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SkinLearn: A YOLO11-Driven App for Automated Skin Disease Diagnosis from Smartphone Images

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Abstract
This study presents SkinLearn, a YOLO11-powered deep learning-based smartphone application (app) designed for real-time skin disease classification using images captured by smartphone cameras. The proposed system addresses critical challenges in mobile-based dermatological diagnosis, such as the diversity of skin conditions, varying image qualities, and computational constraints. By leveraging the enhanced architecture of YOLO11, SkinLearn achieves superior accuracy and speed compared to existing models, making it suitable for on-device deployment in low-resource settings. The model was trained using an open-source skin disease dataset and demonstrated robust performance across multiple disease classes. The YOLO11 model exhibited a 98.3% classification accuracy for skin diseases. The results validate the potential of the system as a practical diagnostic aid for early skin disease identification and clinical decision support. This study contributes to the growing sector of AI-driven mobile healthcare by offering an accessible and scalable solution for dermatological screening.

Keywords: YOLO11, Skin Disease Classification, Deep Learning, Dermatology, TensorFlow Lite.

Introduction

Skin diseases are among the most prevalent human health concerns worldwide, affecting a significant proportion of the global population and placing a substantial burden on healthcare systems. Accurate and timely diagnosis often requires expert dermatologists, whose availability is limited in many low-resource or remote areas. This motivates the development of automated solutions that can aid in early detection.

Recent advances in deep learning, particularly convolutional neural networks (CNNs), have demonstrated dermatologist-level accuracy in classifying skin lesions, trained a network on a total of 129,000 clinical images across more than 2,000 skin conditions, and achieved performance comparable to that of board-certified skin doctors [1]. Other lightweight methods, such as MobileNetV2 combined with Long Short-Term Memory (LSTM) architectures, have been deployed in mobile applications with higher accuracies on benchmark datasets such as HAM10000. Mobile deployment is becoming increasingly viable. Smartphone-based apps built using MobileNet architectures have reached up to 94% accuracy via data augmentation and fine-tuning strategies, as reported by Velasco et al. [2]. A more recent study focused on an M-Health application based on MobileNetV2 and NASNetMobile for classifying prevalent skin conditions, reporting 91.6% accuracy using gallery images and 88.9% accuracy for live camera capture [3].

Automated skin disease diagnosis using deep learning has advanced significantly in recent years. A CNN composed of nine convolutional and two fully connected layers, achieving 91.07% accuracy across ten skin disease classes, which is a promising baseline for deep learning–based dermatological systems [4]. Similarly, several mobile-focused implementations have adopted lightweight models and TensorFlow Lite for on-device inferences. For instance, a ResNet-18–based Android app attained 74.27% accuracy for seven skin conditions using TensorFlow Lite, demonstrating the feasibility of mobile classification [5].

In a previous study demonstrating the development of an Android-based application, researchers integrated MobileNet with fine-tuning and data augmentation techniques, resulting in high classification accuracy for various dermatological conditions. A combination of an LSTM model with MobileNetV2, trained on the dataset HAM10000, achieved over 85% accuracy and exhibited enhanced performance efficiency [6] achieved an acceptable level of accuracy. A MobileNetV2-driven Android application that utilized images taken by smartphones demonstrated a detection accuracy of 95% and a classification accuracy of 70% [7]. A modified version of MobileNet was also incorporated to address the partial hybrid loss function to achieve higher accuracy with images that included colors. Another Android app utilized the Firebase Machine Learning Kit and was built on the SSD-MobileNetV2 architecture, with an accuracy of 93.9% [8]. A hybrid neural network incorporating YOLOv8 demonstrated efficient lesion localization and classification in real time on skin disease images. Despite the low lesion-to-skin contrast and visual similarities between infected and non-diseased areas, different models aim to achieve accurate detection.

Frameworks based on YOLO have been developed, providing improved speed and precision. A model based on YOLO11 that incorporates EfficientNetB0 and ResNet50 reached a precision of 89.8% [9], whereas ViScan (using YOLOv10x) obtained a mAP of 89.2% [10]. An assistant built on YOLOv8 surpassed previous YOLO versions in terms of high accuracy. YOLOv8n-cls demonstrated an inference time of 0.5 ms, which is suitable for mobile applications. In contrast, YOLOv8x-cls achieved both accuracy and precision of 86.2% [11]. Other models, such as SkinScan (EfficientNetB7) and SkinVision (CNN+ViT), achieved sensitivities of 95% and 81.5%, respectively. [12]. DenseNet-161 classified 40 conditions with 75.07% top-1 accuracy [13]. In low-resource settings, lightweight models achieved 89.09% sensitivity at ≥ 90% specificity on smartphones, and binary classifiers reached 80% accuracy for screening applications [14].

Current solutions often sacrifice either inference speed or accuracy or require cloud connectivity, limiting their practicality in low-resource or offline settings. Moreover, most do not exploit object detection frameworks that simultaneously localize and classify lesions in real time. To address these gaps, this study introduces SkinLearn, a YOLO11 (You Only Look Once 11)-based framework tailored for smartphone deployment. SkinLearn integrates lesion localization and disease classification within a single object detection pipeline optimized for accuracy, inference speed, and on-device execution.

Methodology

This study developed a skin lesion classification model using deep learning for mobile platform operation. The model built on the YOLO11 architecture classifies seven different skin lesion types. The dataset used is an open-source dataset that includes skin disease images from the International Skin Imaging Collaboration (ISIC) dataset and other sources. The proposed methodology implements dataset splitting for training and performance evaluation, as well as the necessary preprocessing steps for effective classification. Subsequently, the trained YOLO11 was implemented in an Android application.

The study methodology comprised several key steps. First, the YOLO11 model was trained and validated for the classification of skin diseases using an open-source dataset. The dataset was preprocessed and utilized to support supervised learning and performance assessment. Subsequently, the trained YOLO11 model was integrated into an Android application developed to enable real-time skin-disease detection. Finally, both the model and the mobile application were systematically evaluated to assess their classification accuracy, robustness, and overall performance.

An overview of the proposed method is depicted in Figure 1, where the full system is illustrated from the user end to model image processing to the classification result as output on the app screen.

Figure 2 illustrates the end-to-end deployment pipeline of the proposed YOLO11-based skin disease classification system. The workflow begins with training the model in PyTorch, followed by conversion to the TensorFlow Lite format for mobile compatibility. The resulting TFLite model was then integrated into an Android application using the Android Studio IDE, enabling real-time and offline skin disease identification directly on smartphones.

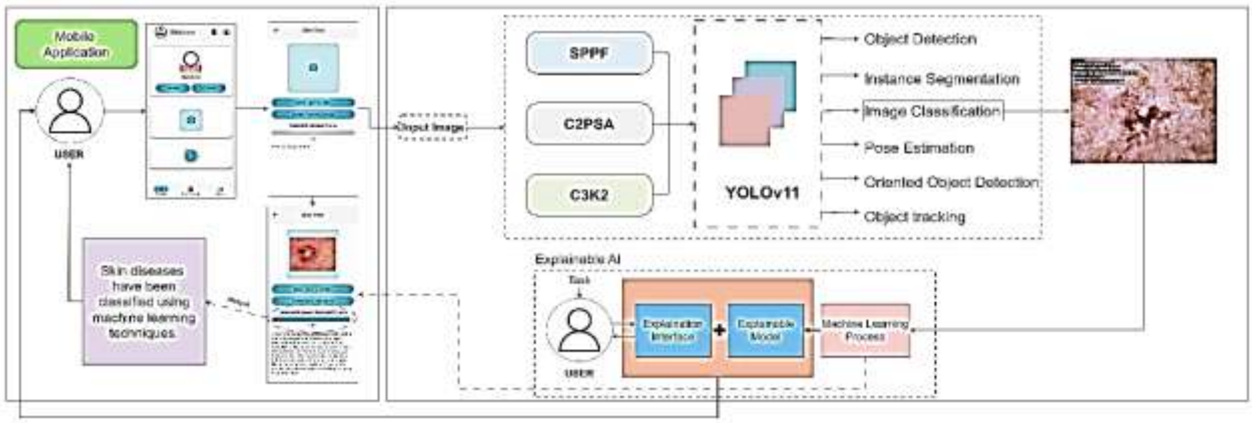

Figure 1. Proposed system overview.

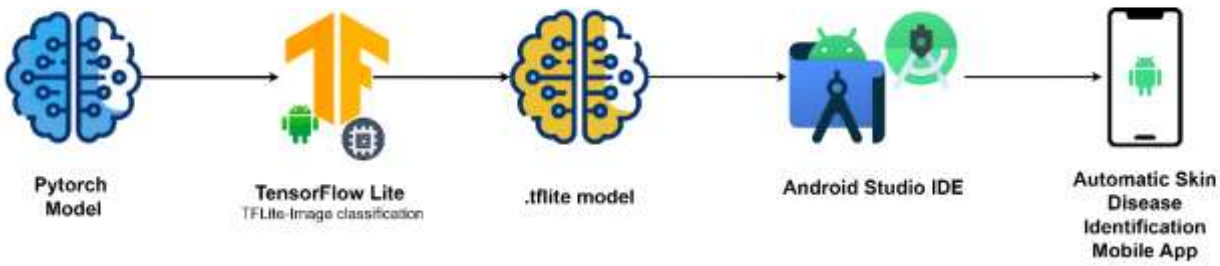

Figure 2. Representation of the app development process with YOLO11 model.

Data Collection

A publicly accessible open-source dataset [15] of high-resolution dermatological images of skin lesions was used. The dataset included seven skin lesion types: actinic keratosis, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevus, and vascular lesions. The images were processed with proper dimensions, which is crucial for the reliable classification and diagnosis of skin lesions. Representative images of the skin lesions in the dataset are presented in Figure 3.

To ensure that each type of skin lesion was fairly included in each group, the full set of 38,459 images was split into training, validation, and test sets in the ratios of 80%, 10%, and 10%, respectively. The following is a summary of the precise image numbers presented in Table 1. The test set of 524 images was completely excluded from the model-building process and was utilized only once to report the final performance metrics, as presented in the results section.

Figure 3. Displaying random images from the dataset.

Table 1. Skin Diseases dataset Summary

Class	Train	Validation	Test	Total
Actinic keratosis	4168	516	516	38459
Basal cell carcinoma	4681	580	580	
Benign keratosis	4731	587	587	
Dermatofibroma	3523	436	436	
Melanoma	4731	587	587	
Melanocytic nevus	4758	590	590	
Vascular lesions	4227	524	524	
Total	30819	3820	3820	

YOLO11 Architecture

YOLO11 is the latest model in the YOLO family and was released in September 2024. It has two architectural improvements compared to YOLOv8. Architectural improvements include the C2PSA block, which highlights important parts of an image, and the SPPF module, which collects multi-scale information.

YOLO11 is a single-stage model for simultaneously detecting and classifying objects in an image. As illustrated in Figure 4, it consists of three main components: Backbone, the Neck, and the Head.

The Backbone handles the feature extraction. A 640×640×3 input image was passed through the convolutional layers and C3k2 blocks while progressively down sampling and extracting hierarchical features from the image. This C3k2 block uses two 3×3 convolution filters to reduce the computational cost while maintaining detail. The backbone output consists of several multi-scale feature maps of different resolutions, which are then utilized in the neck.

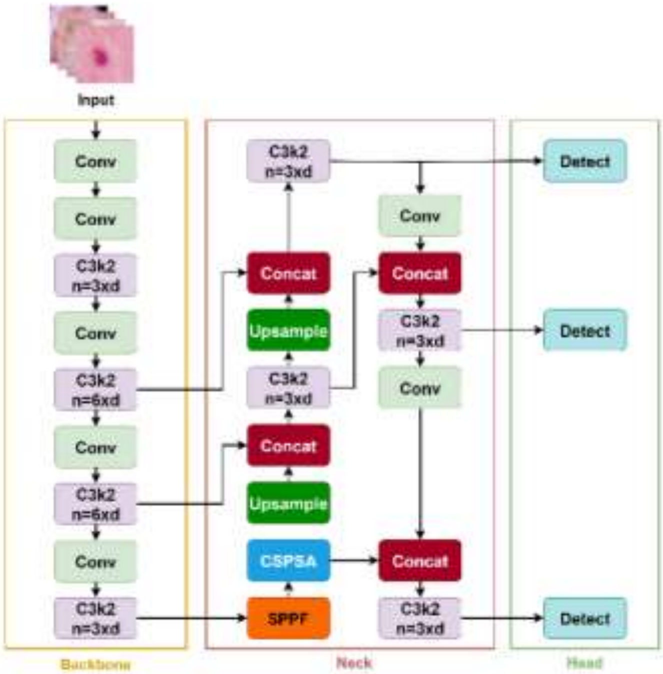

Figure 4. YOLO11 model architecture.

By adding more convolutional layers, concatenation, and up sampling, the neck helps merge the backbone feature maps at various scales. The feature map function from the backbone is merged at a fixed scale by the Spatial Pyramid Pooling Fast (SPPF) module, which allows for the training of the architecture with numerous objects of diverse sizes. The C2PSA (Cross Stage Partial with Spatial Attention) block permits the model to utilize information from multiple scales when merging features and allows the model to place more attention on the most significant portions of the image during feature merging. By combining C3k2, SPPF, and C2PSA, YOLO11 achieves a better trade-off between speed and accuracy, making it a capable classification model for skin lesions in the dataset.

App Development

SkinLearn was developed for the Android operating system. The development pipeline followed a multistage process designed to convert the deep learning model into a lightweight format suitable for on-device inference. The process began with training the YOLO11 model using the PyTorch framework on the skin disease dataset. Once the model reached satisfactory accuracy, it was exported and converted to TensorFlow Lite format. The TFLite model, optimized for mobile environments, was then integrated into an Android application using the Android Studio IDE along with the TensorFlow Lite Image Classification API. The mobile application features a clean user interface that allows users to capture or select skin images and receive instant diagnostic predictions of the skin condition. The workflow of the developed app is demonstrated in Figure 5.

The YOLO11 model was trained on a Google Colab notebook. The experiments were conducted in a Google Colab environment equipped with an NVIDIA Tesla T4 GPU (15.36 GB VRAM, Compute Capability 7.5), with mixed-precision FP16/FP32 enabled for efficient computation. The model was trained for 14 epochs using a 640×640 image size, a batch size of 16, and standard optimizers SGD with 0.01 learning rates.

To evaluate real-world usability, the trained YOLO11 model was deployed in a custom-built Android application. The TensorFlowLite framework offers two primary acceleration techniques. These are delegates and the eXtensible Neural Network Package (XNNPack) library. The XNNPack package uses smartphone Central Processing Unit (CPU) to improve speed by offering optimized applications for operators of floating-point neural networks. Delegates permit the use of smartphone hardware accelerators for machine-learning (ML) tasks.

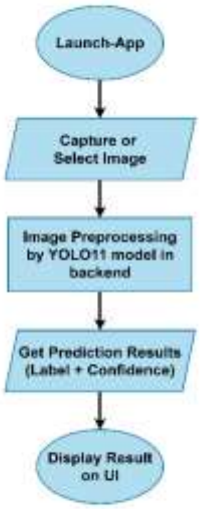

Figure 5. YOLO11-Based developed Android App Workflow.

Results

Classification Results

The classification result for skin lesions by the trained model is shown in Figure 6.

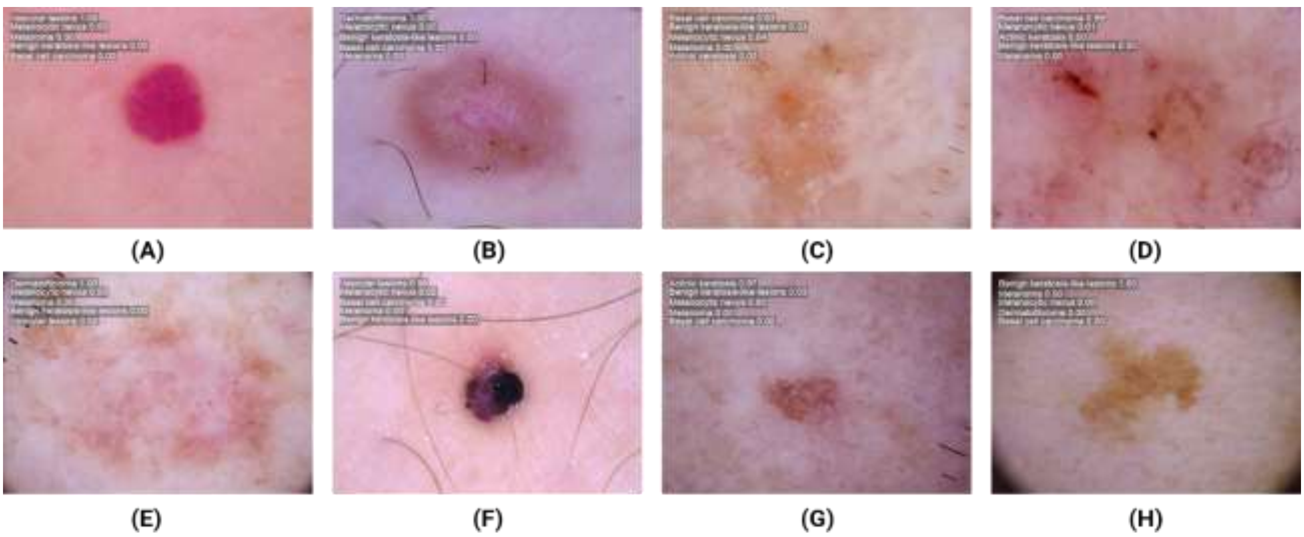

Figure 6. Classification results of the trained YOLO11 model.

Model Performance

The training and validation performances of the YOLO11 model are depicted in Figure 7. The training and validation loss curves showed a consistent decline, indicating effective convergence. The top-1 accuracy steadily improved across epochs, reaching 98.3%, whereas the top-5 accuracy quickly saturated at 100%, demonstrating the model's strong classification ability and reliability in ranking the correct skin disease among predictions.

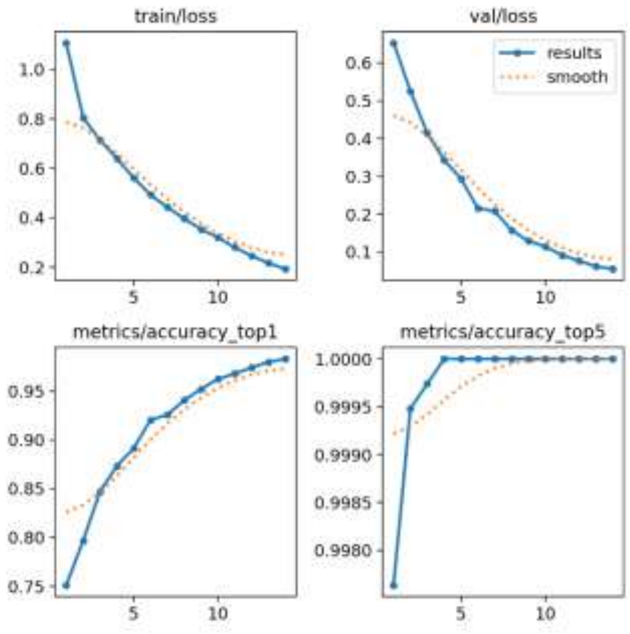

Figure 7. Training results of the YOLO11 model.

The confusion matrix (Figure 8) indicates that the YOLO11 model performed robustly in classifying skin diseases.

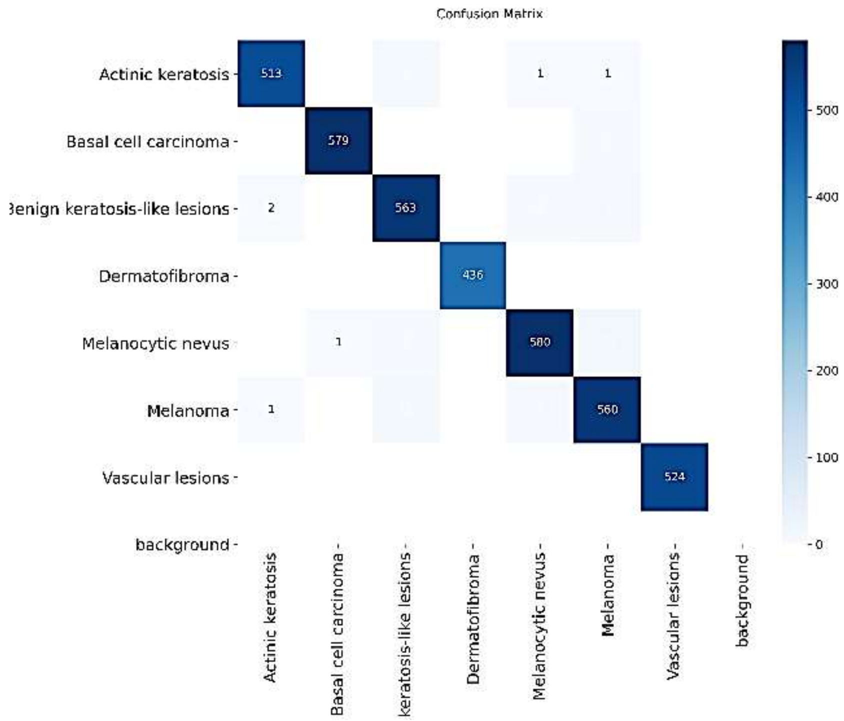

Figure 8. Confusion matrix of the YOLO11 model.

Experiment with Android Application

The app allows users to capture or select skin images and receive instant disease predictions labeled with the disease class and accuracy. Sample screenshots of the SkinLearn app's user interface and prediction results with disease description and classification are shown in Figure 9. All predictions were performed on the smartphone without the Internet.

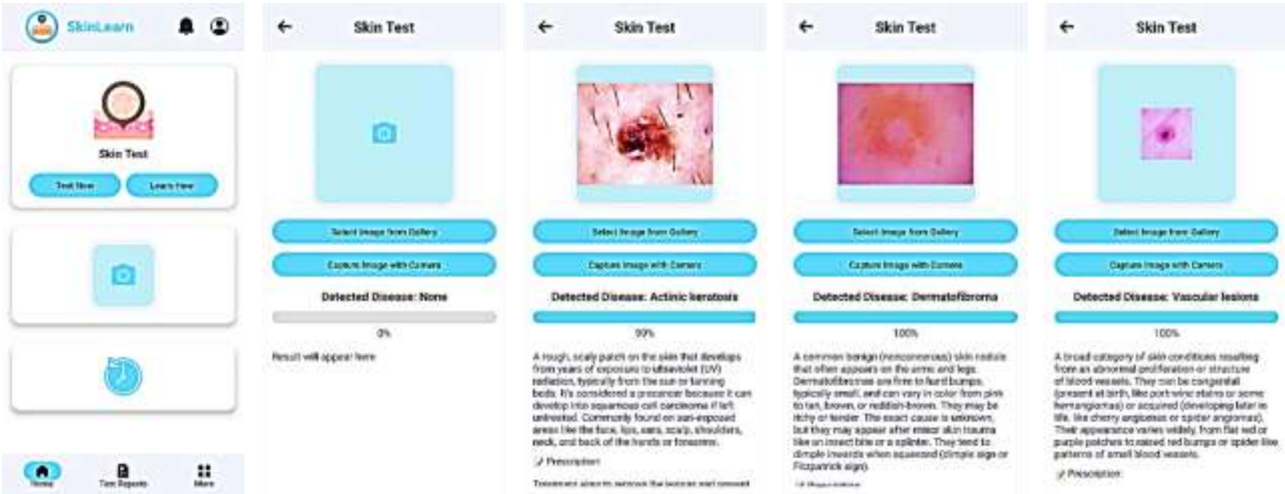

Figure 9. SkinLearn app's user dashboard and prediction performance.

Discussion

Development and implementation of SkinLearn, a YOLO11-based deep learning framework designed for real-time classification of skin diseases from smartphone images, was successful. The results demonstrate that high diagnostic performance can be achieved using lightweight, mobile-compatible models, highlighting the potential of such systems to support dermatological assessment in low-resource and remote environments. The model achieved a top accuracy of 98.3% and 100%, indicating strong generalization across the evaluated dataset.

A key contribution of this work lies in the successful end-to-end deployment of the trained model within an Android application. This integration confirms the feasibility of performing accurate, real-time skin disease classification directly on mobile devices, without reliance on cloud-based computation. Such an approach not only reduces latency but also enhances accessibility, privacy, and usability in real-world scenarios. The mobile implementation further demonstrates that advanced deep learning architectures like YOLO11 can be effectively adapted for resource-constrained platforms while maintaining high performance.

Despite these promising outcomes, several areas for improvement remain. Expanding the range of detectable skin conditions and incorporating additional clinical metadata could further enhance diagnostic reliability. Additionally, continued optimization of model efficiency will be essential to ensure compatibility across a wider spectrum of mobile devices and operating conditions. Overall, the findings underscore the practical potential of mobile-based AI tools in dermatology and support their broader adoption in accessible healthcare solutions.

List of Abbreviations: Not applicable.

Author Contributions: U.S.: Conceptualization, Methodology, Software Writing - Original Draft, Coding. P.B.: Conceptualization, Methodology, Writing—Original Draft, Supervision. T.C.S.: Data curing, Reviewing and editing.

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