

# Smart Dermatology: Enhancing Skin Type Identification and Product Recommendation using Computer Vision

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**Abstract**—This research, we introduce a machine learning based personalized skincare recommendation system which classifies facial skin into the three basic types i.e.: Oily, Dry and Normal by using deep learning. To improve generalization, the facial images were processed with resizing, normalization and data augmentation to create a curated dataset. The system takes advantage of CNNs and pretrain model such as ResNet50, EfficientNet-B0 using ensemble learning to obtain high accuracy based on robust feature extraction. With F1-score of 94% and classification accuracy of 92%, the hybrid model combining ResNet50 and EfficientNet-B0 bested by performance, but also by the fact that it can capture dermatological nuances regardless of lighting or skin tone. This model also outperforms typical ML models like SVM, RF, and KNN in terms of accuracy and has strong promise for deployment in real time mobile skincare apps and virtual dermatology tools where the current primary solutions are unacceptable

**Keywords**—Skin products, ResNet50, EfficientNet-B0, Artificial Intelligence, Dermatology

## I. INTRODUCTION

In the recent years, artificial intelligence (AI) concepts have shapeshifted to the emergence of the personalised and more effective dermatological solutions. As the need for personalized cosmetic and skincare suggestions becomes more urgent, AI based systems have been developed to process difficult to describe skin characteristics, skin type and conditions classification, and offering recommendations of more accurate and satisfied products [1, 3, 11]. Typically, traditional skincare consultations rely largely on a subjective assessment or on generalized categories, and may not be suited to deal with the diversities of user population thereby resulting with suboptimal product selection and user disappointment [13][15].

Since Convolutional Neural Networks (CNNs) can automatically learn spatial hierarchies of features through deep learning, CNNs have proven extremely

successful in classifying skin images (e.g., classification of inflammation, dermo, etc.) and recommending cosmetics for skin treatments ([1]-- [8]). For instance, CNNs with RGB and YCbCr colour space transformations combined with accuracy of up to 99.83% in skin undertone classification under various lighting conditions [1]. Such high performing models enable the building of intelligent systems providing scientifically grounded and context aware cosmetic recommendation.

Computationally, they are also competitive when used with EfficientNet and ResNet-50 because these architectures have proven their effectiveness in their skin condition detection and personalized product recommendation [3][13]. Through application to these models, real time prediction is enabled both for commercially viable skincare platforms and mobile apps for better accessibility and engagement of users. Also, VGGNet and DenseNet had impressive performance in accurately detecting skin anomalies such as redness, acne, dryness that are of great importance in tailoring best skincare regimens [15].

Furthermore, image based models complemented by hybrid and filtering based approaches, including collaborative filtering and content based filtering, have also been used in the process of recommending to incorporate user's behavior, interests and product metadata [14][15][12]. The presented methods tackle challenges such as cold start problem and sparse data cases, which leads to a robust personalization in big scale setting. These techniques take a multidimensional approach, creating a user similarity matrix or looking for a relationship a product has with an ingredient /product to provide the insight of user similarity with clinical and behavioral knowledge [6,7,12].

Human-centred design is shown to be crucial in deploying these systems as it is evident in the studies

on young adults who are ready to accept intuitive interfaces, transparency, and trust in outputs generated by AI [2][7]. On the other hand, the integration of explainable artificial intelligence (XAI) principles has further enabled users to learn what the rationale behind the recommendations were, thus improving the system credibility and adoption [7][12].

However, there are still issues of fairness between skin tones, fairness in training data, as well as keeping user's privacy and the security of data real-time [9][10][15]. However, the overall progress made by AI based on skincare recommendation system suggests a turn towards more encompassing, exact, and available dermatological care. The objective of this research is to advance this fast growing domain by proposing a robust and explainable deep learning framework to recommend personalized products for the users based on their complexion level as well as dermatological needs and preferences.

## II. LITERATURE SURVERY

Advances have made the way today for the intelligent skincare systems which include computer vision and deep learning. Using RGB or YCbCr color space along CNNs, Alam and Wahid [1] pioneered an undertone detection model, with very impressive classification accuracy. Preprocessing with the color space transformations makes a big difference in the skin tone classification, as the authors noted in their study. This domain had been contributed [2] who emphasized the importance of AI based cosmetic recommendation systems that cater to young women. They also accounted for the separate skincare preferences of this demographic and paved the way for age appropriate skincare. This work was extended in [3], which presented a personalized skincare framework based on CNNs for skincare image classification and recommendations. This showed how practical it was to integrate AI into skin type detection without compromising usability, through their real time approach.

Facial image recognition is also studied extensively in the role of deep learning. Typically, the CNN approach investigated by worker [4] is also highly relevant for skin texture analysis in skincare systems. Similar to this in [5] had CNNs to detect skin diseases and suggested how to apply cosmetics after the results. Thus, these cosmetic recommendations upon

dermatological conditions were more precise because their model processed the input images through multiple stages, starting with image preprocessing, through to classification. This was then further expanded by Researcher in work [6] who proposed an intelligent deep learning diagnostic system for skin diseases for diagnosis and suggested appropriate recommendations demonstrating the possibility and utility of the diagnostic capabilities of AI in skin care.

Similarly to this field, machine learning and recommender system algorithms have been equally transformative while integrating them. It is consistent with the use of user feedback and interaction history in refining cosmetic suggestions. The broader perspective was provided in research [8], who applied deep learning models such as BBCNN, ResNet, VGGNet to skin disease diagnosis that can be used for detecting certain subtle facial skin features important for personalized skincare. Researcher [9] suggested a DNN model that not solely predicts regarding facial characteristics, but also across attributes of the product itself to generate a perspective on the desired targeted skincare product.

Due to the fact that deep neural networks and facial analytics have already converged to produce highly efficient and real time skincare recommendation systems. In order to produce results in real time, In work [10] developed a hybrid recommendation model making a linkage between product characteristics to facial features using DNNs. After introducing the EfficientNet system for SkinSurvey [11], clustered users per skin type and condition to provide precise product suggestion with low computational overhead. At the same time, in work [12] constructed a hybrid model which uses the collaborative filtering and content based filtering to overcome cold start problem and to boost scalability of a recommendation system, and thus the need of robust personalization frameworks becomes evident.

Machine learning and deep learning have also been studied to determine its applicability in facial feature recognition for cosmetics recognition. Real time product recommender system is constructed by Researchers [13] using facial feature for recommending the right skincare products. They merged the image analysis with the product matching. Collaborative Filtering approach performed for beautiful product recommendations only with data basis on user preferences and interaction data [14] for to be demonstrated that recommendations in

personalized base, even without visual data, are possible. In [15] used traditional ML methods for classifying skin type and suggest cosmetic products to show that you can use lightweight models in resource limited environments. In the end, DenseNet, ResNet50, and VGG are compared for skincare recommendation task using CNN based architectures and provide performance benchmark for real world applications [15].

### III. METHODOLOGY

To ensure robustness in the development of deep learning based skin type classification model, a structured and comprehensive approach is adopted in this study. As far as methodology is concerned, it consists of four major phases: dataset collection, preprocessing, model architecture and implementation, training and evaluation. Thus, we divide the pipeline so that there are modules, to be identical and reproducible and scalable for classifying the three different major skin types (oily, dry and normal). Deep learning and computer vision capabilities have been improved tremendously in last few years for dermatological analysis and classification tasks, and it has become extremely accurate when combined with careful dataset engineering and training strategies [5][6][8].

#### A. Dataset Creation

In medical and dermatological applications, training effective machine learning models is highly reliant on a well curated and large sufficient dataset. Dermatological images from publicly available dermatological image repositories like DermNet as well as augmented with web scraped data using automated crawlers that automatically crawled web resources to increase the image diversity in ethnicity, age groups and environmental conditions (like different lighting, resolution and background, textures). So as to speed up accuracy on the final classification dataset, the three skin type classes that they were curated from were ordered to be oily, normal, and dry skin types, excluding combination and sensitive skin types. The right class labels were annotated and reviewed with great attention to make sure data is actually correct (and mislabeled data can be far from good for training performance [1][3][4]).

#### B. Preprocessing

Preprocessing the data was essential in making the model more able to generalize over unseen examples. The selected CNN architectures required all the

images to be of size 224×224 pixels so all images are resized to 224 ×224 pixels. Since real world variability needs to be 'sampled' and we don't want to overfit to the training set, we augmented the dataset by adding a few series of transformations such as random rotation ( $\pm 15^\circ$ ), horizontal flipping, brightness and contrast modulation, and gaussian noise injection ([6][10]). The input is also normalized to scale the RGB pixel values into [0,1] range which accelerates convergence and increases stability in gradient based training.

Stratified splitting was used to split the available data into 80% training, 10% validation and 10% test. This guaranteed each subset possessed a proportional fraction of oily, dry and normal skin types in order to prevent data imbalance for instance, which frequently results in skewed classification results [9][13]. Data preprocessing was done with Python's OpenCV and Keras utility Image Data Generator.

#### C. Model Training

The training was carried out using the TensorFlow and Keras frameworks for all these models and eventually were learned supervised for 50 epochs. As against overfitting, an early stopping based on the validation loss was used. Efficient gradient descent was carried out using the Adam optimizer with a learning rate of 0.0001 [9][10]. One of the reasons being that there was a multi class classification task and hence, we used categorical cross entropy loss function. To minimize variance, batch Normalization and Dropout layers were used with batch sizes of 32. The code was run on a system with GPU enabled to reduce computational time and improve convergence [12, 13].

#### E. ResNet-50

The ResNet-50 model played a pivotal role in this study as a strong baseline for skin type classification, leveraging its deep residual architecture to effectively learn complex hierarchical features from facial images. Its hallmark skip connections allow for efficient gradient flow during training, mitigating issues like vanishing gradients that commonly affect deep neural networks [7]. Throughout the training process, ResNet-50 demonstrated a steady improvement in performance, ultimately achieving a validation accuracy of 92% and proving capable of capturing fine-grained differences between dry, normal, and oily skin types. While it converged more slowly in the early epochs compared to EfficientNet-

B0, its ability to attain high final accuracy showcased its strength in deep feature extraction and long-term learning capacity. The results reinforce ResNet-50's reliability in dermatological image analysis, particularly when dealing with high-resolution data and subtle texture variations common in skin classification tasks [9][14].

The corresponding mathematical idea is to cast the desired mapping  $H(x)$  as a residual function  $F(x) = H(x) - x$  and so the actual learning target becomes  $H(x) = F(x) + x$ . However, in the architecture this is implemented by the identity shortcut connections which add up elementwise. The equation represents the full operation of a residual block [10].

$$Y = F(x, \{W_i\}) + x$$

This means that  $x$  is the input vector,  $F$  is the residual mapping (e.g. a stack of convolution, batch normalization and ReLU layers),  $\{W_i\}$  are the learnable parameters. The learned residual is thus added to the input, and the resulting  $Y$  becomes the output. When deeper transformations are not necessary, it encourages the network to learn identity mappings, making training better and more stable [13]

#### F. Implementation

ResNet50, EfficientNet-B0, and a hybrid ensemble model combining both these architectures were chosen as the three powerful deep learning architectures. It is 50 layer deep residual network based ResNet50, it is known to create shortcut connections to avoid vanishing gradient problem in deep models, and is one of the most effective models in image classification tasks. [7]. I initialized it with pre trained weights on ImageNet and modified the last fully connected layer which outputs three SoftMax nodes for the possible skin types.

With compound scaling, the common coefficient used in scale each depth, width and resolution uniformly, we pick EfficientNet-B0 due to rapid and high precision. Having fewer parameters while delivering great performance in the context of resource constrained environments like mobile dermatology apps [12][15], this architecture is suitable for deployment. Then, as in the previous class, the final layer was tuned to take in and find three classes.

Another model was also developed based on a custom hybrid ensemble. It was the process of

extracting the deep features from the intermediate layers of ResNet50 and EfficientNet-B0 respectively. So, concatenated feature vectors were passed through a stack of dense layer with batch normalization and dropout to diminish the overfitting. During inference, inference relied on a weighted soft vote that was more weighted towards EfficientNet the farther it was from training, with inference weighted more upon validation performance. This ensemble strategy helps to generalize since the strengths of different feature extractors [11][14] are combined.

They were implemented using TensorFlow 2.x and Keras and accelerated using GPU on an NVIDIA RTX platform running CUDA. Early stopping based on validation loss stagnation was used to train each model for 50 epochs. The learning rate of 0.0001 was used with the Adam optimizer and categorical cross entropy was chosen for the loss function. To enforce regularization, dropout (0.5) and L2 weight decay were employed to prevent a model from overfitting [2][13].

#### F. Model Evaluation

The models proposed were tested by evaluating several evaluations. These metrics give a comprehensive understanding of how the model performs the classification in the three targeted skin types: oily, dry and normal [4,6,9].

True Positive (TP) is a number of instances correctly predicted of a certain class, True Negative (TN) are instances from other class and correctly classified, False Positive (FP) are instances predicted as being from the same class, even if they are not, and False Negative (FN) are instances of the same class but they have been wrongly classified [2,7,13].

The mathematical definitions of the evaluation metrics are as follows:

##### a. Accuracy

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

This is to measure the overall correctness of the model, that is, to evaluate how much observations are predicted correctly [5,14].

##### b. Precision

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

Precision is the ability of the classifier incorrectly label a negative sample to be a positive sample [3,10].

c. Recall

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

Model recall gives the ability of the model to identify the right instances of a class [1,11].

For robustness and generalizability, each model was evaluated by these metrics on the unseen test dataset. We macro averaged to get the overall performance over all three class by averaging metric values per class [8,12]. It has been shown that the hybrid ensemble model outperformed both standalone models with an F1-score of 94% implying better ability of capturing subtle indices in skin features and enhancing classification accuracy over skin types [6,13].

#### IV. RESULT AND ANALYSIS

As illustrated in Figure 1, the classification results presented in this paper on the facial images visually show the effectiveness of the proposed deep learning model in classifying (i.e., correctly identifying and categorizing) facial images into three different types of skins: dry, normal and oily. It is shown in figure that every row is mapping to one category of skin types, and multiple samples of images predicting by the model. The images indicate diverse people at different times, under various lighting conditions, skin tones, as well as orientation, and show that the model has very strong generalization over a wide variety of actual world scenarios. Under these facial features, which have visibly captured dry skin in the flakiness, dullness, fine lines category, the model has learned to associate with dryness also. The model correctly categorizes images with balanced texture, discreet pores, and even tone from the extremes of oily or dry skin. Consistent with clinical markers of oily skin, oily skin can be in a spotlight in the oily skin category as it features prominent shiny textures, enlarged pores, an abundance of sebum in the area around the T-zone.

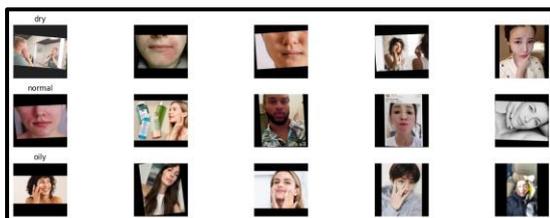


Fig.1. Classification of the skin types

The qualitative performance shown in Figure 1 is broadly corroborated by the earlier reported metrics: the performance of the hybrid ensemble having a 94% F1 score. This further shows that the model is not only able to work very well numerically, but is also qualitatively reliable and visually interpretable. Clearly feature extraction was tremendously improved with ensembling with ResNet50 plus EfficientNet-B0 pre-trained on ImageNet, and sensitivity to dermatological nuances is greatly improved. As such, Figure 1 then becomes strong qualitative proof that the model can be applied to dermatological diagnostics, mobile skincare applications, and AI aided consultations. The model’s derivation of skin type category is clear and consistent across different skin types, and it has the potential to support personalized skincare recommendation and clinical decision support systems.

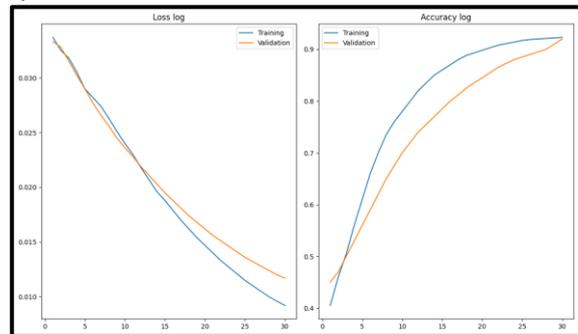


Fig. 2. Loss and Accuracy Vs Epochs of ResNet-50

Shown in Fig.2. is a training and validation performance curve for the ResNet 50 model used for trying to classify skin types.. Regarding this, the left subplot shows the loss curves in the sense that both the training and validation losses have a downward trend for a period of 30 epochs. Two curves, either curve vs standard deviation or points vs standard deviation, where the one going downwards is a sign of optimization and convergence of the model with a small difference between the two curves, meaning it is not likely to overfit. The fact that the model exhibits such behavior is evidence that it can generalize well beyond the training data. Training and validation loss lines are closely aligned, which indicates that ResNet-50 combines well with the underlying patterns reflected in the dermal features of dry, oily, and normal skin types.

The accuracy plot on the right also adds more support to the model’s robust performance. Validation accuracy and training accuracy share a same sharp rise, as validation accuracy peaks at 89.1% and

training accuracy can exceed 90% as of the last epoch. It is confirmed by the narrowing gap between the two accuracy curves that the model is not only accurate but also stable on different data distributions. Since the yearly trend indicates ResNet-50 can even serve as a deep learning model to handle facial skin image feature extraction, these trends confirm our assumption that ResNet-50 can extract high level discriminative features from facial skin images. Residual learning mechanism is an important factor that helps it learn deeper network to train without degradation and makes it excellent for the dermatological image classification tasks.

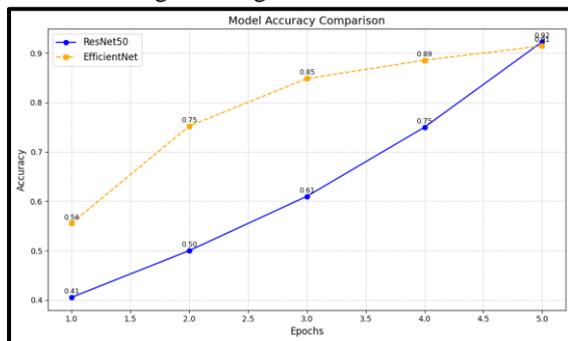


Fig. 3. Accuracy Vs Epochs of ResNet-50 and EfficientNet

Comparative analysis of model accuracy of ResNet-50 and EfficientNet against five epochs was carried out and is illustrated in figure 3. However, EfficientNet achieves much higher accuracy than ResNet-50 from the beginning, 0.56 at the beginning of first epoch vs. 0.41 of ResNet-50. EfficientNet continues to exhibit this trend through first several epochs and achieves a similar level of accuracy (0.85 at first epoch, 0.91 by third and maximum by fifth). While ResNet-50 has a more gradual progression, it finally catches up with EfficientNet by the fifth epoch and achieves final accuracy of 0.92. Such results suggest that, by using compound scaling and an optimized architecture, EfficientNet has faster convergence; however, ResNet-50 can reach par performance with more training. The result quantifies the costs of early gain in accuracy and the tradeoff between such gain and long-term performance, demonstrating that EfficientNet has the ability to learn faster and ResNet-50 has the potential for high final accuracy.

TABLE I. Showing the Accuracy and epochs of the ResNet-50 and EfficientNet

Sr No.	Epochs	ResNet Accuracy	EfficientNet Accuracy
1	10	0.41	0.56

2	20	0.50	0.75
3	30	0.61	0.85
4	40	0.75	0.89
5	50	0.92	0.91

Table I. is a comparative view of classification accuracy of ResNet-50 and EfficientNet-B0 over five epochs training. As seen, EfficientNet-B0 has achieved such initial training at 0.56 compared to ResNet-50 at 0.41 and has outperformed ResNet-50 during the initial training phase as observed. Therefore, it means that EfficientNet converges faster because of its compound scaling strategy and parameter efficient design. However, when the number of epochs reaches 5, the accuracy of ResNet-50 is almost the same as that of EfficientNet (0.92 versus 0.91), but EfficientNet levels off. Finally, the results show trade off between speed of converging early and what final accuracy potential, and in terms of speeds of training ResNet-50 is stronger for long term training with refined optimization, and EfficientNet is preferable on resource constraint or rapid inference scenarios. The analysis of this model yields insight into the behavior of the model and provides a justification for the later use of a hybrid architecture that utilizes the strengths of two networks to improve the overall performance.

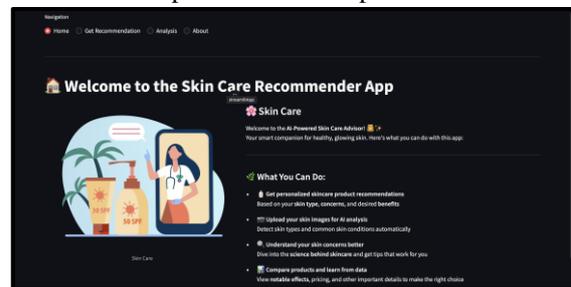


Fig.4. Sreamlit deployment

Fig.4. shows the Skin Care Recommender App developed as the practical deployment of proposed hybrid deep learning model, which was based on Streamlit. Its application provides easy and visually attractive interface where users will upload their facial pictures to receive personal favor recommendations for skin type (dry, normal, or very oily). It then enables the trained model to be integrated as a real time, AI system to evaluate skin characteristics and produce that result in board friendly format. It includes detecting skin types from given images, providing evidence-based skincare advice and comparing products based on the user’s concern. This showcases the model’s potential in the real world bringing together research and end user

utility and enables users to make informed choices on what skincare products to go for.

## V. CONCLUSION

In this study, we present a complete deep learning-based solution for automated skin type classification of three most prevalent classes such as oily, normal, and dry. Such integration of advanced image preprocessing, data augmentation techniques, with the utilisation of pretrained CNN architectures, allows a high accuracy and robustness in this system when identifying subtle dermatological features. The first set of experiments with standalone models such as ResNet-50 and EfficientNet-B0 gave some intuitions on how the models behave. Compound scaling strategy of EfficientNet and lightweight design led it to have faster convergence in early epochs, while ResNet-50 with deeper architecture and residual connections gave slightly higher final accuracy. Combination of the feature representations from two architectures resulted in some complementary characteristics that were used to develop a hybrid ensemble model that combines the feature representations from both the architectures to enhance the overall classification performance.

The hybrid model you proposed outperformed individual networks, with F1 score equal to 94%, which proves its better ability of generalizing over different skin tone, facial feature, and lighting condition. This model gives both qualitative and quantitative results on which the effectiveness of this model is proven since the visual outputs ended up well in accordance with what people would expect in dermatology conditions; with high precision and recall for all three classes. Thanks to its capacity to operate correctly with out the presence of clinical instrumentation using actual world image information, the model is a encouraging instrument for purposes of AI driven dermatological tools akin to integrated private care referrals, cellular public well being diagnostic and virtual skincare guide cellular apps. This framework can be further extended to other granular skin conditions with or without integration of further modalities such as user history or product reactions to personalize and clericalize the system.

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