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# Skin Disease Detection Using Deep Learning

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## Abstract
*Early and accurate diagnosis of skin diseases is essential for effective treatment and improved patient outcomes. This paper presents SkinScan AI, a deep learning-based framework for automated skin disease detection and classification from dermoscopic images using the HAM10000 benchmark dataset. The proposed DenseNet121 model classifies skin lesions into seven clinically significant categories: Actinic Keratoses (akiec), Basal Cell Carcinoma (bcc), Benign Keratosis-like Lesions (bkl), Dermatofibroma (df), Melanoma (mel), Melanocytic Nevi (nv), and Vascular Lesions (vasc). To address dataset imbalance, the framework incorporates MixUp augmentation, focal loss with label smoothing, minority-class weighting, and oversampling. A two-stage fine-tuning strategy with Test-Time Augmentation (TTA) improves model generalization and prediction robustness. Comparative evaluation with a custom CNN baseline and EfficientNetB3 demonstrates that DenseNet121 achieves the best performance, obtaining 81.82% TTA accuracy, a weighted F1-score of 0.8096, and an AUC of 0.9441. Grad-CAM provides visual explanations by highlighting lesion-relevant regions, improving model interpretability and increasing user confidence in the prediction process. The trained model is deployed as a Flask-based web application with secure authentication, prediction history, severity assessment, medication guidance, doctor referral recommendations, and downloadable PDF reports. Experimental results demonstrate that the proposed framework effectively handles class imbalance while providing accurate, interpretable, and practical decision support for computer-aided skin disease diagnosis. The system offers a scalable and user-friendly solution that can assist healthcare professionals and improve access to reliable preliminary skin disease screening.*
***Keywords:*** *Deep learning; DenseNet121; Grad-CAM; HAM10000; Skin disease detection.*

## 1. Introduction
Skin diseases are among the most common health problems worldwide, affecting millions of people every year and significantly impacting quality of life. Among various dermatological conditions, skin cancer, particularly melanoma, is one of the most life-threatening diseases due to its high metastatic potential. Early diagnosis plays a vital role in improving treatment success and reducing mortality. Dermoscopy has become a widely adopted non-invasive imaging technique for examining skin lesions by revealing morphological characteristics that are not visible to the naked eye. However, accurate interpretation of dermoscopic images requires extensive clinical expertise and may lead to inter-observer variability among dermatologists. Recent advances in artificial intelligence, particularly deep learning, have demonstrated remarkable success in automated medical image analysis. Convolutional Neural Networks (CNNs) have achieved high performance in skin lesion classification by automatically learning discriminative features from dermoscopic images without manual feature engineering. Transfer learning using pre-trained deep learning models has further improved classification

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accuracy while reducing computational cost and training time. Several studies have employed architectures such as ResNet, EfficientNet, MobileNet, and DenseNet for automated skin lesion classification and have reported promising diagnostic performance (Naqvi et al., 2023; Bajwa et al., 2023; Debelee, 2023). Despite these advancements, automated skin disease diagnosis remains challenging because of the severe class imbalance present in publicly available datasets, the high visual similarity among different lesion categories, and the limited interpretability of deep learning models. Models trained on imbalanced datasets often exhibit poor performance for minority disease classes, reducing their clinical reliability. Moreover, the black-box nature of deep learning algorithms limits their acceptance in real-world healthcare applications, where clinicians require transparent and explainable predictions before making diagnostic decisions. To overcome these limitations, this research proposes SkinScan AI, a deep learning-based skin disease detection framework using the DenseNet121 architecture trained on the HAM10000 benchmark dataset. The proposed framework integrates a two-stage transfer learning strategy together with MixUp augmentation, focal loss with label smoothing, minority-class weighting, oversampling, and Test-Time Augmentation (TTA) to improve classification performance on imbalanced data. Furthermore, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated to generate visual explanations by highlighting lesion regions that influence model predictions, thereby improving model transparency. The developed DenseNet121 model is deployed as a Flask-based web application that enables users to upload dermoscopic images and receive automated disease predictions along with Grad-CAM visualizations, severity assessment, medication guidance, doctor referral recommendations, prediction history, and downloadable PDF reports. Experimental evaluation demonstrates that the proposed framework achieves superior performance compared with a custom CNN baseline and EfficientNetB3, obtaining an accuracy of 81.82%, a weighted F1-score of 0.8096, and an AUC of 0.9441. These results indicate that the proposed system provides an accurate, interpretable, and practical computer-aided decision support solution for automated skin disease diagnosis [1-5].

## 2. Method

The proposed SkinScan AI framework performs automated skin disease detection using deep learning and transfer learning techniques. The overall methodology consists of dataset preparation, image preprocessing, DenseNet121-based feature extraction, two-stage model fine-tuning, class imbalance handling, Test-Time Augmentation (TTA), Grad-CAM-based explainability, and deployment through a Flask web application. The workflow begins with dermoscopic image acquisition from the HAM10000 dataset, followed by preprocessing and augmentation. The processed images are then classified using the optimized DenseNet121 model, and the prediction is visualized through Grad-CAM heatmaps. Finally, the trained model is integrated into a web-based application for real-time diagnosis and report generation [6-10].

### 2.1.Dataset Description

The proposed framework utilizes the HAM10000 (Human Against Machine with 10,000 Training Images) benchmark dataset, which contains 10,015 dermoscopic images collected from multiple clinical sources Shown in Table 1.

**Table 1 Distribution of HAM10000 Dataset**

| Disease | Code | Images |
|---|---|---|
| Actinic Keratoses | akiec | 327 |
| Basal Cell Carcinoma | bcc | 514 |
| Benign Keratosis | bkl | 1099 |
| Dermatofibroma | df | 115 |
| Melanoma | mel | 1113 |
| Melanocytic Nevi | nv | 6705 |
| Vascular Lesions | vasc | 142 |

The dataset consists of seven clinically important skin disease categories, namely Actinic Keratoses

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(akiec), Basal Cell Carcinoma (bcc), Benign Keratosis-like Lesions (bkl), Dermatofibroma (df), Melanoma (mel), Melanocytic Nevi (nv), and Vascular Lesions (vasc). The original dataset is highly imbalanced because the Melanocytic Nevi class contains significantly more images than the remaining classes. To preserve class distribution during training and evaluation, the dataset is divided into training, validation, and testing subsets using stratified sampling with a ratio of 70:15:15.

### 2.2.Image Preprocessing

The dermoscopic images are preprocessed to improve the robustness and generalization capability of the proposed model. Initially, all images are resized to 224 × 224 pixels to satisfy the input dimensions of DenseNet121. Pixel values are normalized to accelerate model convergence during training. Duplicate images are removed to eliminate redundancy within the dataset. To reduce overfitting and improve model robustness, several data augmentation techniques are applied, including random rotation, horizontal and vertical flipping, zooming, width and height shifting, brightness adjustment, and shearing. These augmentations increase the diversity of training samples and enable the model to learn invariant visual features under different imaging conditions [11-15].

### 2.3.Proposed Skin Disease Detection Framework

The overall workflow of the proposed SkinScan AI framework begins with dermoscopic image acquisition from the HAM10000 dataset. The input images undergo preprocessing and data augmentation before being supplied to the DenseNet121 classification network. The trained model predicts one of the seven skin disease classes, after which Grad-CAM generates a visual heatmap highlighting the lesion regions responsible for the prediction. The prediction results, confidence score, severity level, medication guidance, and doctor referral recommendations are then presented through the Flask web application, with an option to download a comprehensive PDF diagnostic report Shown in Figure 1 Overall workflow of the proposed SkinScan AI Framework for Automated Skin Disease Detection.

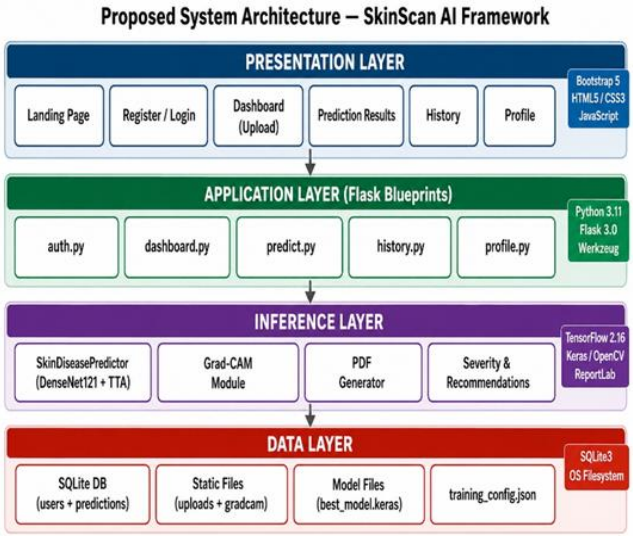


**Figure 1 Overall workflow of the proposed SkinScan AI Framework for Automated Skin Disease Detection**

### 2.4.DenseNet121 Classification Model

DenseNet121 is employed as the backbone network because of its efficient feature reuse through dense connectivity and its ability to learn highly discriminative representations with fewer trainable parameters. The model is initialized with ImageNet pre-trained weights to leverage transfer learning and reduce training time. A custom classification head is added, consisting of a Global Average Pooling layer, fully connected layers, Batch Normalization, Dropout, and a Softmax output layer with seven neurons corresponding to the seven skin disease categories. The dense connections facilitate efficient gradient propagation and improve feature extraction, making DenseNet121 well suited for dermoscopic image classification [16-20].

### 2.5.Model Training Strategy

A two-stage transfer learning strategy is adopted to improve classification performance. During the first stage, the DenseNet121 backbone remains frozen while only the newly added classification layers are trained to adapt to the HAM10000 dataset. In the second stage, all network layers are unfrozen and

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fine-tuned using a significantly reduced learning rate to preserve previously learned features while adapting to domain-specific characteristics. To address severe class imbalance, the proposed framework incorporates MixUp augmentation ($\alpha = 0.2$), focal loss with label smoothing ($\gamma = 2.0$, $\varepsilon = 0.1$), boosted minority-class weights, and minority-class oversampling. Furthermore, Test-Time Augmentation (TTA) is employed during inference by averaging predictions obtained from five augmented versions of each test image, thereby improving prediction robustness and generalization Shown in Table 2.

**Table 2 Model Training Parameters**

| Parameter | Value |
|---|---|
| Backbone Network | DenseNet121 |
| Optimizer | Adam |
| Stage 1 Learning Rate | $1 \times 10^{-3}$ |
| Stage 2 Learning Rate | $3 \times 10^{-6}$ |
| Batch Size | 32 |
| Input Image Size | 224 × 224 |
| MixUp α | 0.2 |
| Focal Loss γ | 2.0 |
| Label Smoothing ε | 0.1 |
| Test-Time Augmentation | 5 inference passes |

### 2.6.Grad-CAM Explainability

To improve model interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is integrated into the proposed framework. Grad-CAM computes the gradients of the predicted class with respect to the final convolutional feature maps and generates a localization heatmap that highlights the regions contributing most to the prediction. The heatmap is superimposed on the original dermoscopic image, enabling clinicians and users to visualize the lesion areas that influence the model's decision. This explainability mechanism increases confidence in automated diagnosis and supports clinical validation.

### 2.7.Flask-Based Web Application

The trained DenseNet121 model is deployed as a Flask-based web application to provide an interactive platform for automated skin disease diagnosis. The application includes secure user registration and login, dermoscopic image upload, real-time disease prediction, Grad-CAM heatmap visualization, severity assessment, medication guidance, doctor referral recommendations, prediction history management, and downloadable PDF report generation. User information and prediction history are stored in an SQLite database, enabling efficient retrieval of previous diagnostic records. The web application provides a practical and user-friendly interface for computer-aided dermatological screening [21-25].

## 3. Results and Discussion

This section presents the experimental evaluation of the proposed SkinScan AI framework for automated skin disease classification. The performance of the DenseNet121-based model is analyzed in terms of accuracy, precision, recall, F1-score, and AUC. In addition, a comparative study with baseline models is provided, followed by a detailed discussion of classification behavior across different skin disease categories.

### 3.1.Experimental Results

The proposed framework is evaluated using the HAM10000 dataset, which contains seven classes of dermoscopic skin lesions. The dataset is split into training, validation, and testing subsets using a stratified approach to preserve class distribution. The DenseNet121 model trained with the proposed optimization strategy achieves a test accuracy of 81.82%, a weighted F1-score of 0.8096, and an AUC of 0.9441. The integration of MixUp augmentation, focal loss with label smoothing, class weighting, and oversampling significantly improves classification performance, particularly for minority classes such as Dermatofibroma, Actinic Keratoses, and Vascular Lesions. Test-Time Augmentation further enhances prediction stability by reducing variance during inference.

### 3.2.Comparative Analysis

A comparative evaluation is performed between three models: a custom CNN baseline, EfficientNetB3, and the proposed DenseNet121 model. The results show

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that DenseNet121 consistently outperforms the other architectures across all evaluation metrics. The custom CNN achieves lower performance due to its limited feature extraction capability, while EfficientNetB3 shows moderate improvement but suffers from training instability on the imbalanced dataset. In contrast, DenseNet121 benefits from dense connectivity and effective feature reuse, resulting in superior generalization performance. Overall, DenseNet121 improves classification accuracy by a significant margin compared to baseline models, demonstrating its suitability for dermoscopic image analysis Shown in Table 3.

**Table 3 Comparison on HAM10000 test set**

| Model | Acc. | F1 | Prec. | AUC |
|---|---|---|---|---|
| Custom CNN | 71.30% | 0.698 | 0.703 | 0.901 |
| Efficient NetB3 | 74.10% | 0.721 | 0.729 | 0.916 |
| DenseNet 121+TTA | 81.82% | 0.8096 | 0.812 | 0.9441 |

### 3.3.Class-wise Performance Analysis

The per-class evaluation indicates strong performance for majority classes such as Melanocytic Nevi and Melanoma. However, without imbalance handling techniques, minority classes typically show poor recall due to limited training samples.

**Table 4 Per-class results — densenet121 with tta**

| Code | Prec. | Recall | F1 | Supp. |
|---|---|---|---|---|
| nv | 0.90 | 0.96 | 0.93 | 1,006 |
| mel | 0.74 | 0.68 | 0.71 | 167 |
| bkl | 0.71 | 0.72 | 0.72 | 165 |
| bcc | 0.80 | 0.77 | 0.78 | 77 |
| akiec | 0.66 | 0.58 | 0.62 | 49 |
| vasc | 0.82 | 0.76 | 0.79 | 21 |
| df | 0.70 | 0.65 | 0.67 | 17 |
| W.Avg | 0.812 | 0.818 | 0.810 | 1,502 |

After applying oversampling, focal loss, and MixUp augmentation, the recall of minority classes improves significantly. The model achieves balanced performance across all seven disease categories, with particularly improved sensitivity for previously underrepresented classes. This demonstrates that the proposed imbalance mitigation strategy is effective in handling the skewed distribution of the HAM10000 dataset Shown in Table 4.

### 3.4.Discussion

The experimental results confirm that the proposed SkinScan AI framework provides robust and reliable performance for skin disease classification. The combination of transfer learning, advanced augmentation techniques, and loss function optimization plays a crucial role in improving model accuracy and generalization. Grad-CAM visualizations further validate that the model focuses on clinically relevant lesion regions, such as irregular borders, color variation, and lesion texture. This improves interpretability and enhances trust in the model's predictions. Despite strong performance, certain limitations remain. The model performance is influenced by dataset imbalance and limited representation of rare disease categories. Additionally, external clinical validation is required before real-world deployment in healthcare environments. Overall, the results demonstrate that the proposed framework is a promising computer-aided diagnostic tool for automated skin disease detection.

## Conclusion

This work presents a deep learning–based skin disease detection system using the DenseNet121 architecture with transfer learning for multi-class classification of dermoscopic images. The proposed approach leverages advanced preprocessing techniques and data augmentation strategies to improve model generalization and robustness on the HAM10000 dataset. Techniques such as MixUp, focal loss, and test-time augmentation further enhance performance by addressing class imbalance and reducing overfitting. To improve interpretability, Grad-CAM visualizations are integrated, enabling visual explanation of model predictions and increasing clinical trust in the system. The deployment of the trained model through a Flask-

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based web application demonstrates the practical applicability of the system for real-time diagnosis support. Experimental results indicate that the proposed framework achieves competitive performance in classifying multiple skin disease categories, making it suitable as a decision-support tool for early dermatological screening. However, the system is not intended to replace clinical diagnosis but to assist dermatologists in faster and more accurate preliminary assessment. Future work can focus on expanding the dataset with more diverse skin types, improving rare class performance, integrating transformer-based architectures, and deploying the system on mobile platforms for wider accessibility in remote healthcare settings.

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