Image-based skin disease detection: Psoriasis, Eczema, and Acne using VGG16 and ResNet-50

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Abstract. Millions of people around the world are affected by skin diseases, which represent a serious health risk. For these illnesses to be effectively treated, a timely and precise diagnosis is essential. This project uses deep learning techniques, specifically the VGG16 architecture and Resnet50 architecture, to provide a reliable solution for the categorization of skin diseases. The creation of an extremely precise and effective model for the automated classification of skin conditions is the main goal of this study. Three different classifications of skin conditions, including psoriasis, eczema, and acne, make up the dataset used in this project. The models are adaptable and capable of managing a variety of dermatological issues because each class in the dataset has been carefully chosen to reflect a broad range of skin disorders. The known convolution neural network (CNN) models called the VGG16 architecture and Resnet50 architecture are used because of their exceptional feature extraction capabilities. Move the pre-trained VGG16 model is refined using learning on the dataset of skin diseases. To guarantee the reliability of the models, a thorough cross-validation procedure is used for training, validation, and testing.

Keywords- Image Classification, VGG16, Resnet50, Transfer Learning, Convolutional Neural Network(CNN) , Tensorflow.

1 Introduction

Dermatology is a highly visual specialty that lends itself strongly to the application of deep learning (DL) methods. Given the increasing volume of skin images captured in clinical practice and through teledermatology, DL models offer new opportunities to streamline disease diagnosis and severity assessment. Recent research has demonstrated this potential: for example, Ahmmed et al. [1] proposed a modified VGG16- based model for detecting actinic keratosis and psoriasis using transfer learning and achieved over 90% accuracy on a publicly available dataset. Similarly, Ibrahim et al. [2] applied VGG16 transfer learning on a

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Kaggle skin cancer dataset using different color-space transformations and reported about 84.24% classification accuracy.

Despite these encouraging results, major challenges remain. Skin disease diagnosis often requires distinguishing subtle visual features across lesions—such as texture, color variation, and border irregularity—which may be difficult for models trained on limited or imbalanced datasets. Additionally, deep model architectures may suffer from overfitting or instability when training data is scarce. These issues underscore the importance of evaluating not just overall accuracy but also model robustness (e.g., validation stability and class-wise performance) when selecting architectures for skin disease classification.

In this study, we compare two widely used deep convolutional architectures—VGG16 and ResNet-50—trained on a curated dataset of acne, eczema, and psoriasis images. We examine how each model performs under identical preprocessing and augmentation protocols, evaluate their strengths and weaknesses, and determine which architecture delivers more reliable performance for dermatological image classification. The findings aim to guide future work on deploying DL-based diagnostic tools in dermatology with practical utility.

2 Related Work

To examine previous studies on skin disease detection via deep learning and transfer learning techniques, a thorough literature study was carried out. Key studies from 2019 to 2025 are compiled in Table 1, which also highlights the datasets, models, and techniques used for the classification of skin diseases. The majority of earlier research has focused on transfer learning to enhance performance with sparse medical datasets by employing pre-trained architectures like CNN variations, VGG16, and ResNet. The comparative evaluation of these studies yielded insightful information that helped choose the architectures for the suggested model in this study.

Recent studies have demonstrated the potential of deep learning and transfer learning techniques for accurate skin disease classification.Singh *et al.* [3] employed a pre-trained VGG16 model, fine-tuned on a custom dataset of skin disease images. The preprocessing steps, including image resizing and augmentation, led to improved classification accuracy compared to traditional machine learning methods. Similarly, Janoria *et al.* [4] utilized the VGG16 architecture with transfer learning to classify dermoscopic images of skin diseases, achieving high accuracy after fine-tuning. Velasco *et al.* [5] conducted a comparative study involving several convolutional neural network (CNN) architectures and reported that while VGG16 attained 44.1% accuracy, MobileNet outperformed others with 94.1% accuracy on a dataset of 3,400 images.

Further, Saranya *et al.* [6] proposed a CNN-based approach for detecting skin diseases from digital images through preprocessing and feature extraction. Kaur *et al.* [7] adopted the Xception model using transfer learning to identify various skin lesions, demonstrating high detection performance. Chakraborty *et al.* [8] introduced *CAD-PsorNet*, a deep transfer learning framework employing VGG16, VGG19, MobileNetV1, and ResNet-50 for psoriasis diagnosis, achieving excellent results on a dataset of 496 image patches. Thomsen *et al.* [9] presented a CNN model for binary classification of multiple-lesion skin diseases, trained on 16,543 images using a multi-task learning approach.

Sah *et al.* [10] combined image processing and deep neural networks for dermatological disease classification, improving accuracy across various skin conditions. Nieniewski *et al.* [11] focused on differentiating psoriasis from other dermatoses using transfer learning on small datasets, obtaining strong results despite limited data. Venkataiah *et al.* [12] enhanced dermatological disease detection by fine-tuning CNN and transfer learning models, reporting improved overall performance. Faghihi *et al.* [13] applied VGG16 and VGG19 architectures for skin cancer detection, achieving significant diagnostic accuracy through fine-tuning.

Gupta *et al.* [14] implemented CNN-based neural networks for skin disease classification, while Amin *et al.* [15] proposed a deep learning method for automated psoriasis detection using preprocessing and augmentation to boost model performance. Islam *et al.* [16] employed a fine-tuned VGG19 model for skin disease classification, achieving better results than conventional CNN models. Javaid *et al.* [17] explored transfer learning with multiple pre-trained models for efficient disease detection. Hammad *et al.* [18] proposed an enhanced deep learning approach for accurate detection of eczema and psoriasis, incorporating advanced optimization techniques to improve precision. Goceri *et al.* [19] compared various CNN architectures for skin lesion classification and provided an in-depth evaluation of model performance.

Lastly, Choy *et al.* [20] presented a comprehensive systematic review of deep learning methods for the diagnosis and monitoring of skin diseases. Their findings highlighted that transfer learning and CNN-based models significantly advance diagnostic accuracy and clinical applicability in dermatological image analysis.

2.1 Research Contribution

Previous studies have not explored the combined use of the VGG16 model with transfer learning and the ResNet50 model for skin disease classification. In contrast, our proposed approach utilizing VGG16 with transfer learning achieved an accuracy of 89.5%, whereas the ResNet50 model attained 72.4% accuracy.

3 Proposed method

3.1 Dataset Description

The dataset used in this research came from open dermatological image sources. It was organized to cover three common skin conditions: psoriasis, eczema, and acne. A total of 3,464 images were included. This total is made up of 643 images for psoriasis, 1,273 for eczema, and 1,548 for acne. The images captured various clinical appearances across different body areas. This variety helps create a representative sample for training and evaluating the model.

The dataset shows a wide range of dermatological presentations, including the red plaques of psoriasis, inflamed lesions of eczema, and both comedonal and pustular patterns of acne. This variation improves the strength of the classification model by exposing it to real-world differences. To make processing easier, the images were standardized to a resolution of 224 × 224 × 3 pixels. This matches the input requirements of the VGG16 architecture.

3.2 Preprocessing and Augmentation

Preprocessing and augmentation are important steps to make sure the dataset is standardized, balanced, and diverse enough for training a deep learning model. The following operations were applied to the images before using them in the VGG16 architecture:

3.2.1 Rescaling and Normalization:

All images were resized to 224×224×3 pixels to match the input dimensions required by VGG16. Pixel intensity values were normalized to a range of [0, 1] by dividing each value by 255. This step ensured uniformity across the dataset, improved convergence during training, and reduced the risk of computational bias from different brightness or contrast.

3.2.2 Data Augmentation:

To enrich the dataset and reduce overfitting, several augmentation techniques were used. These operations expanded the dataset by creating transformed versions of existing images, which helped the model generalize better. The augmentations included :The dataset underwent various image augmentation techniques to enhance diversity and prevent overfitting. Random rotations within a specified degree range were applied to simulate different viewing angles of skin lesions, while zoom operations replicated variations in image capture distances. Horizontal flipping was performed to mimic real-world variations in orientation, and in certain cases, minor shifting and cropping were used to simulate different framing and positioning of lesions. These augmentation methods collectively improved the model's robustness and generalization capability across diverse image conditions.

3.2.3 Handling Class Imbalance:

The dataset had uneven numbers of images across the three classes (acne: 1548, eczema: 1273, psoriasis: 643). To address this imbalance and avoid bias towards majority classes, class weights were calculated based on how many images were in each class. These weights guided the training process by penalizing misclassifications of underrepresented classes more heavily, which improved fairness in classification.

3.3 VGG16 for Skin Disease Classification

A popular convolutional neural network architecture, VGG16 (Visual Geometry Group 16) has 16 weight layers, including convolutional, pooling, and fully connected layers. With only 3 × 3 convolutional filters with stride 1 and 2 × 2 max-pooling filters, the model is renowned for its homogeneous architecture. VGG16 greatly reduces the amount of trainable parameters while achieving the same receptive field as larger filters by stacking numerous tiny convolutional kernels. VGG16 is well-suited for medical imaging applications like skin disease categorization because of its design, which allows for the extraction of both low-level and high level characteristics.

Transfer learning was used to implement VGG16 for this project. The last fully connected layers were swapped out for a bespoke classifier designed for three categories: psoriasis, eczema, and acne. The convolutional basis that had previously been trained on ImageNet was kept, acting as a potent feature extractor. Every image was downsized to 224 × 224 × 3 pixels in order to meet VGG16's input dimensions. In order to improve the resilience of the model,

preprocessing operations included pixel normalization and augmentation techniques like rotation, flipping, and zooming.

Within the VGG16 framework, non-linearity is introduced through the Rectified Linear Unit (ReLU) activation function, defined as:

$$f(x) = \max(0, x) \tag{1}$$

The model can effectively learn intricate dermatological patterns thanks to this activation, which also helps to address vanishing gradient problems. The outputs of the final dense layer were subjected to the Softmax function for the final classification:

$$\sigma(z)i = ez\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}},\ i = 1, \ldots, k \tag{2}$$

where K = 3, corresponding to the three skin disease categories. The Softmax function ensures that predictions are represented as a probability distribution across all classes. The VGG16 model successfully classified the dataset into acne, eczema, and psoriasis by utilizing both broad image features and dermatology-specific attributes by integrating ImageNet pre-trained weights with domain-specific fine-tuning.

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3.4 ResNet-50 for Skin Disease Classification

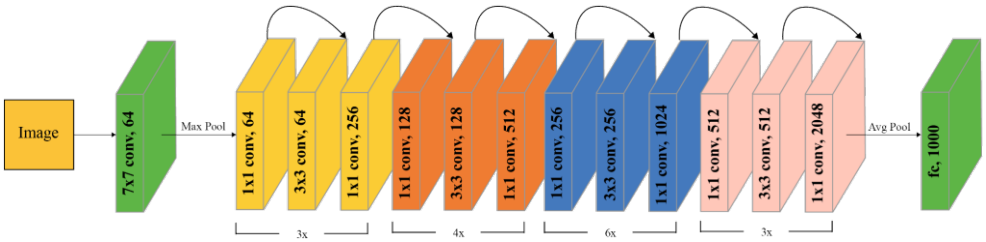

Fig. 1. ResNet-50 architecture

A more complex and sophisticated convolutional neural network design is represented by ResNet-50, or Residual Network with 50 layers. In contrast to conventional CNNs, ResNet 50 uses skip (shortcut) connections to implement residual learning. Because of these connections, the network can avoid several layers, allowing the model to learn residual mappings instead of approximating the desired function directly. This method enables ResNet-50 to reach deeper networks without compromising convergence by mitigating the vanishing gradient issue that frequently plagues very deep networks. Mathematically, the residual mapping is expressed as:

$$y = F(x, W) + x \tag{3}$$

where x denotes the input, F(x,W) represents the residual function learned by convolutional layers with weights W, and y is the resulting output. By reformulating the learning task into residual functions, ResNet-50 ensures better gradient flow and improved training stability in deeper architectures.

Transfer learning was also used in this research to apply ResNet-50. The fully connected layers were swapped out for a custom classification head, and the convolutional base that had previously been trained on ImageNet was adjusted to extract disease-specific features from dermatological images. The dataset was preprocessed in the same way as VGG16, which included augmentation, normalization, and shrinking images to 224 × 224 × 3 pixels. The final step involved assigning probability scores to each of the three disease types using a Softmax output layer. ResNet-50 was chosen because of its deeper design and residual connections, which enable it to capture both low-level and high-level information. Theoretically, its skip connections improve classification performance by allowing shallow-layer characteristics to be refined in deeper layers while being reused. To ascertain whether architecture is more appropriate for classifying skin diseases on sparse data, ResNet-50 was applied to this dataset as a comparison analysis against VGG16.

4 Results and discussion

This section presents the experimental findings from the implementation of two deep learning architectures, VGG16 and ResNet-50, for the classification of dermatological conditions (acne, eczema, and psoriasis). The evaluation highlights dataset preparation, training details, model performance, and a comparative analysis of both approaches.

4.1 Dataset and implementation:

The dataset consisted of 3464 images distributed across three classes: acne (1548), eczema (1273), and psoriasis (643). To handle class imbalance, class weights were applied during training. All images were resized to 224×224×3, normalized to a [0, 1] range, and augmented with rotation, flipping, and zooming to improve generalization.

The dataset was split into 90% for training (3117 images) and 10% for testing (347 images). Identical splits were used for both models to ensure fairness in comparison. Training was performed on Google Colab with a T4 GPU using TensorFlow and Keras. The Adam optimizer with a learning rate of 0.0001, a batch size of 32, and 25 epochs was employed.Representative images from the dataset are shown in Fig. 2, while Fig. 3 demonstrates classification outputs obtained after training the models.

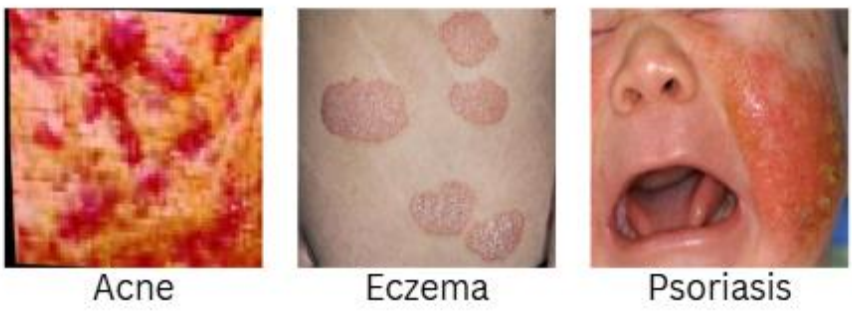

Fig 2. Sample images from the dataset representing acne, eczema, and psoriasis cases

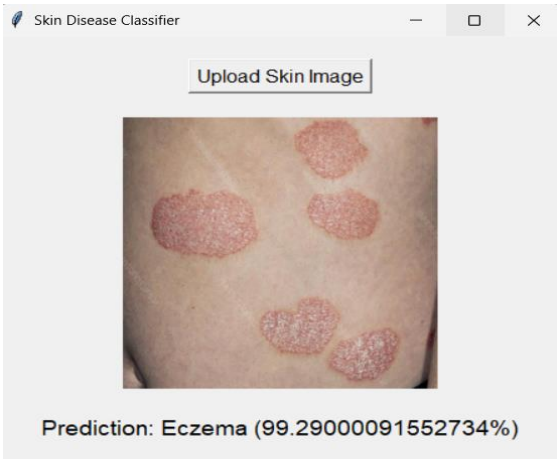

Fig. 3..Example model outputs showing predicted skin disease labels with confidence scores.

4.2 VGG16 Model:

VGG16 was fine-tuned with a custom dense head for classification. The model demonstrated stable convergence with training accuracy of 92.3% and validation accuracy of 89%. On the test set, it achieved 89.5% accuracy with balanced precision, recall, and F1-score (all 0.89), as summarized in Table 1.

The learning curves in Fig. 4 confirm consistent convergence with minimal overfitting, showing smooth progress in both accuracy and loss.

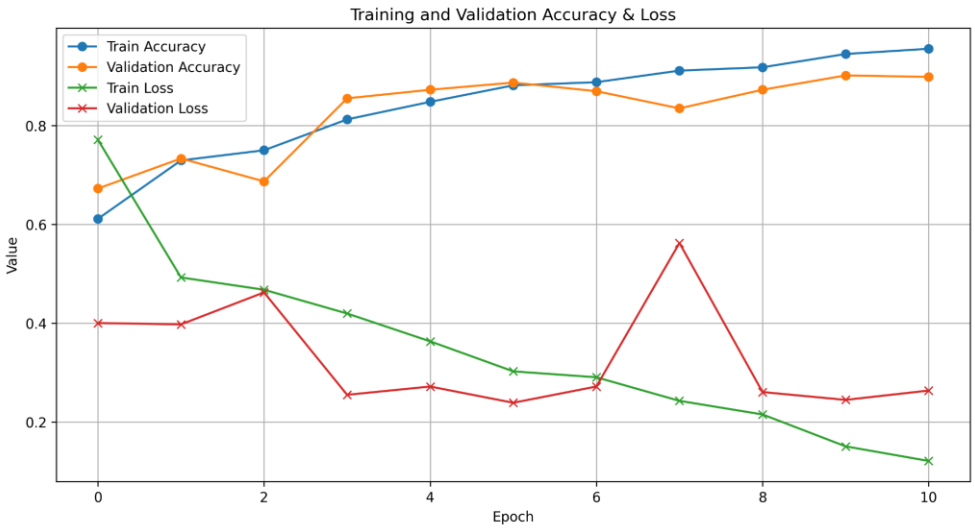

Fig. 4. Training vs. Validation Accuracy and Loss curves for VGG16

Table 1.Test results of vgg16

Accuracy	Precision	Recall	F1-score	Test Set Size
89.5%	0.89	0.89	0.89	347

4.3 ResNet-50 Model:

ResNet-50 was trained under the same configuration. Although it effectively captured hierarchical features through residual learning, its performance was limited by the relatively small dataset. Training accuracy reached 85%, while validation accuracy fluctuated between 70–75%. On the test set, it achieved 72.4% accuracy with precision (0.71), recall (0.73), and F1-score (0.72), as shown in Table 2.

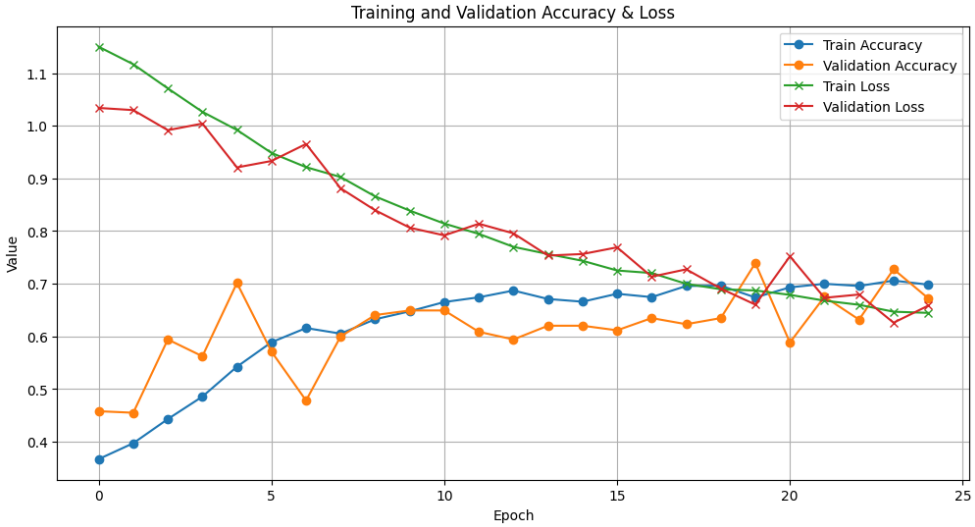

Fig. 5. Training vs. Validation Accuracy and Loss curves for Resnet50

Table 2. Test results of resnet-50

Accuracy	Precision	Recall	F1-score	Test Set Size
72.4%	0.71	0.73	0.72	347

4.4 Comparative Analysis:

The comparative results presented in Table 3 confirm that VGG16 consistently outperformed ResNet-50 across all evaluation metrics. While ResNet-50's deeper architecture is advantageous for very large datasets, the limited dataset size in this study restricted its

potential. VGG16, with its balanced and relatively shallow design, was more effective in extracting dermatology-specific features.

Table 3. Comparative analysis of classification models

Model	Dataset Size	Accuracy	Precision	Recall	F1-score
ResNet-50	3464 images	72.4%	0.71	0.73	0.72
VGG16	3464 images	89.5%	0.89	0.89	0.89

4.5 Additional Observations:

The confusion matrices in Fig. 6 and Fig. 7 provide classwise performance insights. VGG16 showed balanced classification across all categories, while ResNet-50 exhibited higher confusion between eczema and psoriasis.

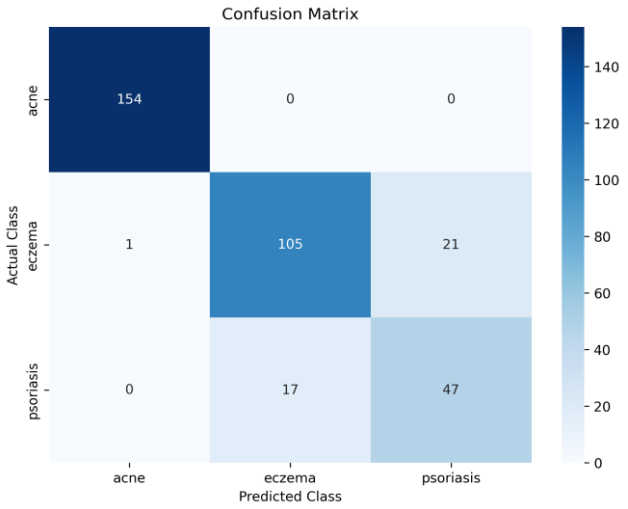

Fig. 6. Confusion matrix for VGG16 classification results.

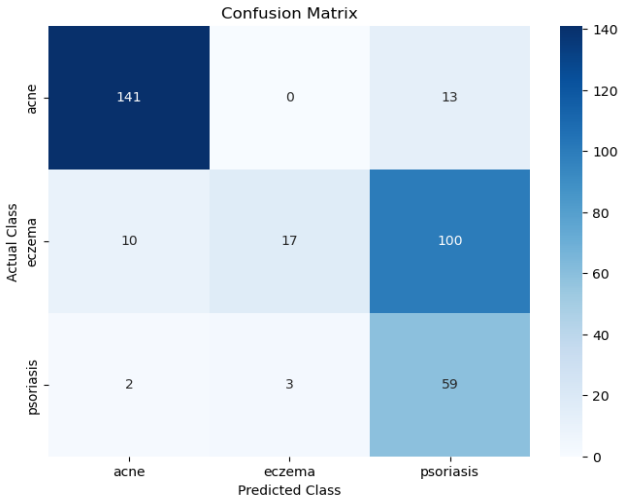

Fig. 7. Confusion matrix for Resnet50 classification results.

4.6 Conclusion of Analysis:

Based on the comparative evaluation, VGG16 was selected as the final model for skin disease classification due to its higher accuracy (89.5%), balanced precision, recall, and F1- score, as well as its stable convergence during training. In contrast, ResNet-50's deeper architecture was less effective on this dataset, leading to lower validation stability and weaker generalization. Overall, VGG16 demonstrated superior robustness in identifying dermatological conditions in small to medium scale image datasets**.**

5 Conclusion :

In this study, we used the VGG16 and ResNet50 architectures to propose a deep learning-based method for autonomous skin disease classification by transfer learning. Images of psoriasis, eczema, and acne were used to train and refine both models on a carefully selected dataset. Comparative investigation revealed that ResNet50 showed faster convergence and superior feature extraction for complicated patterns, whereas VGG16 achieved greater overall validation accuracy of 89.5%.

Overall, the findings show that VGG16 performed better than ResNet50 in terms of accuracy and class-wise F1-scores, which makes it more appropriate for clinical use cases and lightweight deployment where computational resources are few. On the other hand, ResNet50 demonstrated promise for deeper feature representation and scalability in larger datasets.The study can be expanded for subsequent research by adding ensemble or hybrid models, which mix several designs to improve prediction reliability. By incorporating the suggested approach into an online or mobile application, dermatologists and patients may have access to a real-time, easily available diagnostic tool that encourages early identification and improves clinical results.

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