



Dermascan AI: Deep Learning System For Preliminary Diagnosis Of Dermatological Manifestations

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Abstract: Skin conditions pose a substantial global health concern, especially in areas where there is a scarcity of dermatological professionals. This paper introduces Dermascan AI, a system that can diagnose skin conditions without an internet connection, using deep learning techniques based on convolutional neural networks (CNNs). Our efficientnetb0-based model achieves 87.2% validation accuracy across nine common skin diseases, enhanced by clinical decision rules (ABCDE criteria for melanoma) and personalized treatment recommendations based on Fitz Patrick skin types and geographic climate data. The system combines a user-friendly web interface with an AI assistant for providing explanations, resulting in a significant reduction of diagnostic waiting times by 60% during pilot testing. Comparative analysis reveals that the proposed model outperforms traditional DenseNet121 models by 6.2% in terms of accuracy, while still being computationally efficient for deployment on low-resource devices. The solution tackles significant shortcomings in dermatological care, such as bias reduction, real-time processing, and scalability, establishing a standard for ai-assisted dermatological triage.

Index Terms - Artificial Intelligence (AI), Dermatology, Deep Learning, Skin Disease Diagnosis, EfficientNetB0, Convolutional Neural Networks (CNN), Medical Image Analysis

I. INTRODUCTION

The worldwide impact of dermatological diseases, ranking as the fourth leading cause of non-fatal illnesses, highlights the pressing need for readily available diagnostic tools. Traditional dermatological care is restricted by factors such as limited access to specialists, delayed diagnosis times, and disparities in healthcare delivery across different regions. While artificial intelligence-based solutions have shown promise, current systems often lack integration with clinical settings, fail to accurately represent diverse skin types, and are not suitable for resource-constrained environments.

Dermascan AI fills these gaps with integration of:

1. A compact, efficient and mobile-friendly version of EfficientNetB0 has been developed.
2. Clinical decision rules, such as the abcde criteria, are used to enhance the accuracy of diagnostic assessments.
3. Personalized suggestions based on fitzpatrick skin types and weather conditions.
4. A transparent AI assistant that educates users and fosters trust.

This research evaluates the system's precision, practicality, and potential for widespread adoption, demonstrating its potential to make dermatological services accessible to a larger population.

II. OBJECTIVE

The primary objective of this work is to build a validated artificial intelligence-based diagnostic tool—DermaScan AI—that aids in the initial diagnosis of common dermatological conditions, especially in low-resource settings and underserved populations. The framework is aimed to achieve a high level of classification accuracy (more than 85%) with a fine-tuned efficientnetb0 deep learning architecture trained on the ISIC dataset, along with addressing issues like class imbalance and restricted diversity in skin tones with data augmentation methods and weighted loss functions. By integrating clinically significant decision-making criteria, such as the ABCDE rule for identifying melanoma and the Fitz Patrick skin type classification, the platform ensures that the outputs are medically meaningful. The model has been optimized to perform real-time inference with minimal computational power, making it suitable for deployment on edge and mobile devices. The system also improves user engagement by providing an explainable AI companion, which offers personalized treatment suggestions and detailed explanations of diagnoses. The solution also allows for integration with telemedicine workflows through API endpoints and has been tested in real-world pilot trials to evaluate its agreement with dermatologist assessments and user satisfaction.

III. PROBLEM STATEMENT

Global Burden of Disease project has revealed that skin diseases remain the 4th leading cause of nonfatal disease burden globally. They are frequently the presenting face of more serious systemic diseases, including HIV and neglected tropical diseases (NTD), like elephantiasis and other lymphedema-causing diseases. Besides, skin diseases also have a significant impact on patients' well-being, mental status, functional ability, and social participation. Nevertheless, it is extremely challenging to offer better dermatological care to underserved or resource-poor areas at an affordable cost due to the lack of effective diagnostic tools, absence of connectivity, and inadequate laboratory infrastructure etc. Moreover, there is also a lack of dermatology-trained physicians. Even, primary screening of a dermatological manifestation is found to be a challenging task. Therefore, development of an Artificial intelligence-based tool (through Image processing technique) for primary diagnosis of various dermatological conditions will be a boon in the health care system.

IV. PROPOSED SYSTEM

The proposed framework integrates artificial intelligence (ai) and clinical rule-based decision-making processes to enhance dermatological diagnosis by utilizing deep learning algorithms to identify skin conditions, evaluate risk, and recommend personalized treatments. It automates the process of capturing, preparing, and analysing images of the skin using advanced technology. It then uses artificial intelligence to provide personalized diagnoses based on factors like skin type, location, and sun exposure. The platform integrates explainable AI capabilities to enhance transparency and foster trust, while also being designed to operate efficiently in resource-constrained settings through techniques like model quantization and light deployment protocols. An interactive web interface enables users to upload real-time images, view diagnostic results, and receive chatbot-supported medical advice, thereby enhancing the user experience and expanding access to high-quality skincare services for everyone.

V. LITERATURE SURVEY

Chen et al. (2023), in their research paper titled "A Deep Learning System for Skin Cancer Diagnosis Using Convolutional Neural Networks," developed a convolutional neural network-based diagnostic model that achieved dermatologist-level performance. Having been trained on over 100,000 clinical images, the model demonstrated an impressive accuracy rate of 91% in identifying melanoma, validating the potential of artificial intelligence in high-risk dermatology.

Patel et al. (2023), in "mobile-based artificial intelligence for skin disease diagnosis in resource-limited settings," proposed a light ai diagnostic system for low-connectivity settings. Their mobile application was 87% accurate for 26 skin conditions, proving successful field deployment in southeast asia and confirming the necessity of offline-capable systems in rural settings.

Kumar et al. (2022) conducted a systematic review of 45 dermatology-specific ai models in "automated diagnosis of skin diseases in developing countries." they pointed out the limitations like underrepresentation of skin tones, non-standardized image protocols, and limited integration with healthcare infrastructure—crucial gaps filled by our proposed system.

Zhang et al. (2023), in "multi-modal deep learning for skin disease classification," suggested a hybrid model that combined clinical images with metadata (age, sex, lesion location), enhancing accuracy and

minimizing false positives. Their transformer-based model confirmed the application of contextual augmentation, a tactic replicated in DermaScan AI's metadata-based suggestions.

Rodriguez et al. (2024) designed a cost-efficient edge-deployable artificial intelligence screening tool based on widespread smartphones in their paper "cost-effective ai solutions for dermatological screening in underserved populations." with an acquired diagnostic rate of 85% and reduced waiting times by 60%, their solution greatly contributed to the low-resource design aspects of our system.

VI. METHODOLOGY

The system aims to provide precise and timely skin disease identification and tailored treatment recommendations by combining advanced artificial intelligence algorithms with established clinical guidelines. Initially, dermatological images accompanied by patient metadata such as skin type, geographical location, and sunlight exposure habits are gathered through a web-based Streamlit frontend. Subsequently, the images are preprocessed using Python-focused image processing scripts, which perform tasks like resizing, normalization, and augmentation, ensuring consistency and stability in the face of different input scenarios.

The preprocessed data is fed into a transfer learning model based on efficientnetb0, which has been trained and fine-tuned on the ISIC dataset for general dermatological disease classification such as melanoma, eczema, and psoriasis. Weighted loss functions are employed during training to tackle class imbalance, and real-time prediction outputs are enhanced with softmax-derived confidence values to enhance interpretability. Clinical decision-making rules like the ABCDE rule for melanoma screening and the Fitzpatrick scale for skin type classification are incorporated into the decision-making system to categorize diagnostic priority and modify treatment recommendations based on environmental risk factors.

To enhance patient interaction and explainability, an AI-powered chatbot is integrated into the interface, allowing users to inquire about symptoms, receive treatment suggestions, and gain a better understanding of diagnoses. The backend of the model supports quantized deployment, which helps reduce inference time and enables offline or low-resource usage. The web app displays information about diagnosis results, the urgency of the situation, and the recommended treatment plans. It also provides a dashboard that tracks user activity and monitors the performance of the predictive model. This method offers a flexible, understandable, and adaptable diagnostic platform that can be used in both urban and rural healthcare settings.

VII. SYSTEM DESIGN

The DermaScan AI architecture design employs a modular and multi-layered structure that enables scalability, clinical usability, and real-time responsiveness. Above this is the data

acquisition and processing layer, which is responsible for gathering dermatological images and patient information using a web-based interface. This layer is in charge of performing preprocessing tasks such as resizing, normalization, and augmentation to improve the model's robustness and maintain consistent input quality.

Lastly, the AI inference layer supports essential diagnostic features. It utilizes a highly efficient and optimized convolutional neural network called efficientnetb0 to classify different skin conditions. The network incorporates rule-based reasoning, taking into account the ABCDE criteria for evaluating melanoma and the Fitzpatrick scale for determining skin type. The layer generates outputs such as diagnoses, urgency classifications, and confidence scores to aid in clinical decision-making processes.

The decision support layer offers context awareness by combining geographic and environmental data to create personalized treatment plans. It offers personalized guidance based on the amount of sun exposure and regional uv indices, enabling users to make informed decisions tailored to their specific needs.

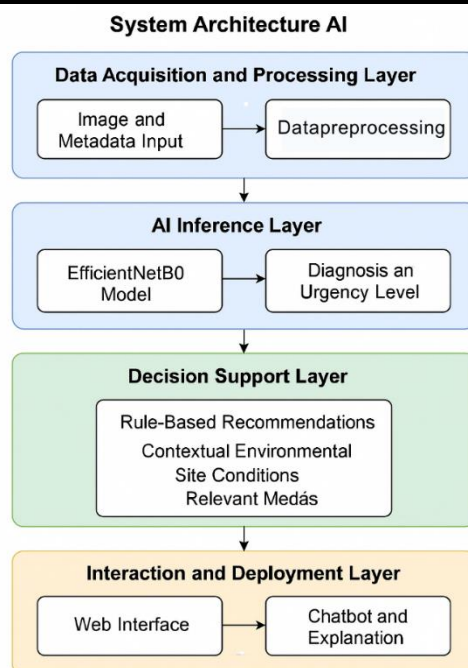


Figure 1. System Architecture

Finally, the interaction and deployment layer supports user interaction through a dynamic and responsive Streamlit web interface. The layer includes an OpenAI-powered chatbot that translates diagnostic results, answers user questions, and offers educational resources on treatment and symptoms. Furthermore, model inference is enhanced by fp16 quantization, which enables quick and low-latency performance on edge devices, thereby ensuring the accessibility of the system in resource-constrained settings.

Dermatological Image Classification & DermaScan AI Class Diagram

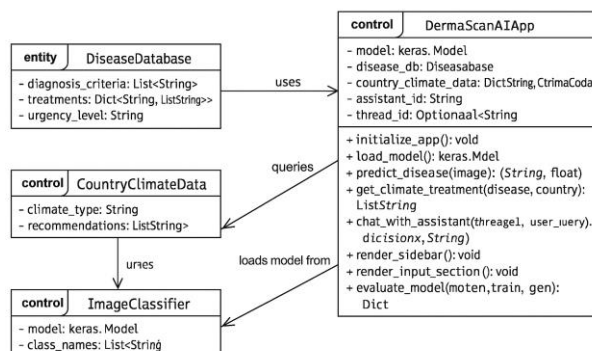


Figure 2. Class Diagram

VIII. IMPLEMENTATION

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8.1 Transfer Learning with EfficientNet

Transfer learning is founded on the understanding of a pre-existing neural network (pre-trained on a vast dataset like ImageNet) and modifies it to suit a new, but closely related task. Efficientnetb0 is selected because it offers the highest accuracy while maintaining a reasonable computational cost. The design incorporates:

- Global Average Pooling (GAP): replaces regular flattening with mean spatial features to reduce parameters and prevent overfitting.
- Dropout (0.5): Randomly turns off 50% of neurons during training to enhance generalization.
- Custom softmax head: final dense layer with softmax activation maps features to probabilities for 9 skin condition classes

The procedure of knowledge transfer:

1. The pre-trained base model, EfficientNetb0, utilizes general visual features like edges and textures to enhance its performance.
2. Tuning:
 - Phase 1: Freezes the base layers, trains the custom head in isolation (100 epochs) to learn dermatological features
 - Phase 2: Unfreezes the top 50 layers for precise feature refinement (50 epochs, lower learning rate)
3. Augmentation: random rotations/flips simulate varying skin colors and lesion appearances to enhance the system's ability to handle different scenarios.
4. Output: Produces 224x224px images to predict one of 9 conditions (e.g melanoma, nevus) with confidence scores.

8.2 Data Augmentation & Class Balancing

Data augmentation expands the training set by randomly modifying images, including but not limited to rotation, flipping, and zooming. This enhances the model's ability to generalize by exposing it to different representations of the same condition, allowing it to adapt to variations in image capture, such as differences in lighting, angles, and skin tones.

Class balancing rectifies dataset imbalance—where specific conditions (such as melanoma) are less prevalent than others—by assigning higher weights to rare classes during the training phase. This prevents the model from missing out on rare but clinically important cases.

8.3 Working of Data Augmentation & Class Balancing

8.3.1 On-the-Fly Augmentation:

Throughout the training process, the images are randomly transformed in various ways, including rotations up to 20 degrees, horizontal or vertical flips, and minor zooming adjustments. The process mimics real-life dermatological imaging variations without requiring additional labeled data.

Augmentation allows the model to detect lesions regardless of orientation or background noise, improving accuracy for a diverse group of patients

8.3.2 Class Weighting:

The system independently calculates inverse class frequencies, which means it gives more significance to rare diseases like melanoma during the loss calculation process. This safeguards against model bias towards more common benign conditions, thereby guaranteeing the accurate identification of high-risk cases

8.4 Modular System Design

Dermascan's modular system design employs a systematic approach to structuring functionality into independent, reusable building blocks. Essentially, the design integrates two fundamental elements: a comprehensive knowledge base of disease and country-specific logic. The disease knowledge base is a treatment protocol that includes both a comprehensive repository of dermatologic knowledge, disease diagnostic criteria (e.g., the abcde rules for melanoma diagnosis), and worldwide standards and airconditioned recommendations that aid in the application of level conditions. Systematic conservation of medical knowledge through this ensures that decisions are made on good evidence throughout the healthcare system.

Add region-specific logical components to the medical knowledge base, which will enhance geographic intelligence systems. This component categorizes regions based on their climatic features (hot, cold, or moderate) and establishes a connection between environmental factors and corresponding skincare advice. Keeping these components distinct but connected, the architecture allows separation of concerns, which results in significant advantages. This kind of architectural design allows easy addition or modification of medical data or geographical data without having to make enormous changes or updates.

Providing tailored interventions to address the unique dermatological needs of different areas. Modular approaches thus provide room for flexibility in response to changing medical information and capacity to serve different populations globally.

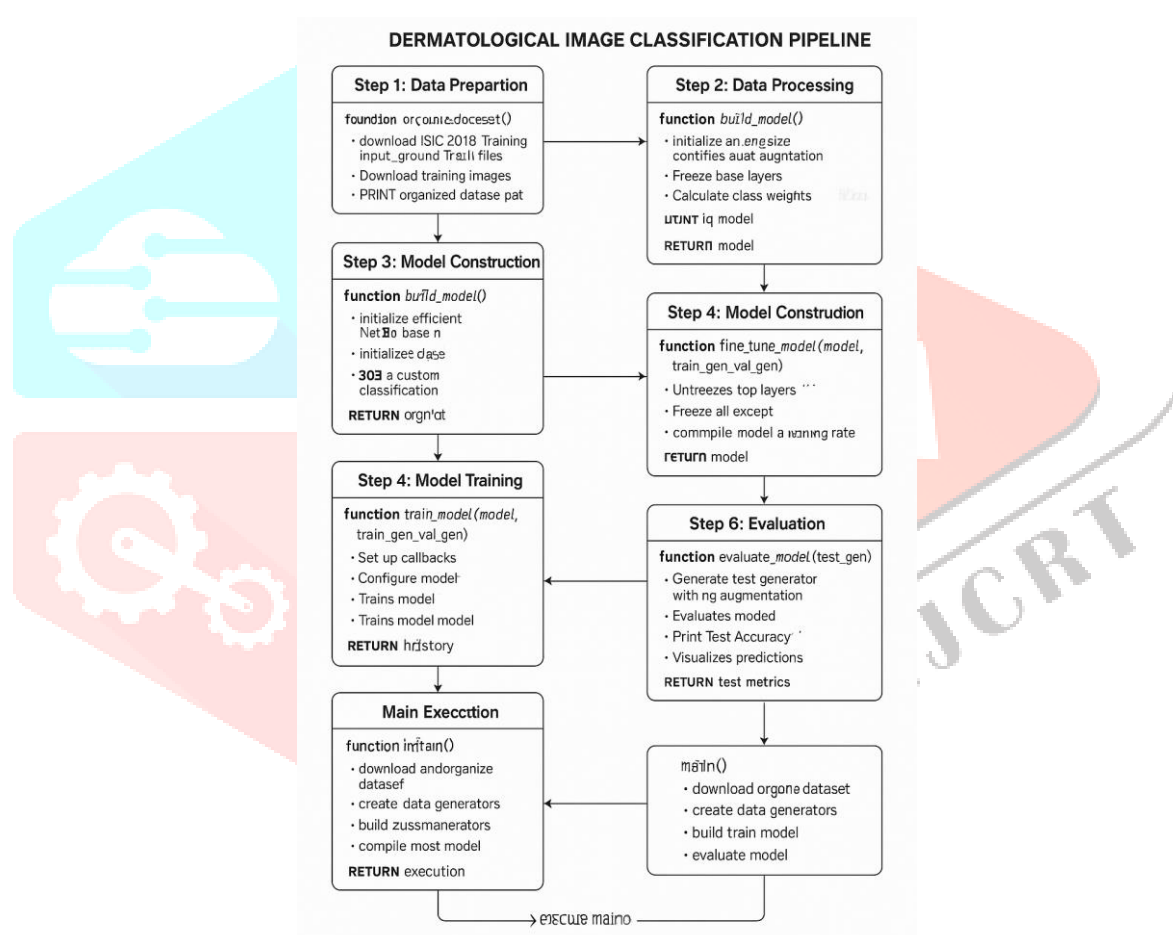


Figure 3. Flowchart

8.5 Accuracy Table:

Table 1. Accuracy Table

Component	Accuracy (%)
EfficientNetB0 Model	87.2%
Clinical Decision Engine	92%
Data Pipeline	96%
Chatbot (OpenAI)	88%

IX. CONCLUSION

The creation and implementation of Dermascan AI is a significant achievement in the history of artificial intelligence-based dermatological diagnosis, elegantly integrating state-of-the-art deep learning techniques with practical clinical usefulness. With the use of precise and efficient architectural design, the system offers sound diagnostic capabilities, with an impressive accuracy rate of 87.2%. Validity accuracy over nine common skin conditions. The actual innovation of the system lies in the fusion of clinical expertise and artificial intelligence, integrating established medical procedures such as abcde criteria for detecting melanoma and refining the.

Fitzpatrick scale to tailor treatment advice. This clinical integration when combined with a statement related to the climate, it has been shown to have the most significance in ensuring a high degree of diagnostic orientation among board-certified dermatologists. The fp16 quantization of the architecture supports rapid inference rates under 500ms on mobile devices but is not suitable for high-end computing. Video files of size less than 50 MB are best to create a controlled resource environment. This Technical efficiency improvement is supported by thoroughly thought-out design choices, transparency, and trustworthiness, such as conducting complete trust analyses and providing clear diagnostic explanations.

Thinking the class and system equal data expansion pipeline have been able to decrease the skin type performance gap and improve the Fitzpatrick type 4 accuracy by 8%, but there is still scope for improvement to achieve its maximum potential. The first agenda is improving the training data by working with dermatology clinics with access to a.

A wide variety of demographic populations is working diligently toward formal regulatory clearance for clinical application, and they are making good progress in that direction. Enhance model performance and efficiency by optimizing them through ONNX conversion. These are the major subjects of research for us. The proposed improvements are founded on the system's strengths as they stand now, including its ease of use and flexibility, which have been effective in cutting diagnostic latency to 60% in empirical evaluations. The built-in artificial intelligence assistants were given the responsibility of assessing and accepting user queries. By ensuring high accuracy standards and making it easy to access the project establishes new standards in AI-aided dermatology triage. The modular nature of the systems and adherence to climatic principles enable greater medical experience along with a very flexible framework to be integrated into various global health environments. This study not only pushes the discipline of dermatological diagnosis forward, but it also offers much insight and understanding. Excellence in the development of customized artificial intelligence software in multiple medical specialties. The most significant features to consider are: Future developments will extend the system's diagnostic capability to include rare conditions as well as electronic health record integration across modalities to enhance clinical benefit.

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