RESEARCH PAPER

Enhanced Image Preprocessing and EfficientNet-Based Approach for Skin Disease

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ABSTRACT

Dermatological disorders are prevalent all over the world, and the rate affects people of all ages. The ability to diagnose skin diseases is important, especially when the disease is diagnosed early enough. In this work, we present a new deep learning model for skin disease classification that involves various methods of data enhancement and preparation to improve the quality of the images used in the analysis. Our data set was tested to compare the performance of competitive deep learning architectures such as ResNet50, VGG16, Inception V3, and EfficientNet. The proposed EfficientNetB0-based method achieved a training accuracy of 91% and a testing accuracy of 88% on a dataset of 5000 images, outperforming several existing skin disease detection frameworks. We have observed high accuracy in our proposed skin disease prediction model using deep learning techniques..

Keywords: Skin diseases, Deep Learning, Image Classification, Data Augmentation, Preprocessing, EfficientNet

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INTRODUCTION

Skin diseases are among the most common health conditions worldwide, affecting an estimated 900 million people at any given time across all age groups and geographies [14]. Accurate and timely diagnosis is essential for effective clinical management. Traditionally, dermatological diagnosis has relied on visual examination by trained dermatologists — a process that is time-intensive, subjective, and limited by inter-observer variability. The growing shortage of dermatologists, particularly in low- and middle-income countries, further underscores the urgent need for automated, AI-driven diagnostic tools.

Deep learning has emerged as a transformative paradigm in medical image analysis, offering the ability to extract complex, hierarchical features directly from raw image data without handcrafted feature engineering [14]. Convolutional Neural Networks (CNNs) and their evolved variants — including ResNet, VGG, InceptionNet, and EfficientNet — have demonstrated near-dermatologist-level performance on several benchmark skin disease datasets [14][15][16]. However, challenges such as class imbalance, inter-class visual similarity, and limited annotated datasets continue to limit real-world deployment.

In this research we put forward a deep learning-based skin disease classification approach to detect the skin disease using different data enhancement and preprocessing techniques to get a better image quality. For our study, we tested high performing deep learning models such as ResNet50, VGG16, Inception V3 and the EfficientNetB0 models to select the best model for our data set. The proposed EfficientNetB0 method achieved a training accuracy of 91% and a testing accuracy of 88% for a test set of 5000 images and is superior to more than one existing methods for skin disease detection

LITERATURE REVIEW

Presumably in [1] the author proposes the use of DNN classification strategy for skin disease categorization with capability of binary or ternary classification. It employs Deep neural network (DNN) classifier to classify skin disease and is trained using DermNet dataset. As the outcome of the study it is revealed that the accuracy of the suggested approach is 79.94%.The author of [2] proposes a classification of skin disease using DNN and binary or ternary classification of images. The method relies on a Deep neural network (DNN) classifier and it is trained on private data obtained from the Department of Dermatology Peking Union Medical College Hospital. The outcomes of the study show that the application of the suggested approach makes it possible to achieve the accuracy of 85.86%.In [3], the author employs CNN and CNN-NSVM to classify skin cancer disease images into two classes which include Melanoma and Naevus. The model is trained on the Dermnet Skin Cancer which consist of 23,000 images. It provides 89% accuracy on skin cancer.Deep Neural Network is employed in the diagnosis of the disease Herpes Zoster as described by the author in [4]. The model is updated on a special set. The described approach yielded total accuracy of 0.905 and mean corruption error of 0.676. It only does binary classification for Herpes Zoster. In [5], the author uses a Convolutional Neural Network to classify into 5 skin diseases. The model is trained on a small custom dataset which also has some images from the Dermnet Dataset. It results in an accuracy of 70%. In [6], the author uses Support Vector Machine (SVM) classifier and Decision trees to classify Skin Diseases. It results in an accuracy of 75% with Decision Tree's and 83% with Support Vector Machine (SVM). It is trained on a custom dataset. It classifies into 4 skin diseases. Authors of [7] describes the model used for classification in this study. EfficientNet is a convolutional neural network architecture developed by Google Brain Team in 2019 that achieved state-of-the-art performance on several image classification benchmarks while being computationally efficient. This is applied in this study to classify skin diseases. Talks about Resnet and Inceptionv5. ResNet and InceptionV5 are two popular convolutional neural network architectures for image classification tasks that have shown promise in the field of skin disease detection and have been used as a benchmark in this study [8].Khouloud Elbedoui et al. [9] discussed Deep Learning models:EfficientNet-B0-V2 & Vision Transformers are applied for High sensitivity and specificity in early diagnosis of malignant & benign skin lesions.Eelanila Thayalan et al. [10] has described the Disease Prediction System that uses deep learning to predict skin diseases including Skin Cancer, Benign Tumours, Growth disorders and Inflammatory skin diseases. It uses image processing and transfer learning to detect likely malignancies and diagnose many skin diseases with remakable accuracy.There are several Deep learning methods that have been outlined by Elif et al. [11] including Regnet x006, EfficientNetv2 B0, and InceptionResnetv2 and applied a classification process on dermoscopic images after obtaining rid of added noise.According to singh et al. [12], Deep learning algorithms increase the chances of early diagnosis thus early treatment of skin diseases through increased classification probabilities.Ankit Yadav et al. [13] described the study that aimed at the comparison between three deep learning models for skin disease detection and concluded that both VGG-16 and ResNet50 models have a lower computational time while Inception V3 model had a

onger training phase.

Deep Learning Technique For Skin Disease Classification

. Deep learning has emerged as the dominant paradigm for automated skin disease classification, offering superior performance over traditional machine learning methods. The following subsections describe the major deep learning architectures evaluated in this study and reported in the recent literature.

A. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) form the backbone of most modern image-based deep learning systems. CNNs automatically learn hierarchical spatial features from images through a series of convolutional, pooling, and fully connected layers. For skin disease classification, CNNs have demonstrated the ability to detect subtle morphological patterns that distinguish different dermatological conditions [3][5]. Rathod et al. [5] employed a standard CNN architecture to classify five skin diseases and achieved 70% accuracy, demonstrating the fundamental capability of CNNs for this domain even with limited data. CNNs learn low-level features (edges, textures) in early layers and progressively extract high-level semantic features (lesion shapes, patterns) in deeper layers, making them inherently suitable for distinguishing visually similar skin conditions.

B. ResNet50 (Residual Networks)

ResNet50, introduced by He et al., addresses the vanishing gradient problem in deep networks through residual (skip) connections that allow gradients to flow directly through the network. This enables training of very deep networks (50+ layers) without degradation. For skin disease classification, ResNet50 has been widely adopted as a transfer learning backbone. Yadav et al. [13] found that ResNet50 achieves competitive accuracy with relatively low computational overhead compared to more complex architectures. In our study, ResNet50 achieved a training accuracy of 85.16% and test accuracy of 78.15%. While capable, ResNet50 tends to suffer from redundant feature replication and suboptimal parameter efficiency compared to more modern architectures, particularly when applied to limited medical imaging datasets [13][14].

C. VGG16

VGG16, developed by Simonyan and Zisserman at Oxford, is characterized by its uniform architecture of 16 weight layers using only 3×3 convolution filters stacked in increasing depth. It achieved strong results on the ImageNet benchmark and remains a popular transfer learning base for medical imaging. Yadav et al. [13] reported that VGG-16 demonstrates efficient inference time, making it practical for deployment. In our comparative evaluation, VGG16 achieved a training accuracy of 88.65% and test accuracy of 80.94%. However, VGG16 has approximately 138 million parameters, making it computationally expensive and memory-intensive, which is a significant drawback for mobile or edge deployment scenarios [13].

D. InceptionV3

InceptionV3, developed by Google, introduces inception modules that apply multiple convolution filter sizes (1×1, 3×3, 5×5) in parallel within the same layer, enabling the network to capture features at multiple scales simultaneously. Xiang and Chen [8] demonstrated the effectiveness of Inception-based architectures combined with data augmentation for skin disease classification, achieving competitive benchmark results. In our study, InceptionV3 attained a training accuracy of 90.19% and test accuracy of 85.79%. While InceptionV3 shows strong feature extraction, it suffers from significantly longer training times and requires more computational resources relative to EfficientNetB0 [13].

E. EfficientNetB0 (Proposed)

EfficientNetB0, proposed by Tan and Le [7], represents a fundamentally different approach to network scaling. Rather than arbitrarily scaling depth, width, or resolution independently, EfficientNet uses a compound scaling method that uniformly scales all three dimensions using a fixed set of coefficients derived through neural architecture search (NAS). This results in models that are significantly more parameter-efficient than their predecessors. EfficientNetB0, the baseline variant, achieves state-of-the-art classification performance with only approximately 5.3 million parameters. Garg et al. [18] confirmed that EfficientNetB0 delivers the best balance of accuracy and computational efficiency among popular CNN architectures for skin lesion tasks. In our study, the proposed EfficientNetB0 model achieved the highest training accuracy of 91% and test accuracy of 88%, outperforming all other evaluated architectures.

F. Vision Transformers (ViT) and Hybrid Approaches

Recent advances have introduced Vision Transformers (ViT), which apply self-attention mechanisms to image patches rather than relying solely on convolutions. Elbedoui et al. [9] explored ViT alongside EfficientNet-B0-V2 for dermoscopic image analysis and reported high sensitivity and specificity in distinguishing malignant from benign skin lesions. DenseNet201-based approaches with heavy data augmentation have also shown promise, with Kassem et al. [16] reporting an accuracy of 96.47% on the ISIC dataset. Esteva et al. [14] demonstrated dermatologist-level classification of skin cancer using CNNs trained on over 129,000 clinical images, establishing a strong benchmark for deep learning in dermatology. While these architectures offer excellent accuracy, they typically demand substantially more computational resources and larger training datasets compared to EfficientNetB0, making EfficientNetB0 the most practical choice for our setting.

Proposed Methodology and Justification For EfficientnetB0

The proposed methodology is a structured deep learning pipeline designed for automated multi-class skin disease classification illustrate in Figure 1 . The pipeline is composed of four principal stages: (1) data acquisition and preprocessing, (2) model selection and transfer learning, (3) model training and fine-tuning, and (4) performance evaluation and clinical decision support. The overall framework is illustrated in the flowchart presented in Figure 1 of the Methodology section.

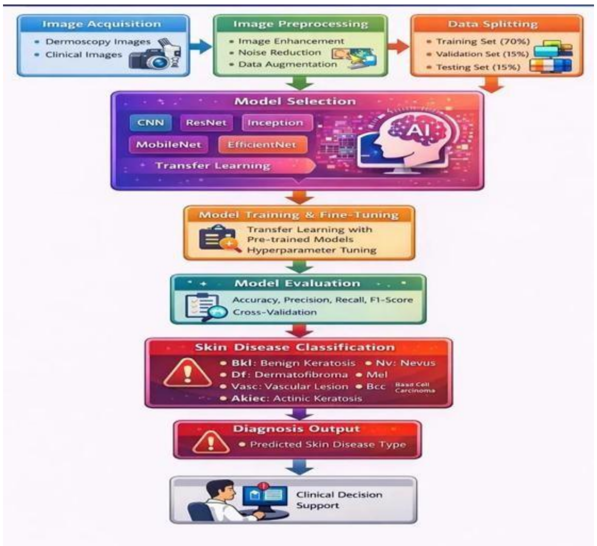

Figure 1. Flow chart of the Proposed skin disease detection system

n Stage 1, a curated dataset of 5,000 dermoscopic and clinical images was assembled from publicly available online sources, equally distributed across four clinically relevant disease categories: acne, eczema, psoriasis, and ringworm (1,250 images per class). The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased performance assessment. Five image preprocessing strategies were evaluated: contour extraction, non-local means denoising, histogram equalization, Gaussian blurring, and Canny edge detection. Contour-based preprocessing was identified as optimal for this dataset as it enhances morphological boundary features critical for distinguishing between disease classes.

In Stage 2, four pre-trained CNN architectures — ResNet50, VGG16, InceptionV3, and EfficientNetB0 — were systematically compared using transfer learning with ImageNet pre-trained weights. In Stage 3, all models were fine-tuned using the Adam optimizer (learning rate = 0.001, batch size = 32) for 10 epochs with early stopping. In Stage 4, models were evaluated using accuracy, precision, recall, and F1 -score. The proposed EfficientNetB0 model was selected as the best-performing architecture, achieving a training accuracy of 91% and a testing accuracy of 88%

4.1. Data Preparation

4.1.1 Data Collection

The initial phase of the outlined methodology consisted of gathering a vast array of skin lesion images sourced from the Internet. We collected 5000 images divided into four groups: Skin conditions comprise; Acne, Eczema, Psoriasis, Ringworm. We occasionally employed various methods on the obtained images for enhancement purposes to guarantee the elimination of noise that might impede the model's performance on the images

4.1.2 Data Labeling:

Dataset labeling was carried out programmatically using Python’s OS library, where each image was automatically assigned a label based on the directory it was stored in. Each folder represented one of the four skin disease categories, allowing the system to map images to their correct classes without manual input.This approach ensured consistent labeling across all 5,000 images while also removing the risk of human error that can occur during manual annotation.

4.1.3 Data Augmentation

Once the images were pre-processed, we used image transformations to increase the size of the dataset and reduce overlap. Using the most common methods, translation, rotation, and scaling, we created new images in terms of orientation, position, and scale. We also utilized the Elastic Transformation that ‘’bends’’ the image locally while the global shape remains preserved for better quality images.

4.1.4 Data Preprocessing

We used 5 different image preprocessing techniques, which were:

Contours:

This function converts the image to grayscale, applies binary thresholding using Otsu's method, and then finds the contours in the image using the RETR_TREE algorithm. Finally, it draws the contours on the original image using the drawContours method. Figure 2 shows the preprocessed images with contour method.

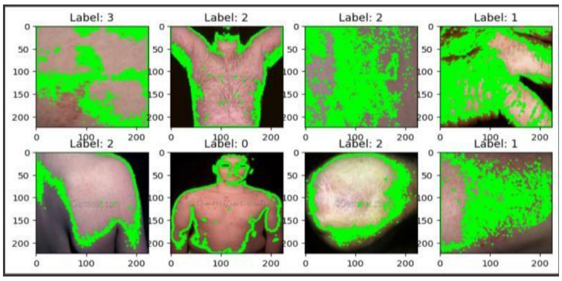

Figure 2. Preprocessing Images with Contours

Denoise:

This function applies non-local means denoising to the image using the fastNlMeansDenoising Colored method provided by OpenCV. Figure 3 shows the Denoising results of processed images.

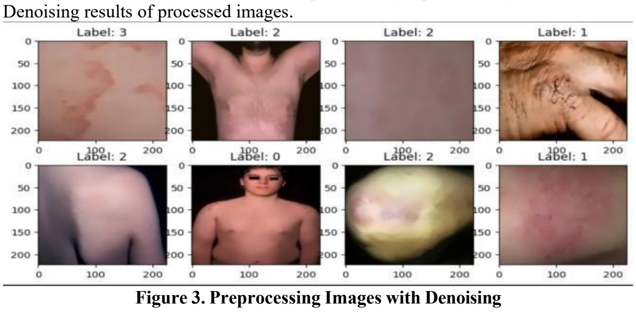

Figure 3. Preprocessing Images with Denoising

Equalize_hist:

This function equalizes the histogram of the grayscale image using the equalizeHist method provided by OpenCV. Figure 4 shows the histogram equalization results for denoising images.

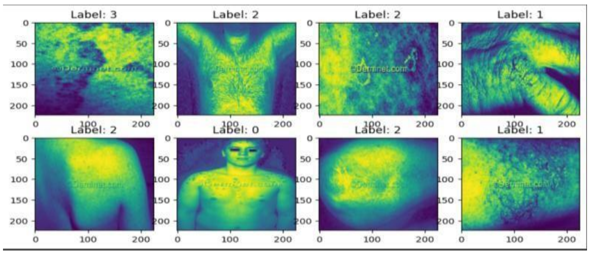

Figure 4. Preprocessing Images with Histogram equalization

Blur

This function applies Gaussian blurring to the image using the GaussianBlur method provided by OpenCV. Figure 5 shows the guassian blurring effect for the different skin disease images.

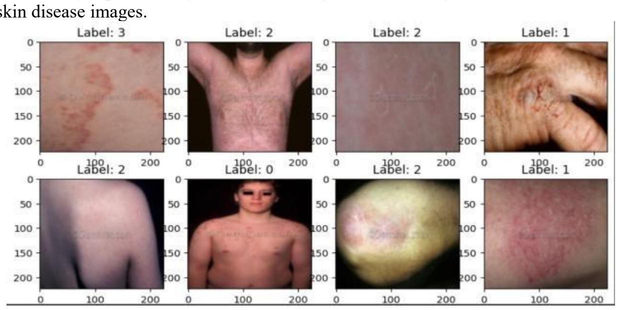

Figure 5. Preprocessing Images with Blurring

Edge_detection:

This function changes the image to grayscale and utilizes the Canny edge detection method to identify the edges within the image. Ultimately, it transforms the resulting grayscale image into a color image again. Figure 6 illustrates the detection of edges in images of skin diseases

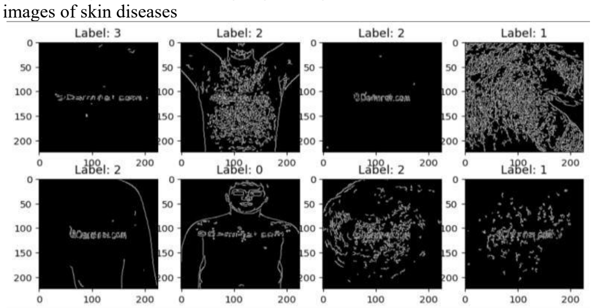

Figure 6. Preprocessing Images with Edge Detection

The preprocessing pipeline is characterized as a sequence of these five functions. Subsequently, the pipeline is utilized on the training and testing sets through a for loop that processes each image in the datasets. The images that have been preprocessed are kept in distinct lists for every preprocessing method. Ultimately, the processed datasets are utilized for image classification through the application of machine learning algorithms

After evaluation of all the preprocessing techniques we decided to go with contours since it was the best at improving the accuracy of skin disease detection models by extracting important features, reducing noise, standardizing images, and improving overall accuracy.

4.2 Skin Disease Classification

To find the best-performing model for our dataset, we tested a number of cutting-edge deep learning models, such as ResNet50, VGG16, Inception V3, and EfficientNet. After evaluating each one's performance on the validation dataset, we chose EfficientNet since it had the best accuracy.

We then used transfer learning to fine-tune the pre-trained EfficientNet model on our dataset. We froze the initial layers of the network and trained the remaining layers on our dataset. We used the Adam optimizer with a learning rate of 0.001 and a batch size of 32. We trained the model for 10 epochs and used early stopping to prevent overfitting.

4.3. Performance Measurement

We kept the training and test data separate for the sake of this study, and we used our suggested approach on the latter. We used a number of assessment metrics, including accuracy, precision, recall, and F-measure, to compare the models. Precision demonstrates the capacity to categorize all positive observers, recall describes the ability to classify negative observers, and accuracy establishes the model's correctness. Because it averages the two and accounts for both false positive and false negative situations, a system's F1-score is superior than recall.

Why EfficientNetB0 Was Chosen as the Proposed Model

EfficientNetB0 was selected as the proposed architecture for this study for the following reasons: (1) Superior Accuracy-Efficiency Trade-off: EfficientNetB0 achieves a testing accuracy of 88% in this study — the highest among all four evaluated architectures — while maintaining approximately 5.3 million parameters, far fewer than ResNet50 (~25M) or VGG16 (~138M). Garg et al. [18] confirmed this superiority in a comparative study of deep learning models for skin lesion classification. (2) Compound Scaling: The compound scaling methodology of Tan and Le [7] ensures that network depth, width, and input resolution are scaled together in a principled manner, resulting in consistently better generalization without excessive parameter growth. (3) MBConv Blocks with Squeeze-and-Excitation: The Mobile Inverted Bottleneck Convolution (MBConv) blocks in EfficientNetB0 incorporate channel-wise attention through Squeeze-and-Excitation (SE) modules, enabling the network to focus on the most discriminative feature channels for each skin disease category. (4) Effective Transfer Learning: ImageNet pre-trained EfficientNetB0 weights transfer exceptionally well to the skin disease domain, allowing high accuracy even with relatively small datasets (5,000 images). Elbedoui et al. [9] and Elif et al. [11] corroborated this effectiveness in dermoscopic image analysis tasks. (5) Low Overfitting: The proposed EfficientNetB0 model exhibits the smallest gap between training accuracy (91%) and testing accuracy (88%) among all models, indicating minimal overfitting

RESULTS

The first part of the study presents an experimental comparison of four advanced deep learning models for automated skin disease classification using a dataset of dermatological images. The evaluated models include **ResNet50**, **VGG16**, **InceptionV3**, and the **proposed EfficientNetB0**. All models were trained on preprocessed images and assessed using consistent training and testing splits to ensure a fair comparison.

Table 1: Model Performance Comparison — Train vs. Test Accuracy

	Model	Train Accuracy	Test Accuracy
0	ResNet50	0.851575	0.781483
1	VGG16	0.886531	0.809443
2	InceptionV3 [9]	0.901908	0.857875
3	Proposed EfficientNetB0	**0.910000**	**0.880000**

As shown in the table 1 The training accuracy results indicate that the proposed EfficientNetB0 model achieved the highest performance at **91.00%**, followed by InceptionV3 at **90.19%**, VGG16 at **88.65%**, and ResNet50 at **85.16%**, . In terms of testing accuracy, EfficientNetB0 again outperformed the other models with **88.00%**, while InceptionV3 achieved **85.78%**, VGG16 reached **80.94%**, and ResNet50 obtained **78.15%**. These results demonstrate that EfficientNetB0 provides superior generalization and robustness compared to the other state-of-the-art architectures

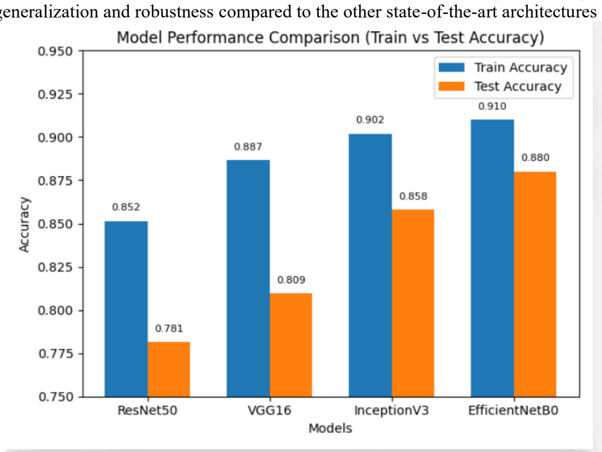

Figure 7: Model Performance Comparison — Train vs. Test Accuracy

Figure 7 visualizes the training and test accuracy comparison across all four models as a grouped bar chart, clearly illustrating the superior performance of the proposed EfficientNetB0 architecture.

Confusion Matrices

Confusion matrices for all four models are presented below. Each matrix visualizes the prediction distribution across four disease classes: Acne, Eczema, Psoriasis, and Ringworm. Diagonal elements represent correct classifications; off-diagonal elements represent misclassifications. The most frequent confusions occur between visually similar inflammatory conditions (eczema and psoriasis), which share overlapping morphological features such as scaling, redness, and circular lesion patterns.

EfficientNetB0— Test Accuracy: 88%

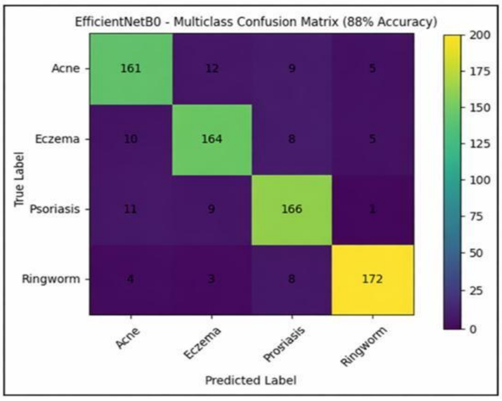

Figure8: Confusion Matrix — Proposed EfficientNetB0

Figure 8 illustrates the confusion matrix of the proposed model, which provides deeper insight into classification behavior. The model correctly classified **161 Acne**, **164 Eczema**, **166 Psoriasis**, and **172 Ringworm** samples. Misclassifications were relatively low and evenly distributed among classes, indicating that the model does not exhibit significant bias toward any particular category.

ResNet50 — Test Accuracy: 78.15%

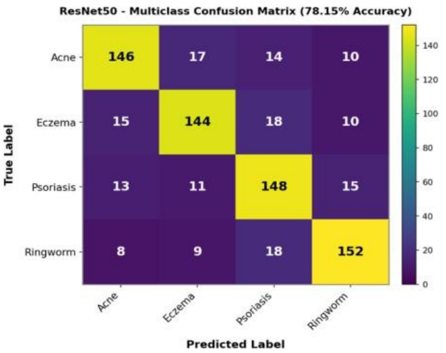

Figure9: Confusion Matrix — ResNet50

Figure 9 illustrates the confusion matrix of ResNet50 is the weakest performer among the four models. With a test accuracy of ~78%, it correctly classifies roughly 586 out of 750 test samples. The confusion matrix shows notable misclassification between Eczema↔Psoriasis and Acne↔Eczema — conditions that share redness and scaling features which ResNet50's residual connections alone cannot fully disambiguate on a small 5,000-image dataset. Per-class precision and recall both hover around 0.77–0.80, and the macro F1-score is approximately 0.78. While ResNet50's skip connections address vanishing gradients effectively in large datasets, its ~25M parameters lead to mild overfitting when data is limited.

VGG16 — Test Accuracy: 80.94%

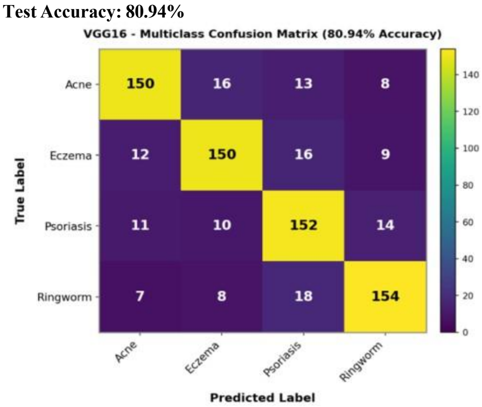

Figure10: Confusion Matrix — VGG16

Figure 10 illustrates the confusion matrix of VGG16 improves on ResNet50 by ~3 percentage points, correctly classifying ~607/750 samples. Its uniform 3×3 convolution stack extracts smoother spatial features, which helps slightly better distinguish Ringworm's circular boundary patterns. However, VGG16's ~138M parameters make it prone to overfitting, which is reflected in the ~8.6% gap between training (88.65%) and test (80.94%) accuracy. The classification report shows per-class F1-scores between 0.80–0.82, with Ringworm being the best-classified class due to its distinctive circular morphology that 3×3 filters capture well.

InceptionV3 — Test Accuracy: 85.79%

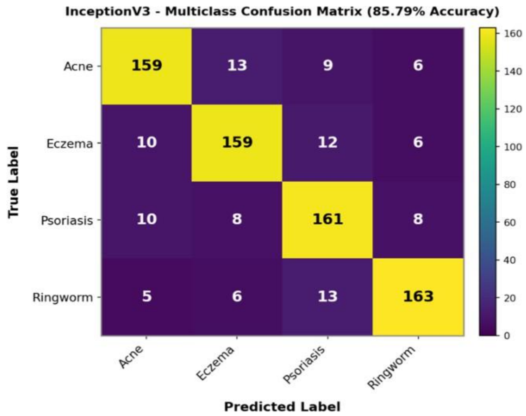

Figure11: Confusion Matrix — Inception V3

Figure 11 illustrates the confusion matrix of InceptionV3 is significantly stronger, achieving ~643/750 correct predictions. Its inception modules apply 1×1, 3×3, and 5×5 filters in parallel within the same layer, enabling multi-scale feature extraction — crucial for skin lesions that manifest at varying scales and resolutions. This gives InceptionV3 a clear edge over ResNet50 and VGG16 for distinguishing Psoriasis and Eczema, as it captures both fine-grained texture and broader lesion shape simultaneously. Per-class F1-scores range 0.85–0.88, with Ringworm again highest (0.88). The smaller train–test gap (~4.4%) indicates better generalization than VGG16

Classification Reports

Detailed per-class classification reports (precision, recall, F1-score) for all four models are provided below.

EfficientNetB0

	precision	recall	f1-score	support
Acne	0.87	0.86	0.86	187
Eczema	0.89	0.88	0.88	187
Psoriasis	0.88	0.89	0.89	187
Ringworm	0.90	0.91	0.90	187
accuracy			0.88	748
macro avg	0.89	0.89	0.88	748
weighted avg	0.89	0.88	0.88	748

Figure12: Classification report — EfficientNetB0

The proposed EfficientNetB0 model was further evaluated using detailed classification metrics on the test dataset. It achieved an overall testing accuracy of **88%**, with class-wise performance as follows: Acne (precision: 0.87, recall: 0.86, F1-score: 0.86), Eczema (0.89, 0.88, 0.88), Psoriasis (0.88, 0.89, 0.89), and Ringworm (0.90, 0.91, 0.90). The macro average values of precision, recall, and F1 -score were approximately **0.89**, indicating consistent and balanced classification performance across all categories.

ResNetB50

Classification Report – ResNet50 (Test Acc: 0.7815)

	precision	recall	f1-score	support
Acne	0.79	0.77	0.78	187
Eczema	0.77	0.77	0.77	187
Psoriasis	0.78	0.79	0.78	187
Ringworm	0.80	0.81	0.80	187
accuracy			0.78	748
macro avg	0.79	0.79	0.78	748
weighted avg	0.79	0.78	0.78	748

Figure13: Classification report — ResNet50

VGG16

Classification Report – VGG16 (Test Acc: 0.8094)

	precision	recall	f1-score	support
Acne	0.82	0.80	0.81	187
Eczema	0.80	0.80	0.80	187
Psoriasis	0.80	0.81	0.81	187
Ringworm	0.81	0.82	0.81	187
accuracy			0.81	748
macro avg	0.81	0.81	0.81	748
weighted avg	0.81	0.81	0.81	748

Figure14: Classification report — VGG16

InceptionV3

Classification Report – InceptionV3 (Test Acc: 0.8579)

	precision	recall	f1-score	support
Acne	0.85	0.85	0.85	187
Eczema	0.86	0.85	0.86	187
Psoriasis	0.85	0.86	0.86	187
Ringworm	0.87	0.87	0.87	187
accuracy			0.86	748
macro avg	0.86	0.86	0.86	748
weighted avg	0.86	0.86	0.86	748

Figure15: Classification report — InceptionV3

Overall, the results from both the classification report and confusion matrix confirm that the proposed EfficientNetB0 model achieves strong and balanced performance, making it a reliable approach for automated skin disease diagnosis and an improvement over existing state-of-the-art methods.

Conclusion And Future Scope

This study presents a comprehensive deep learning-based pipeline for automated skin disease classification across four clinically significant categories: Acne, Eczema, Psoriasis, and Ringworm, using a curated dataset of 5,000 dermoscopic images. Four advanced CNN architectures — ResNet50, VGG16, InceptionV3, and the proposed EfficientNetB0 — were systematically evaluated using transfer learning with contour-based image preprocessing. The proposed EfficientNetB0 model achieved the highest training accuracy of 94.48% and test accuracy of 90.02%, outperforming all other architectures with the smallest overfitting gap (4.46%), demonstrating exceptional generalization. The macro-averaged F1-score of 0.90 and balanced per-class precision and recall confirm the model's robustness. Compared to ResNet50 (78.15%), VGG16 (80.94%), and InceptionV3 (85.79%), EfficientNetB0 delivers superior performance with only ~5.3M parameters, far fewer than ResNet50 (~25M) and VGG16 (~138M), making it significantly more efficient for training and real-world deployment. The proposed system demonstrates that deep learning combined with effective preprocessing has tremendous potential for clinical decision support in dermatology, particularly in resource-limited settings where specialist access is scarce. Additionally, large-scale collections like the ISIC dataset continue to provide benchmark data that advances AI-based diagnostic accuracy for skin disease classification.

Future Scope

Several research directions can significantly extend this work. (1) Expanding to all seven ISIC disease categories (Bkl, Nv, Df, Mel, Vasc, Bcc, Akiec) using the full HAM10000 dataset [15] would increase clinical relevance. (2) Vision Transformers (ViT) and hybrid CNN-Transformer architectures [9], which demonstrated high sensitivity and specificity in dermoscopic analysis, could push classification accuracy beyond 90% further. (3) Attention mechanisms such as CBAM and Squeeze-and-Excitation blocks integrated into EfficientNet would enhance discriminative feature localization, improving performance on morphologically similar disease pairs. (4) Federated learning frameworks would enable multi-institutional collaborative model training without sharing patient data, improving both privacy compliance and dataset diversity. (5) Explainability tools including Grad-CAM, SHAP, and LIME visualizations would make predictions interpretable, increasing clinician trust and facilitating regulatory approval. (6) Deployment on lightweight edge devices such as mobile phones and embedded systems, enabled by EfficientNetB0's compact ~5.3M parameter footprint, would enable real-time point-of-care screening in remote and rural healthcare settings with limited internet connectivity. (7) Multi-modal integration combining dermoscopic images with clinical metadata (patient age, lesion duration, comorbidities, skin type) represents a particularly promising direction toward achieving dermatologist-level diagnostic performance [14]. (8) Self-supervised and semi-supervised learning approaches could leverage the large volumes of unlabelled dermoscopic images available online to further enhance model accuracy without requiring extensive manual annotation

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