature contrast when paired with deep learning, particularly in applications related to skin analysis and dermatology<sup>11,18</sup>.

These preprocessing techniques enhance the overall quality of the images, which improve<sup>s</sup> the efficiency of deep learning-based models for classification<sup>9,13</sup>.

### **Feature Extraction**

Feature extraction improves classification accuracy by capturing essential patterns from facial skin images. This study employs a hybrid approach integrating deep learning-based and traditional feature extraction techniques to enhance classification robustness.

Deep learning-based feature extraction uses pre-trained CNN architectures such as ResNet50, VGG16, and EfficientNetB0. These architectures automatically learn hierarchical representations of skin texture, pore structures, and hydration levels<sup>6,7,8</sup>. These models utilize convolutional layers to extract meaningful high-level features, ensuring an accurate distinction between different skin types.

In addition to deep learning, texture-based features are extracted using the Histogram of Oriented Gradients (HOG) method. By analyzing gradient orientations, which are essential for differentiating between skin characteristics<sup>11,12,20</sup> HOG is able to capture the structural and textural features of the skin. This method guarantees the efficient use of fine-grained information about texture variations in classification.

Additionally, MobileNetV2, a small and effective CNN, is used for deep feature extraction<sup>5,6</sup> in order to improve feature representation. Pretrained on ImageNet, MobileNetV2 is fine-tuned to adapt specifically to the skin classification task, allowing for efficient learning of discriminative features.

Concatenating the extracted texture-based (HOG) and deep learning-based (CNN) features into a comprehensive feature vector maximizes classification performance. The fusion of high-level and low-level data improves the classification accuracy and generalizability of the model<sup>14,21</sup>. This work offers a dependable pipeline for precise facial skin type classification by fusing deep learning and classical learning-based features.

### **Classification**

This study employs VGG16 and ResNet50, two widely used deep learning models, to classify the combined feature vector into one of three skin types: oily, dry, or normal.

VGG16, a deep convolutional neural network (CNN), is utilized for feature extraction and classification<sup>6,8</sup>. The most discriminative information is maintained while the feature

dimensionality is reduced by applying a Global Average Pooling (GAP) layer prior to the fully linked layers in order to increase computational efficiency. After that, the retrieved features are adjusted to enhance generalization and classification performance. Finally, a softmax layer outputs the probability distribution across the three skin type categories—oily, normal, or dry.

ResNet50, a deep residual network<sup>5</sup>(CNN), is an alternative classifier<sup>7</sup>. ResNet50's residual connections mitigate the vanishing gradient problem, enabling efficient learning of deep hierarchical features. Like VGG16, a GAP layer reduces dimensionality before the fully connected layers, ensuring optimal computational efficiency<sup>13</sup>. The model is then fine-tuned to extract relevant skin features, and a softmax layer predicts the final skin type category.

The Adam optimizer<sup>17,22</sup>, which dynamically modifies the learning rate for effective training, is used to optimize both models. The categorical cross-entropy loss function is used to train the models to ensure successful multi-class classification, and confusion matrix analysis and accuracy measures are used to assess performance<sup>9</sup>.

## RESULTS

To ensure consistency and reliability in performance assessment, 5-fold cross-validation was used to evaluate the classification performance of the ResNet50 and VGG16 models. The model's ability to distinguish facial skin types into three groups—oily, Normal, and Dry—was analyzed primarily using the accuracy and confusion matrix analysis.

The average accuracy of the ResNet50-based classifier across fivefold is 84.16%, with a standard deviation of 4.58%, as shown in **Table 1**: Classification of the Dataset using K-means Clustering

| Skin type | No of Images |
|-----------|--------------|
| Oily      | 69           |
| Normal    | 50           |
| Dry       | 47           |

This suggests a good ability to extract discriminative information for skin type classification.

By comparison, the classifier based on VGG16 had an average accuracy of 80.39%, with a standard deviation of 1.59%, as shown in **Table 2 (a): Accuracies and Standard Deviation from VGG-16**

| <b>Cross Validation</b> | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5 | Avg Accuracy   |
|-------------------------|--------|--------|--------|--------|--------|----------------|
| <b>Accuracy</b>         | 77.27% | 81.82% | 80.95% | 80.95% | 80.95% | 80.39% ± 1.59% |

**Table 2 (b): Accuracies and Standard Deviation from Resnet-50**

| <b>Cross Validation</b> | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5 | Avg Accuracy   |
|-------------------------|--------|--------|--------|--------|--------|----------------|
| <b>Accuracy</b>         | 86.36% | 77.27% | 85.71% | 90.48% | 80.95% | 84.16% ± 4.58% |

The model's performance was consistent over many folds despite being marginally lower than ResNet50.

Confusion matrices, which provide information on classification patterns and possible misclassifications among skin types, were produced for every fold to evaluate model behaviour in more detail. These matrices show the accuracy with which each model can differentiate between oily, normal, and dry skin categories.

ResNet50 outperformed VGG16 overall, certainly as a result of its deeper architecture and residual connections, which enhance feature extraction and representation. Both models provide encouraging classification results, demonstrating the effectiveness of deep learning methods for classifying facial skin.

## **DISCUSSION**

This study combines traditional feature extraction with existing CNN architectures to show the effectiveness of deep learning in facial skin type classification. Histogram of Oriented Gradients (HOG) for texture analysis and MobileNetV2 for deep feature extraction were combined to create an accurate representation of skin characteristics. Using ResNet50 and VGG16, the study successfully separated the facial skin into three groups: normal, dry, and oily.

ResNet50 outperforms VGG16 based on the results, allowing for smoother gradient flow and deeper feature extraction through its residual connections<sup>1,7</sup>. Prior research demonstrating the advantages of deeper networks for skin classification tasks<sup>13</sup> is in parallel to these findings.. Even though VGG16 achieved somewhat lower accuracy, it exhibited more outstanding stability across numerous folds, confirming its robustness<sup>6</sup>. The hybrid approach, which combines traditional and deep learning-based feature extraction techniques—a methodology not frequently addressed in earlier works—is one of this study's main contributions. While CLAHE-based contrast enhancement improved image clarity and helped in feature extraction, applying Gaussian Blur and Bilateral Filtering successfully reduced noise. In order to improve model performance and input images, several preprocessing procedures were essential.

Despite promising results, certain limitations must be acknowledged. Despite being balanced, the dataset is still limited (166 photos), which could have an impact on the model's capacity to generalize across different skin types and ethnicities. Future research should concentrate on increasing the dataset by adding more significant diverse samples, such as variations in skin tones, lighting conditions, and environmental factors<sup>12</sup>. While this study employed 5-fold cross-validation, further validation using real-world dermatological images from clinical settings could enhance practical applicability<sup>18</sup>.

Using hybrid feature extraction, advanced deep learning models, and strong preprocessing methods, this study develops a new framework for classifying facial skin types. Future research should explore integrating self-supervised learning, transformer-based architectures, and multimodal data (e.g., spectral imaging, dermatological scans) further to enhance accuracy and clinical relevance in AI-driven dermatology solutions<sup>9</sup>.

To increase classification accuracy, future studies must look at hybrid feature extraction strategies that make use of modern texture analysis techniques as Wavelet Transform-based features<sup>4</sup> or Local Binary Patterns (LBP). Working with transformer-based models or attention mechanisms may also improve feature selection and model ability<sup>13</sup>. This study lays the foundation for personalized skin care products by showing how deep learning can be used to automatically classify facial skin types. Further studies should concentrate on expanding datasets, enhancing preprocessing methods, and integrating real-time analysis<sup>4</sup> for practical application in the dermatology and cosmetic industries.

This study discusses deep learning-based methods for classifying facial skin types, using ResNet50 and VGG16 for classification and MobileNet for feature extraction. As ResNet50 had residual connections, it performed better and improved feature learning. Even though it was marginally less accurate, VGG16 performed progressively. The results show how deep learning could be used to automate the classification of skin types for dermatological purposes. Future research can concentrate on hybrid feature extraction,

more enormous datasets, and more model modifications to increase accuracy. Practical usability in dermatology and skincare may also be improved by combining real-time analysis and personalizing tools. Investigating the effects of various skin diseases and environmental factors will strengthen the model's generalizability.

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