Improving Mobile-Based Early Skin Disease Diagnosis for Melanin-Rich Skins

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Abstract

The use of Computer Vision in skin disease diagnosis has become widespread, particularly with the development of Convolutional Neural Networks (CNNs) in recent years [1]. However, one significant issue persists - the under-representation of skins of colour in datasets, resulting in biased models. This paper presents the design and development of a mobile-based application specifically aimed at detecting skin diseases in individuals with dark skin tones. To achieve this, transfer learning on a pre-trained CNN model (ResNet50v2) [13] was utilized for classification [2], where the model was trained on a diverse dataset obtained from various sources. The dataset was filtered, augmented, and preprocessed to ensure representation of coloured skins. A comprehensive preprocessing pipeline was developed to improve performance on melanin-rich skins, while maintaining the model's robustness for lighter skin tones. Four models were trained for different body parts to narrow down the search and each of the model achieved over 0.8 F1-Score. The mobile application was purposefully developed to allow easy accessibility, enabling early diagnosis of skin diseases by empowering both civilians to monitor their skin health at home and practitioners to enhance their diagnostic capabilities.

1 Introduction

According to the World Health Organisation (WHO), 30% to 70% of the world population has experienced skin diseases. The diagnosis of skin diseases can be challenging to human dermatologists [4] and delays in diagnosis increase risks of complications in patients and can lead to higher medical costs. WHO's study in 2020 also showed that there are only 4.4 dermatologists per a million population in South Africa and it is not that different in other African countries [12], this means African countries can benefit a lot from computer based diagnosis due to shortage of expertise per population than most European and American countries.

The application of Machine Learning in Computer Vision, particularly the development of CNNs, has revolutionized the use of AI in skin disease diagnosis [3]. These tools have shown promise in improving accuracy, reducing cost, and facilitating early diagnosis when made accessible to the wider population.

However, a significant challenge arises with the current computer aided skin disease diagnosis tools, they exhibit bias towards different skin races. Coloured skins, including melanin-rich skins, are often under-represented due to various reasons such as low participation in research, socio-economic reasons, etc, resulting in models that perform poorly when diagnosing people of colour. This bias

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has been shown in various areas as well, from mistaking images of black people for gorillas to misinterpreting blinking in Asians and favouring only white individuals as attractive [5]. Addressing this bias is crucial to ensure equitable and accurate skin disease detection for all populations.

2 Related Work

Skin disease classification using Convolutional Neural Networks (CNNs) has gained significant attention in recent research. CNNs have demonstrated their power in accurately identifying various skin conditions, providing valuable support to patients and dermatologists in diagnosis [1, 3]. Various mobile applications have been developed for this purpose but they do not perform well on Africans and other coloured skins.

One of the primary challenges in training CNNs is the demand for large-scale annotated datasets. Annotated data is crucial for training deep learning models effectively, enabling them to generalize well and achieve high accuracy on unseen data. To address this challenge, researchers have curated publicly available skin disease datasets [7, 8, 9], containing images from diverse populations. However, it has been noted that these datasets often lack adequate representation of skins of colour, particularly melanin-rich skins [5, 6].

The under-representation of diverse skin tones in existing datasets leads to biased models, where diagnostic accuracy is compromised for individuals with dark skin tones. This bias can potentially result in misdiagnosis and disparities in healthcare outcomes. To mitigate these kinds of issues, recent studies have explored various approaches, such as data augmentation [10], transfer learning [2], and domain adaptation [11], to enhance model's performance on limited datasets.

This paper presents the design and development of a novel approach for skin disease classification, with a particular focus on addressing the challenges related to skins of colour. By exploring innovative preprocessing techniques and leveraging transfer learning with a diverse dataset, it aims at creating a robust model capable of accurate diagnosis across different skin tones.

3 Dataset

One of the most significant challenges in training a robust skin disease classification model is dealing with imbalanced datasets, where skins of colour are under-represented. Additionally, when targeting melanin-rich skins, the scarcity of data becomes a critical issue. To address these challenges, different datasets were utilized, including Fitzpatrick17k [7], Dermnet [8], and Diverse Dermatology Images [9].

To ensure that the dataset encompasses a diverse representation of skins, a filtering process was applied to remove most white skin images using YCBCR color ranges, focusing on retaining darker skin tones. The goal was to create a comprehensive dataset that accounts for the wide spectrum of skin tones, with particular emphasis on melanin-rich skins.

For skin disease classification, the following diseases were targeted: Acne Vulgaris, Melanoma, Urticaria, Lichen Planus, Scabies, Folliculitis, Squamous Cell Carcinoma, Rosacea, Basal Cell Carcinoma, Psoriasis, and Allergic Contact Dermatitis. After the filtering and cleaning process, each of these disease categories had 300 images. However, such a small dataset size is insufficient for training a robust model effectively.

To augment the dataset and increase its size, various image augmentation techniques were employed. These techniques included rotation, cropping, flipping, translation, brightness adjustments, contrast adjustments, and shearing. By applying these transformations to the original images, the dataset was significantly expanded, creating a more comprehensive and diverse collection of skin images for training the skin disease classification models.

4 Data Preprocessing and Model Training

Apart from variant skin tones, in the real world, skin disease classification models also encounter a variety of challenges, including images captured from different smartphone cameras with varying qualities and diverse environmental conditions. Failing to address these factors critically can lead to

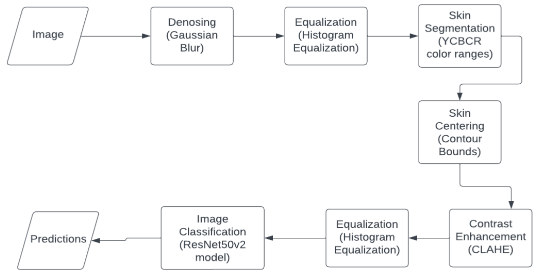

Figure 1: Image Processing Pipeline.

suboptimal model performance in real-world scenarios. To ensure the robustness of the models and to minimize the impact of skin tone variations during classification, a comprehensive data pre-processing pipeline was employed that prepares the images before they are fed into the model, while preserving their essential features.

Figure 2: Raw Image.

Preprocessing

Figure 3: Processed Image.

4.1 Preprocessing

The images undergo a series of preprocessing techniques to optimize them for the model's input. These steps involve common operations such as resizing and normalization to achieve consistency in image dimensions and pixel values across the dataset. Specific techniques tailored to the task were also employed to enhance the performance and robustness of the models

Firstly, images undergo denoising using **Gaussian Blur** [14] to reduce the influence of less important features in the image, enhancing the image's overall clarity. Next, **Histogram Equalization** [15] is applied to equalize the image, balancing its features and skin tones while also enhancing contrast, which is particularly beneficial for skin segmentation purposes.

Skin segmentation is a critical step in this pre-processing pipeline, as it helps in isolating the skin region from the rest of the image. The **YCBCR color space** [16] is utilized to identify and remove parts of the image whose pixel values do not fall within the skin colour range. This process ensures that the subsequent analysis focuses solely on the relevant skin regions. To further refine the segmentation, the skin part is **centred** within bounding boxes.

Subsequently, **Contrast Limited Adaptive Histogram Equalization (CLAHE)** [17] is employed to emphasize the skin lesions' details in the image. CLAHE is particularly effective in enhancing localized contrast, making it an ideal choice for highlighting skin abnormalities. Furthermore, to fine-tune the contrast, another round of **histogram equalization** is followed up.

The combination of these preprocessing techniques results in an optimized and refined image that emphasizes the skin lesions' critical features. By intelligently enhancing contrast and centring the skin regions, the pre-processed images are well-prepared for subsequent model training and skin disease classification. This pipeline aims at minimizing the impact of noise and irrelevant features including skin tone in the images while maximizing the visibility of skin lesions.

Table 1: Models Metrics - *All the models are based on ResNet50v2 with a learning rate of 0.0001 and batch size of 64*

Model	Accuracy	F1 Score	Epochs
Face	81%	0.80	30
Arms & Hands	77%	0.75	50
Upper Body	83%	0.81	50
Legs & Feet	76%	0.75	50

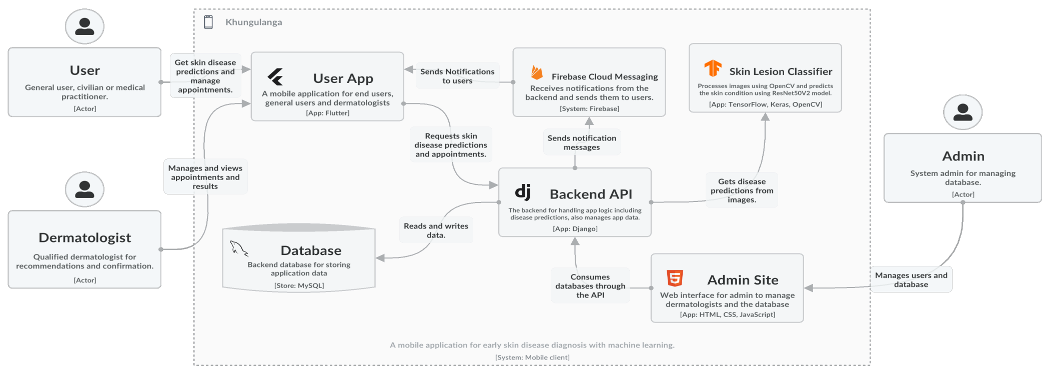

Figure 4: Application Architecture.

4.2 Model Training

By utilising the resources offered by Google Colab, models were trained using transfer learning to fine-tune ResNet50v2 (CNN model pre-trained on imagenet, which has shown to offer better performance in skin disease classification). Through extensive experimentation and fine-tuning, the models achieved impressive accuracy in classifying various skin conditions. The transfer learning approach leveraged the rich feature representations learned by ResNet50v2 on the large-scale ImageNet dataset, allowing the models to benefit from this knowledge and adapt it to the specific task of skin disease classification.

A total of four models were trained as shown in table 1. Each of the models targeted diseases that are common for the corresponding body part. This helped in narrowing down the diagnosis by eliminating unlikely diseases, for example scabies are more to attack the limbs than the face.

5 Application Architecture

The application as shown in figure 2 consists of a Django back-end API that hosts the models and a Flutter front-end mobile application to be used by the general public for diagnosis and authorized dermatologist to offer recommendations and confirm diagnosis, and manage appointments with skin disease patients for further examinations.

6 Conclusion

In conclusion, this paper contributes to bridging the gap in skin disease classification for dark-skinned individuals, improving healthcare outcomes, and promoting early detection and treatment. By implementing a comprehensive data pre-processing pipeline, the impact of noise and irrelevant features, including skin tone variations was minimized, while maximizing the visibility of skin lesions.. Future research endeavors may further explore the application's potential in real-world settings and extend the model's capabilities to include additional skin conditions and demographic variations. They can also improve on the parameters to include other symptoms during diagnosis and work on explainable models.

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