

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

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## Under-representation of Melanin-Rich Skins

Current Computer-Aided Skin Disease diagnosis tools, 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 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 [1]. Addressing this bias is crucial to ensure equitable and accurate skin disease detection for all populations.

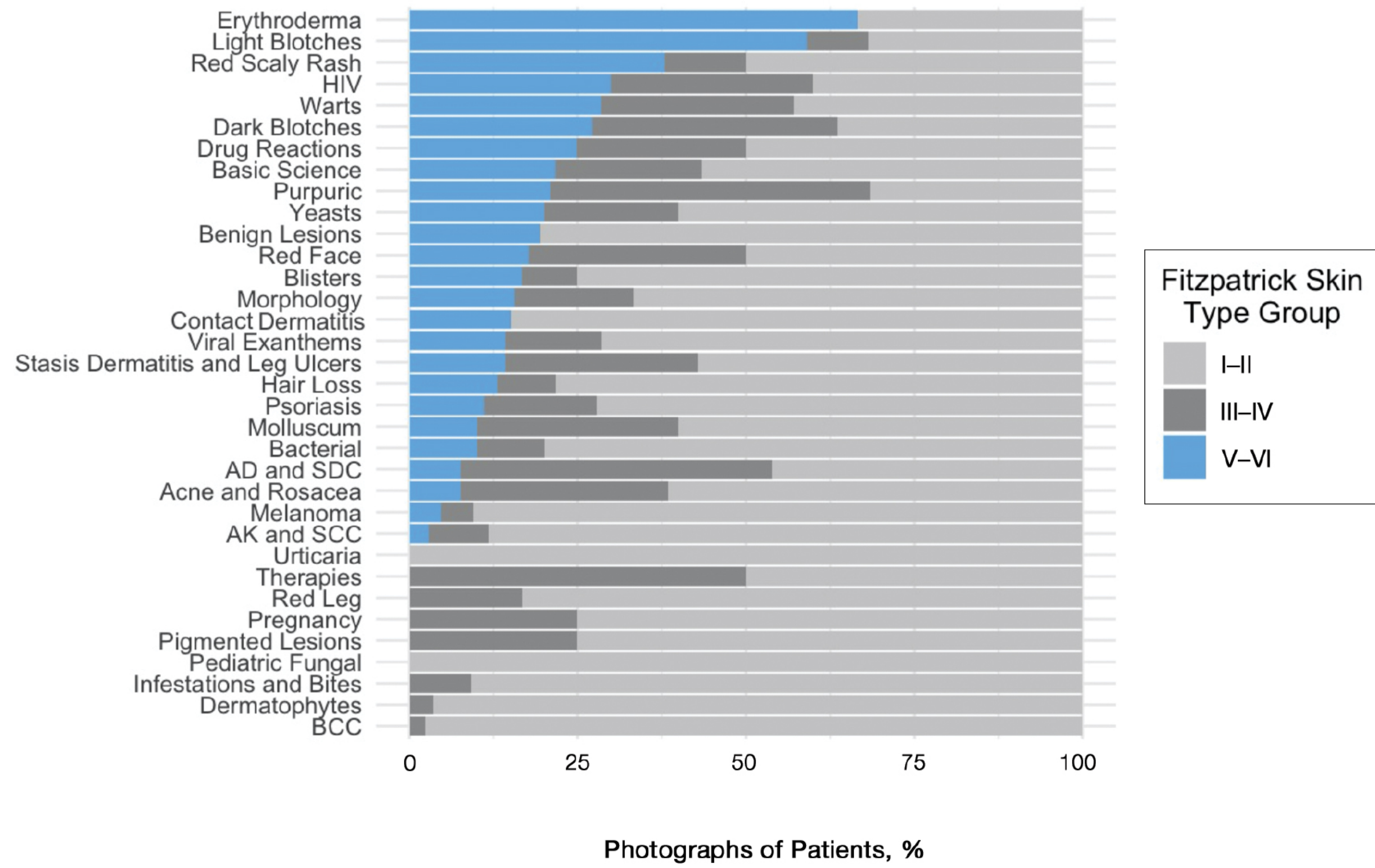


Figure 1. A percentage of images of Fitzpatrick skin group per skin disease

Public skin image datasets that are used to train algorithms to detect skin problems don't include enough information about skin tone. And within the datasets where skin tone information is available, only a very small number of images are of darker skin – so algorithms built using these datasets do not perform well for people who are not white.[2]

## Application Architecture

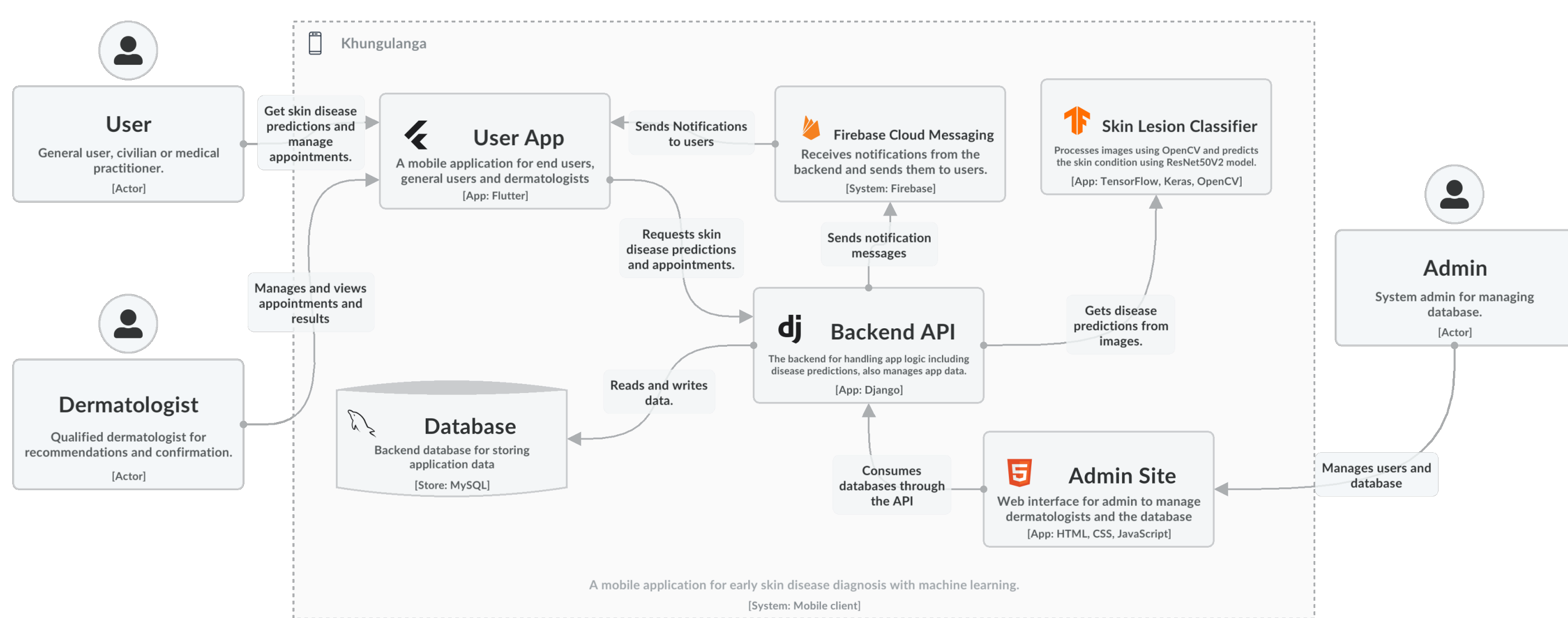


Figure 2. Application Architecture.

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.

## Data Collection

Due to the scarcity of darker skin images, dataset from various sources can be utilized with filtering to obtain a balanced diverse representation of skins. In this research datasets from the following sources were used:

- Fitzpatrick17k
- Dermnet
- Diverse Dermatology Images

To achieve the goal of improving performance melanin-rich skins a filtering process was applied to remove most white skin images using YcbCr color ranges, focusing on retaining darker skin tones. This resulted in a few images of 300 per class which were then augmented.

## Targeted Skin Diseases

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.

## Data Preprocessing

To ensure the robustness of the models in different environments and cameras, 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.

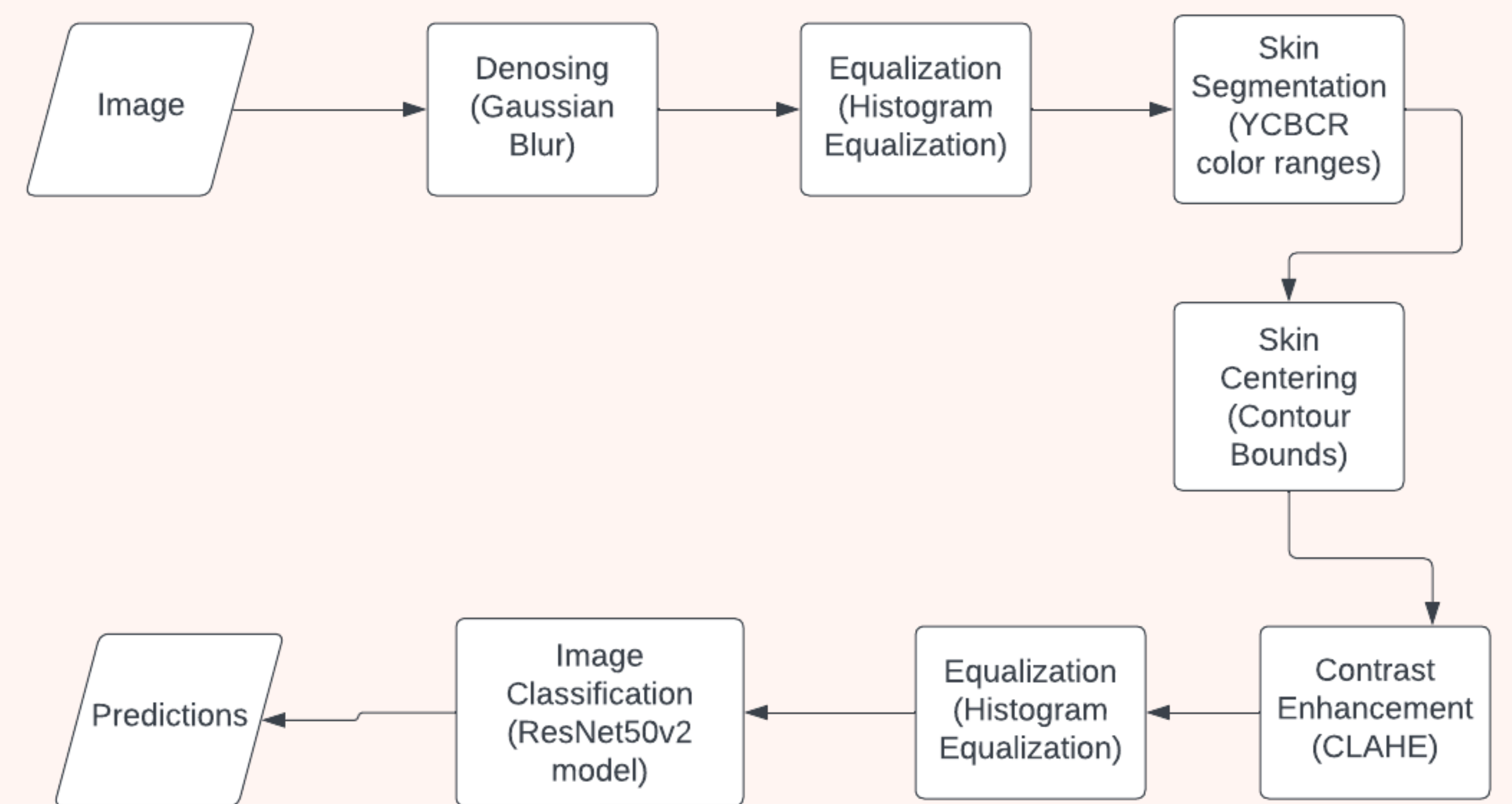


Figure 3. Image preprocessing pipeline



Figure 4. Raw Image.

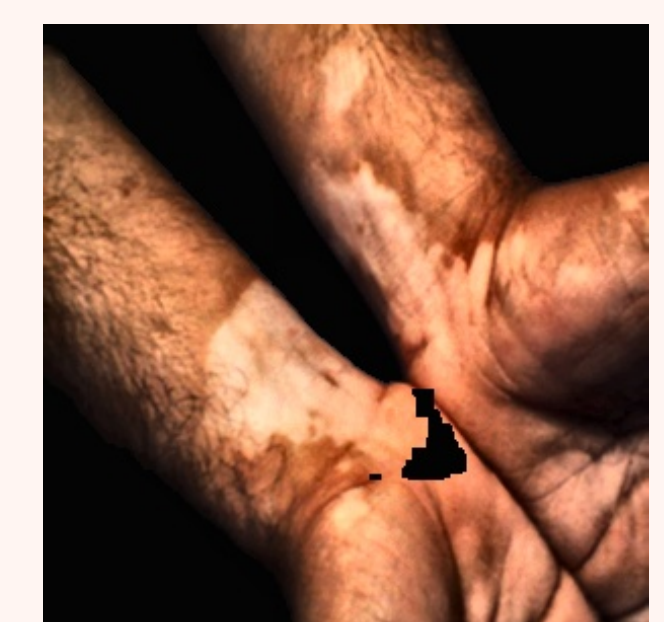


Figure 5. Processed Image.

## Model Training

A total of four models were trained, 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.

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

## 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, and improve the preprocessing by including techniques like hair-removal. They can also improve on the parameters to include other symptoms during diagnosis and work on explainable models.

## References

- [1] Distribution of skin type diversity in photographs from the AAD diversity in medicine poster contest, 2023.
- [2] DermNet New Zealand Trust. Dermatology images, n.d.
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- [4] Stanford University. Diverse dermatology images, n.d.
- [5] Nicole Wetsman. Public skin image datasets lacking diverse skin tone information, November 9 2021.
- [6] Sophia Wong. Ai-driven dermatology could leave dark-skinned patients behind, 8 2018.