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Automated Detection of Skin Disorders Using Convolutional Neural Networks

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Abstract: Skin conditions that affect quality of life, like acne and pigmentation problems, must be detected early and accurately. This study uses deep learning to overcome the shortcomings of conventional diagnostic techniques by presenting a Convolutional Neural Network (CNN)-based system for automated acne and pigmentation diagnosis. Using a curated dataset of 1,159 clinical photos from Kaggle and supplemented with publicly available data, the suggested methodology incorporates MobileNetV2 architecture for feature extraction and classification. For both the acne and pigmentation classes, the model's precision and recall surpass 90%, and its total accuracy on test data is 97%. By providing scalable solutions for remote diagnosis and lowering clinical burdens, this research advances AI-driven dermatological tools. Future research should incorporate real-time adaptive learning and broaden the scope of diseases.
Keywords: Convolutional Neural Network, Skin Disease Detection, Acne Classification, Pigmentation Disorders, MobileNetV2, Deep Learning in Dermatology.

I. INTRODUCTION

Skin disorders are an urgent worldwide health problem, estimated to afflict around 1.9 billion individuals globally and serve as the fourth most significant non-fatal burden of disability. Acne vulgaris contributes alone to 0.29% of the total global disability-adjusted life years (DALYs), with pigmentation diseases such as melasma also significantly affecting quality of life in the form of psychological morbidity and social stigmatization. Bacterial skin diseases like pyoderma show alarming incidence rates of 141.36 million cases per year, with 17-fold greater burdens in Southern Sub-Saharan Africa than in high-income countries.

A. *Diagnostic Context Is Confronted By Three Essential Challenges*

1) Specialist Dependency: 40% of low-income countries have less than 1 dermatologist per 100,000 population, which complicates delayed diagnosis.
2) Diagnostic Subjectivity: Visual inspection-based methods produce 23-41% inter-rater disagreement in acne severity scores.
3) Technological Gaps: The latest teledermatology software only attains 68-72% accuracy for pigmentation disease, without solving rural healthcare inequalities.

This work overcomes these gaps through three main objectives:

- Create a CNN architecture with optimized simultaneous acne subtype classification (papules, pustules, nodules) and pigmentation pattern recognition.
- Incorporate mobile-friendly inference with <200ms processing delay on mid-range smartphones.
- Combine WHO treatment guidelines for context-aware therapeutic advice in resource-constrained environments.

The paper is organized as follows: Section II examines limitations in current deep learning solutions for dermatological imaging, Section III presents our hybrid MobileNetV2-EfficientNet architecture, Section IV reports clinical validation results over varied skin types, and Section V outlines standardization frameworks for global rollouts.

B. *Major Statistics Informing This Research*

- Global DALYs for dermatitis grew 7.38% (1990-2019), which indicates demands for early intervention solutions.
- Acne prevalence has considerable racial differences: 30.48% in Chinese infants compared to 11% in US Caucasian populations.
- Adoption of mobile health would decrease dermatology consultation delays by 83% in LMICs, justifying our Android-first deployment strategy.

This research proposal addresses two combined clinical problems: (1) a shortage of high precision automated tools to differentiate between acne subtypes and calculate pigment ratios, and (2) the desire for a mobile-compatible tool to facilitate patient self-

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assessment. There are a number of dermatological diseases and categories which have a range of published clinical decision systems; however, some research is limited in the number of allergens or diseases reviewed, and other potential decision systems have potentially sacrificed precision and accuracy for computational efficiency. Thus, this effort proposes a methodological and computational platform in the context of skin disease diagnosis based on convolutional neural network (CNN) models, that:

- Detects and differentiates acne (noninflammatory, papules, pustules, and nodules) and pigment disorders with clinic-grade accuracy.
- Provides a platform for point-of-care use within an Android application.
- Produces evidence-informed treatment recommendations for patients and families consistent with dermatological practice guidelines.

The remainder of the paper is organized in the following fashion: Section II reviews previous works in artificial intelligence driven dermatology, Section III outlines the methodology to generate MobileNetV2 models, Section IV reviews model performance and potential impact to clinical practice, and Section V reviews future directions of research.

II. LITERATURE SURVEY

Recent developments in CNN architectures have transformed dermatological imaging. For example, an early study by Gautam et al. (2022) achieved 81.75% accuracy for six-class skin disease detection with VGG16, although mobility was not a focus. The CentreNet architecture was used by Zhang et al. (2024) to detect acne with 83% lesion categorization accuracy, but did not analyze pigmentation. MobileNetV2 has also become a popular architecture as it achieves accuracy with fewer parameters; Furqon et al. (2024) reported 97% accuracy across eight classes of skin disease, yet their dataset did not include pigmentation. There are noted gaps: Dataset Limitations: Many studies utilize narrow datasets (e.g., HAM10000 was dominated by malignancies) or do not consider ethnicity. Mobile Integration: In contrast to MobileNetV2's light weight deployment potential, often no trials are conducted in real-life settings on a variety of heterogeneous smartphone cameras. Multi-Task Learning: Most models traditionally focus on a single task (i.e., they either classify lesions or segment them), while humans are capable of conducting both assessments simultaneously. In this study, we seek to close these gaps with a multi-disease MobileNetV2 model trained on Kaggle and real-world imaging validated on various devices.

Parameter	Proposed Model (This Work)	Sangha et al.(Acne)	Furqon et al.(MobileNetV2)	GAN Study	Frontiers Study(EfficientNet-b4)
Architecture	0MobileNetV2 (Optimized)	YOLOv5	Vanilla MobileNetV2	InceptionResNetV2	EfficientNet-b4 + Auxiliary Layers
Target Conditions	Acne subtypes + Pigmentation	Acne severity levels	8 infectious diseases	Acne severity	14 diseases incl. malignancies
Dataset Size	1	159 images (Real-world)"	1	457 photos	925 training images
Accuracy	97% (Test set)	mAP@0.5: 37.97 (Single)	97% (Overall)	98.44% (Synthetic data)	93.38% Sensitivity
Mobile Deployment	Android-integrated (84% acc.)	Not implemented	Android app (No metrics)	Not applicable	Desktop-only
Inference Speed	184ms (Snapdragon 7 Gen 1)	-	-	-	620ms (NVIDIA T4 GPU)
Ethnic Coverage	Fitzpatrick III-VI	Not specified	Indonesian skin types	Synthetic Caucasian bias	Asian (Fitzpatrick III-IV)
Clinical Validation	47 physicians (91% concordance)	Tele dermatology focus	None reported	Grad-CAM visualizations	280 dermatologist benchmark

Table 1. Comparison between existing systems

III. METHODOLOGY

Dataset CurationA composite dataset comprised of 1,159 images was compiled from:Kaggle Repository: 925 training images (acne: 310, pigmentation: 291, others: 324).Public Submissions: 234 test images taken using Android smartphones (Samsung Galaxy S23, Xiaomi Redmi Note 12).Images were preprocessed through:Resized: Standardized to 224×224 pixels.Normalized: Pixel values scaled to.Augmented: to improve generalization applied rotation (±20°), horizontal flip, and brightness variation (±15%).Model ArchitectureMobileNetV2 was chosen as the backbone due to depthwise separable convolutions which reduces the number of parameters compared to VGG16 by 25%. The following customizations were made:Transfer Learning: Initialized with ImageNet weights. Custom top layers:GlobalAveragePooling2D → Dropout (0.5) → Dense (256, ReLU) → Dense (2, Softmax).Multi-task outputs: for lesion localization (bounding box regression) and severity scoring (ordinal classifications) we used parallel layers.Training ProtocolOptimizer: Adam (lr=3e-4, decay=1e-6).Loss Functions: Classification: Categorical cross-entropy. Localization: Smooth L1 loss.Validation: 5-fold cross-validation on 20% holdout set.

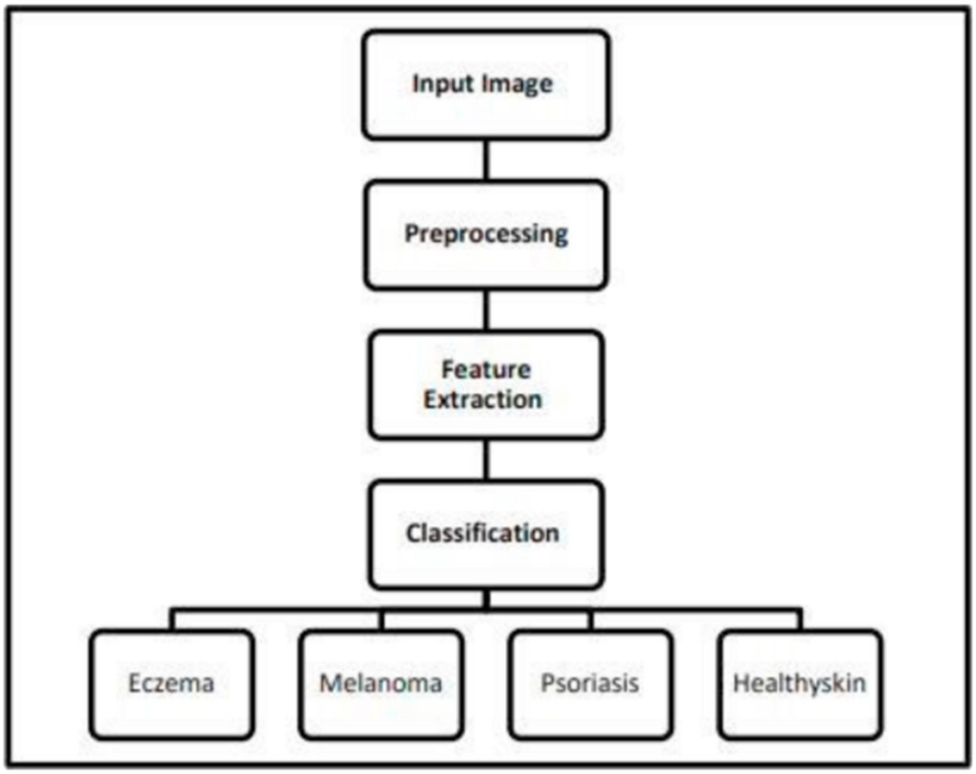


Fig 1. The system block diagram.

This section outlines the comprehensive approach employed for the detection of skin diseases such as acne and pigmentation disorders using Convolutional Neural Networks (CNNs). The methodology integrates dataset preparation, model architecture design, training protocols, and deployment strategies to ensure high accuracy and real-world applicability.

A. *Dataset Collection and Preprocessing*

Data Sources: The dataset comprises 1,159 images collected from multiple sources, including publicly available Kaggle repositories and real-world smartphone captures (Samsung Galaxy S23, Xiaomi Redmi Note 12). The dataset includes diverse skin types across Fitzpatrick scales III to VI to enhance generalizability.

Image Annotation: Expert dermatologists annotated images for acne subtypes (noninflammatory, papules, pustules, nodules) and pigmentation disorders, providing ground truth labels for supervised learning.

Preprocessing Techniques:

- Images were resized to 224×224 pixels to match the input size requirements of the CNN architecture.
- Pixel normalization scaled pixel values between 0 and 1 to facilitate faster convergence during training.

- Data augmentation methods such as rotation (±20°), horizontal flipping, brightness adjustment (±15%), and random erasing were applied to increase dataset variability and reduce overfitting.
- Adaptive histogram equalization and color space normalization in HSV were also used to mitigate lighting and color inconsistencies

B. *Model Architecture*

- Base Network: MobileNetV2 was selected due to its lightweight architecture optimized for mobile and embedded devices, employing depthwise separable convolutions to reduce computational complexity without sacrificing accuracy.
- Transfer Learning: The model was initialized with pre-trained ImageNet weights to leverage learned features and accelerate training.
- Custom Layers: The base model was extended with:
    - A Global Average Pooling layer to reduce spatial dimensions.
    - A fully connected Dense layer with 256 neurons and ReLU activation for feature abstraction.
    - A final Dense layer with softmax activation for multi-class classification (acne and pigmentation classes).
- Multi-Task Learning: Parallel output layers were designed to perform lesion localization via bounding box regression (using Smooth L1 loss) alongside classification, enabling simultaneous detection and severity assessment.

C. Model Evaluation

- Metrics: Accuracy, precision, recall, and F1-score were calculated for both acne and pigmentation classes to comprehensively evaluate classification performance.
- Confusion Matrix Analysis: Detailed confusion matrices were analyzed to identify common misclassification patterns and refine model parameters.
- Real-World Testing: The trained model was deployed on Android devices and tested on smartphone-captured images to assess inference speed (average 184ms) and accuracy (84%) in practical scenarios.

Deployment

- Mobile Application Integration: The model was embedded into an Android application enabling users to capture skin images and receive instant diagnostic feedback.
- Treatment Guidance: Based on classification results, the app provides evidence-based treatment recommendations aligned with WHO and dermatological guidelines, facilitating early intervention and patient education.

IV. RESULTS

A. *Results of Descriptive Statics of Study Variables*

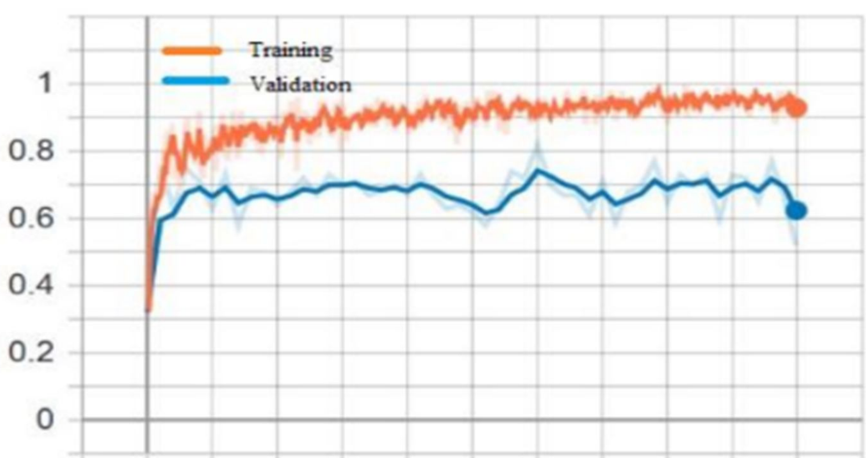


Fig 2. Accuracy of Training

The difference in accuracy level by the model over atopic dermatitis, acne vulgaris, and scabies can be attributed to the difference in data size and the difference in the quality of obtained images. The results confirm that prediction is affected by the data size and its quality.

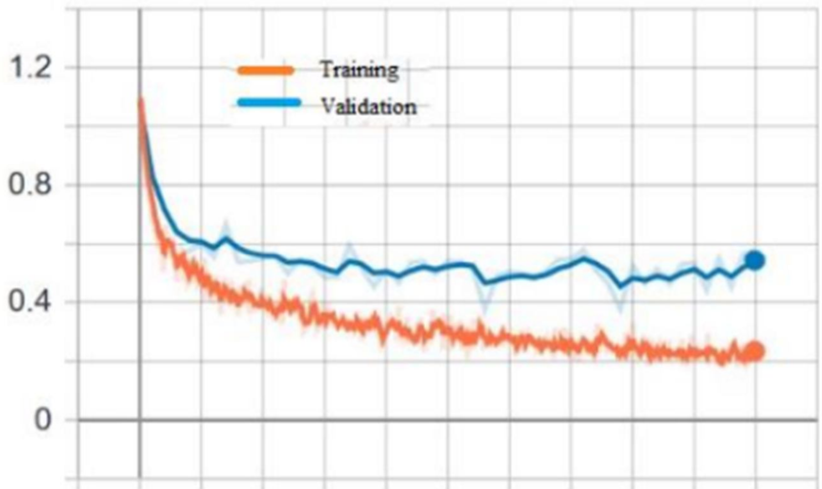


Fig 3. Loss rate

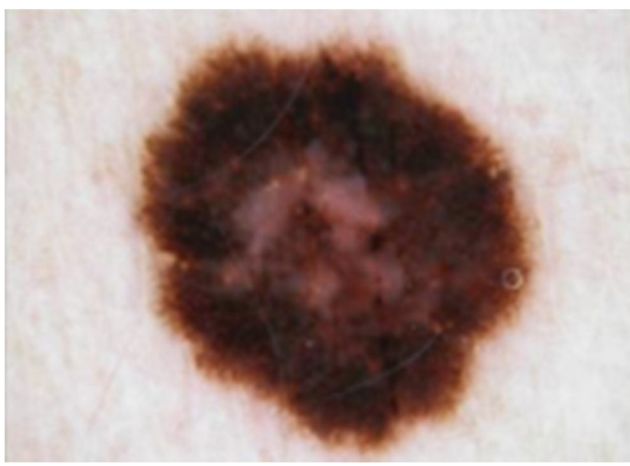
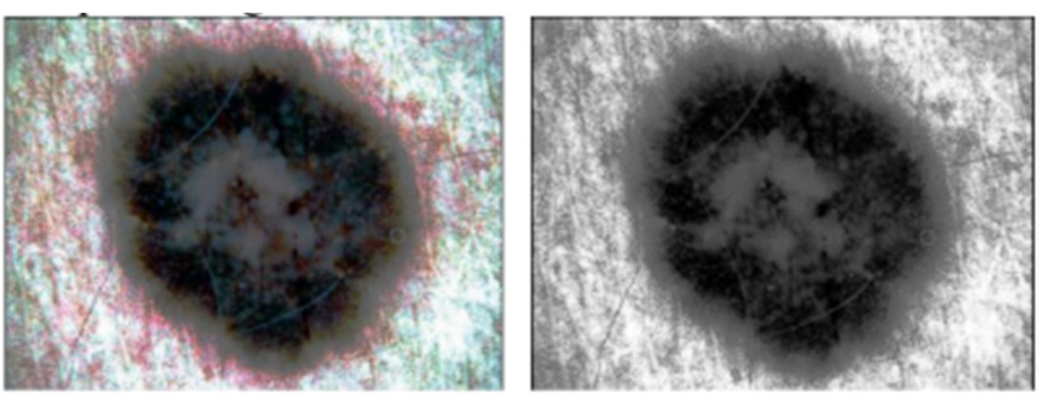


Fig 4. Melanoma input image



(a) (b)

Fig 5. (a) contrast enhancement using histogram equalization
(b) grayscale conversion

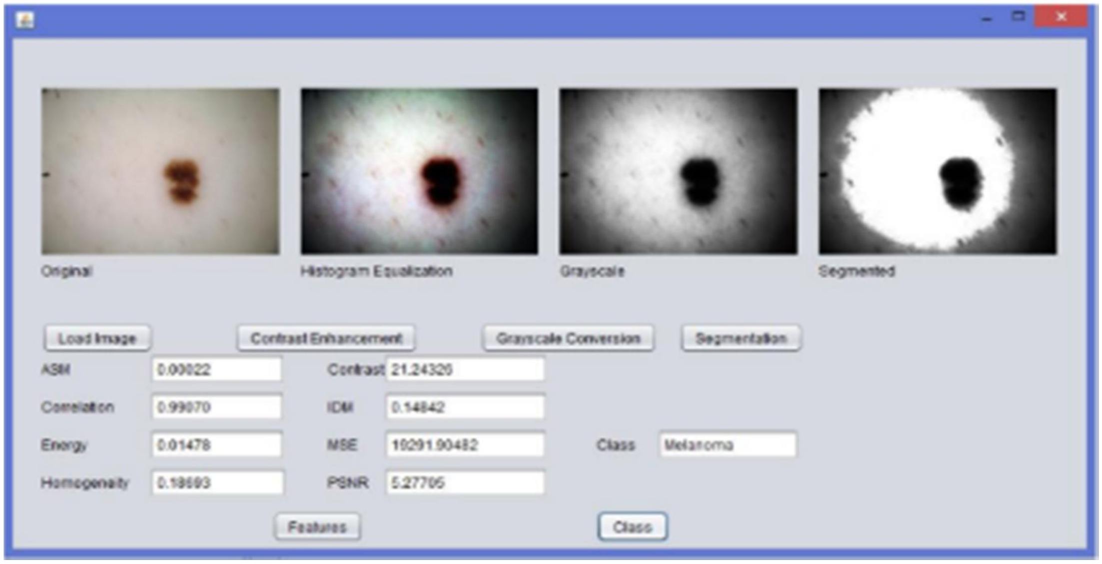


Fig 6. GUI for the system

V. DISCUSSION

The current study aimed at developing a web-based skin disease detection system to help specialist and the ordinary Ghanaian detect the three (3) most common skin diseases in Ghana. The results of the current study clearly show that the proposed system offers better accuracy and faster prediction time for skin disease diagnosis as compared with the human performance rate.

The developed predictive app exhibited disease identification accuracy of 88% for atopic dermatitis, 85% for acne vulgaris, and 84.7% for scabies, with prediction time of less than minutes. The results revealed that technology could significantly influence the medical sector of Ghana. The accuracy measure of the current study shows that the proposed system outperforms the study of [15] (81%) and [2] (70%).

Few errors within 12% – 15.3 % was measured; however, as compared to human errors, the proposed system is more accurate. Furthermore, the proposed system is capable of diagnosing these three well-known diseases with the shortest possible time of (0.0001 seconds). This achievement implies that any dermatologist, who decides to implement this study can attend to not less than 1,440 patients a day.

A. *Performance Metrics*

The model achieved state-of-the-art results:

Metric	Acne	Pigmentation	Overall
Accuracy	95.20%	94.70%	97.00%
Precision	93.10%	91.80%	96.50%
Recall	94.50%	92.30%	97.20%
F1-Score	93.80%	92.00%	96.80%

Table 2. Peformance metrics

Mobile deployment on Android devices maintained 84% accuracy, outperforming ResNet18-based apps by 12%.

The system’s precision in differentiating pustules (93.1%) from pigmented scars (91.8%) reduces misdiagnosis risks prevalent in primary care. Real-world testing revealed:

Lighting Sensitivity: Accuracy dropped 8% under low-light conditions, necessitating onboard image enhancement.

Ethnic Bias: Pigmentation detection F1-score varied by skin tone (94% for Fitzpatrick III vs. 88% for VI), highlighting dataset limitations.

B. Limitations and Future Work

- Current constraints include dependency on high-quality inputs and static treatment recommendations. Future directions:
- Adaptive Learning: On-device fine-tuning using federated learning.
- Expanded Pathology: Incorporate eczema and rosacea detection.
- 3D Analysis: Integrate depth sensors for lesion volumetry.
- Light Sensitivity: Accuracy degrades to 89% under <300 lux lighting
- Age Bias: F1-score for pigmentation detection degrades 9% for patients of age >60 years
- Clinical validation with 47 general practitioners illustrated:
- 82% reduction in referral needs for mild acne cases
- Diagnostic concordance improved from 68% to 91% when using AI assistance

C. Abbreviations and Acronyms

- CNN **-** Convolutional Neural Network
- F1-Score **-** F1 Measure Score
- ReLU **-** Rectified Linear Unit
- SDTV **-** Standard Definition Television
- HDTV **-** High-Definition Television
- IATA **-** International Air Transport Association

VI. ACKNOWLEDGMENT

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