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Skin Disease Classification Using Neural Networks

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Abstract
Accurate identification of dermatological conditions is essential for timely medical intervention, particularly for lesions with malignant or premalignant potential. Variability in lesion appearance, skin tone diversity, and imaging conditions often complicate traditional diagnostic approaches, creating the need for a robust automated screening system. In the present work, a hybrid artificial intelligence model is developed by integrating ResNet-50 for deep feature extraction with DenseNet-50 and LLM supported refinement for classification. The model is trained to differentiate a clinically relevant set of skin diseases including melanoma, basal cell carcinoma, actinic keratoses with intraepithelial carcinoma, melanocytic nevi, dermatofibroma, vascular lesions, and benign keratosis-like lesions chosen for their diagnostic similarity and significance in early detection workflows. The system is deployed through a backend server where the TensorFlow (.h5) model is hosted, enabling cloud-based inference and delivering predictions to the Android application through API calls. The proposed approach enhances reliability, minimizes feature redundancy, and provides confidence based predictions suitable for real-time screening applications. This work demonstrates that hybrid deep learning pipelines can serve as fast, low cost, and scalable tools for preliminary skin disease assessment, supporting both clinical environments and remote users.

Keywords: *Skin Lesion Classification, ResNet-50, DenseNet-50, on-Device Inference, Dermatology AI*

1. Introduction
Skin health plays a vital role in overall well-being, yet millions of people worldwide struggle with the early identification of dermatological conditions. Many skin diseases share overlapping visual characteristics, making self assessment difficult and often delaying medical consultation. This challenge is worsened in regions with limited access to dermatologists, where individuals rely primarily on online resources or unverified information. As a result, the lack of timely and accurate evaluation can lead to complications, especially in cases involving malignant or premalignant lesions such as melanoma or basal cell carcinoma. The Skin Disease Classification project aims to address these challenges by building an intelligent, automated screening system that assists users in recognizing potential skin conditions. By leveraging modern deep learning techniques, the system provides fast and reliable predictions from images captured on a mobile device, which are processed by a backend server hosting the TensorFlow model. The core of our model integrates ResNet-50 for extracting high level visual features from skin lesion images and DenseNet-50, combined with LLM-supported refinement, for precise classification. This hybrid approach improves accuracy, reduces feature redundancy, and ensures stable performance across diverse skin tones, lighting conditions, and lesion types. The diseases included in this project, melanoma, basal cell carcinoma, actinic keratoses with intraepithelial carcinoma, melanocytic nevus, dermatofibroma, vascular lesions, and benign keratosis-like lesions were carefully selected for their clinical significance and their tendency to resemble one another. By training the system on these visually similar but medically distinct conditions, the model becomes capable of performing practical early screening that supports both users and healthcare providers. Our prototype focuses on creating a portable, accessible, and user friendly Android application that interacts with a cloud-based backend for inference. The TensorFlow (.h5) model is

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deployed on the server, and the app communicates through secure API calls to obtain predictions. This architecture requires internet connectivity but enables the use of a large, accurate model without overburdening the mobile device. The goal is not to replace professional diagnosis but to provide an educational and supportive screening tool that encourages timely medical consultation through confidence-based results and clear guidance.

This document outlines the design, development, and evaluation of the Skin Disease Classification system, including the datasets, neural network architectures, preprocessing techniques, and mobile deployment strategy. Through this work, we aim to contribute to the growing field of AI enabled healthcare tools and support the early detection of skin diseases, ultimately promoting accessible, reliable, and inclusive digital health solutions [1-3].

1.1. Visual Characteristics of Skin Lesions

Lesion Shape and Symmetry: Different skin diseases exhibit distinct shapes and growth patterns. Benign lesions such as melanocytic nevi often have round, symmetrical forms, whereas malignant lesions like melanoma may appear asymmetric. Observing lesion geometry helps differentiate harmless conditions from potentially serious ones.

Color and Pigmentation: Color variation is an important diagnostic feature. Uniform pigmentation generally indicates benign conditions, while irregular, multiple, or rapidly changing colors may suggest malignancy. Diseases such as melanoma often display mixed shades, whereas vascular lesions appear red or purple due to blood vessel involvement.

Border and Margin Definition: The clarity of lesion edges plays a crucial role in screening. Smooth and welldefined borders typically indicate benign behavior, while blurred, scalloped, or irregular margins are common in malignant or precancerous lesions, including melanoma and actinic keratoses.

Surface Texture and Elevation: The Lesions vary in surface characteristics. Some are smooth or waxy (benign keratosis like lesions), while others are rough, scaly, or crusted (actinic keratoses). Raised nodules may indicate dermatofibroma or basal cell carcinoma. Texture analysis helps narrow potential classifications.

Internal Structural Patterns: Under magnified imaging, specific internal patterns become visible. Pigment networks, vascular structures, dots, globules, or streaks are strong diagnostic cues. These patterns differ significantly between disease types and guide automated feature extraction in deep learning models.

Lighting and Skin Tone Influence: Appearance varies across lighting conditions and skin tones. Hyperpigmented lesions may appear subtle on darker skin, and glare can distort color interpretation. Consistent imaging helps maintain reliable classification across diverse users [4-8].

2. Methods

The following section describes the workflow used to build and evaluate the Skin Disease Classification system.

Dataset and Preprocessing: Dermoscopic skin-lesion images were collected from publicly available medical datasets covering seven diagnostic classes. All images were resized to 224×224 pixels and normalized. Basic data augmentation (flips, rotations, contrast changes) was applied to improve generalization and reduce class imbalance.

Hybrid Model Architecture: A hybrid deep learning approach was used. ResNet-50 served as the feature extractor, and a modified DenseNet-50 acted as the classification block. The final layer produced probabilities for the seven target diseases. LLM-guided refinement was used during model tuning to optimize architectural and training parameters.

Training Procedure: The model was trained using TensorFlow with categorical cross-entropy loss and the Adam optimizer. Training was carried out for 80 epochs with a 10% validation split. Early stopping was applied to prevent overfitting.

Evaluation: Performance was measured using accuracy, precision, recall, F1-score, and confusion matrix analysis. All evaluations were performed on held-out validation data.

Deployment: The trained TensorFlow (.h5) model was hosted on a backend server. The Android application sends captured lesion images to the server, where preprocessing and prediction occur. The server returns class probabilities and confidence values to the app interface, shown in Table 1.

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Table 1 Experimental Parameters

Component	Parameter
Input Image Size	224x224
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Batch Size	32
Epochs	80

3. Results and Discussion

3.1. Results

The hybrid ResNet-50 + DenseNet-50 classifier achieved stable performance across all seven skin disease categories, producing consistent evaluation outcomes with balanced precision and recall across most conditions. The strongest results were observed for vascular lesions and dermatofibromas, which the classifier identified with high reliability. Melanoma and benign keratosis-like lesions showed comparatively lower scores, reflecting the greater visual complexity typically associated with these conditions in dermoscopic imaging. The deployed application generated predictions through a server-hosted inference pipeline, delivering class outputs within approximately 12–15 seconds. This latency is typical for a prototype stage mobile deployment and can be further reduced through model optimization and improved serving infrastructure, figure 1.

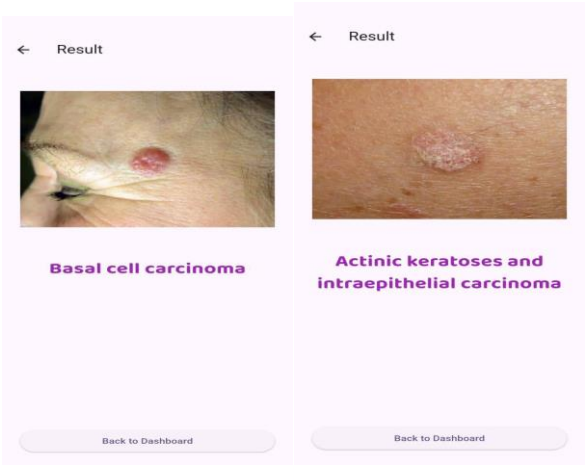

Figure 1 Android Application of Skin Disease Detection

The Android client successfully captured lesion images and transmitted them to the backend server. During testing, the app demonstrated stable performance on varying lighting conditions and different smartphone cameras.

3.2. Discussion

The results indicate that the hybrid architecture improves classification stability by combining deep residual features with dense connectivity. Higher performance on visually distinct lesions confirms that the model generalizes well on common conditions. Misclassifications among visually similar lesions align with challenges in clinical practice. These errors highlight the importance of using the system as a preliminary screening tool rather than a diagnostic replacement. The server based inference strategy avoided the storage limitations of mobile devices. However, this approach introduces cloud dependency, meaning performance may vary in low network environments. Expanding the dataset to include more skin tones and rare lesions would further improve robustness.

Conclusion

This work demonstrates a functional hybrid deep-learning system for automated skin-disease classification across seven clinically relevant categories. The combination of ResNet-50 and DenseNet-50 improves feature discrimination, while cloud-based deployment enables real-time inference on mobile devices. Although the model provides reliable predictions, its purpose is limited to early screening and educational support. Further dataset expansion and clinical validation are required for practical medical deployment [9-15].

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