Skin Disease Diagnosis on Darker Skin Tones

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INTRODUCTION/ABSTRACT

Our project harnesses AI to accurately identify skin diseases in individuals with darker skin tones, addressing existing racial disparities in AI recognition that often lead to misdiagnosis. By sourcing a diverse image dataset from reputable sub-Saharan African hospitals and employing advanced image processing techniques such as Mask RCNN and Superpixel, we optimize images for input into our sophisticated AI model, specifically designed for skin disease identification. Our ultimate objective is to significantly enhance diagnosis accuracy, reduce waiting times, and expedite treatments, contributing to improved healthcare outcomes for individuals with darker skin tones and promoting a more inclusive and equitable approach to medical AI applications.

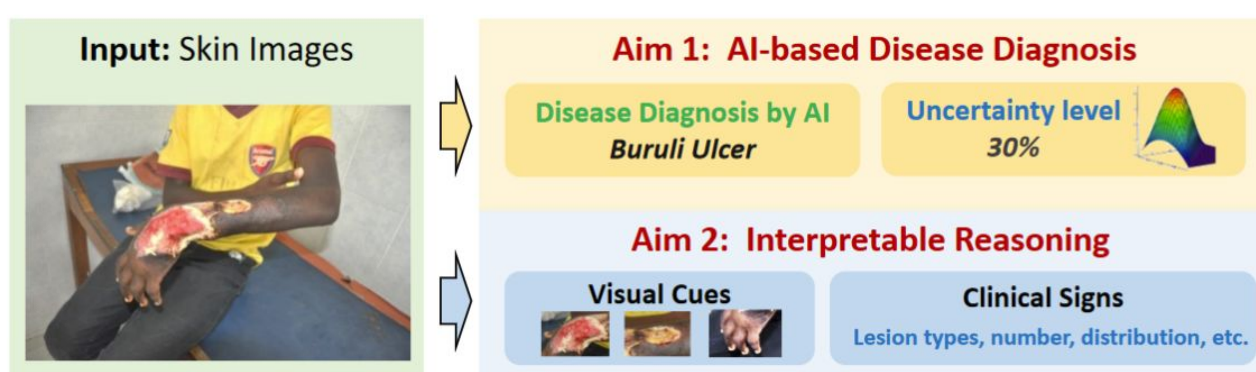


Figure 1. Skin Disease Diagnosis Overview

PROBLEM STATEMENT AND OBJECTIVE

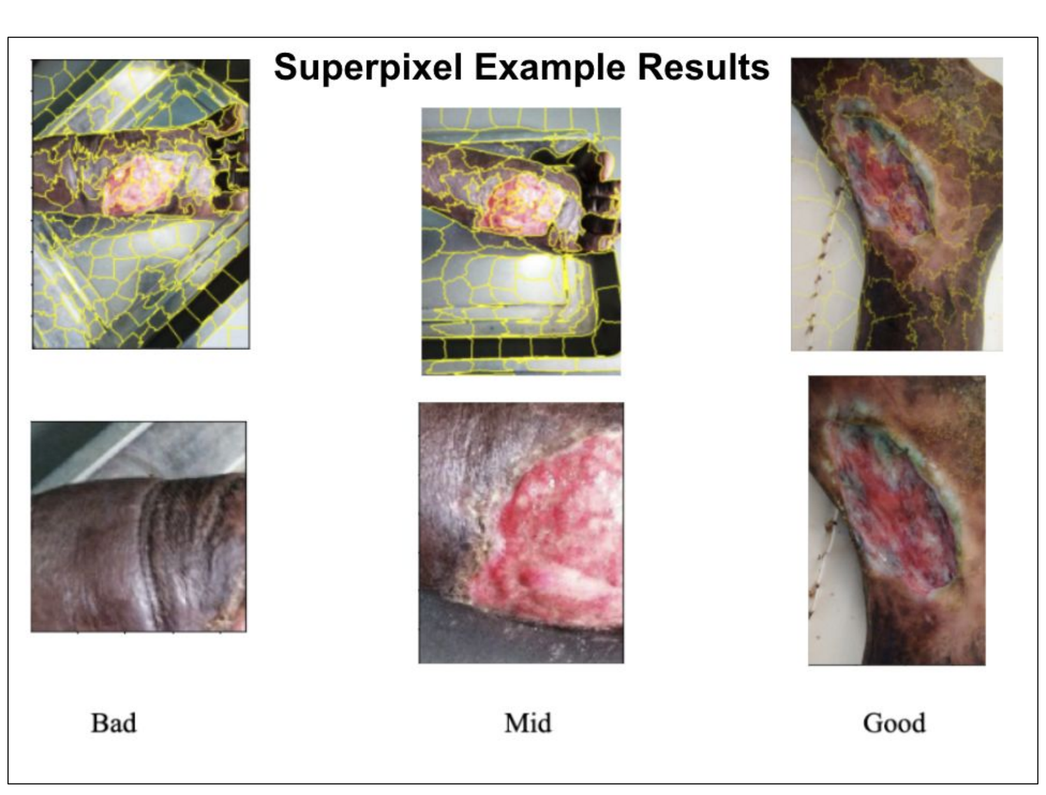
Central Problem: AI recognition systems have shown racial disparities in identifying skin diseases, which can lead to misdiagnosis and inadequate treatment for people with darker skin tones.

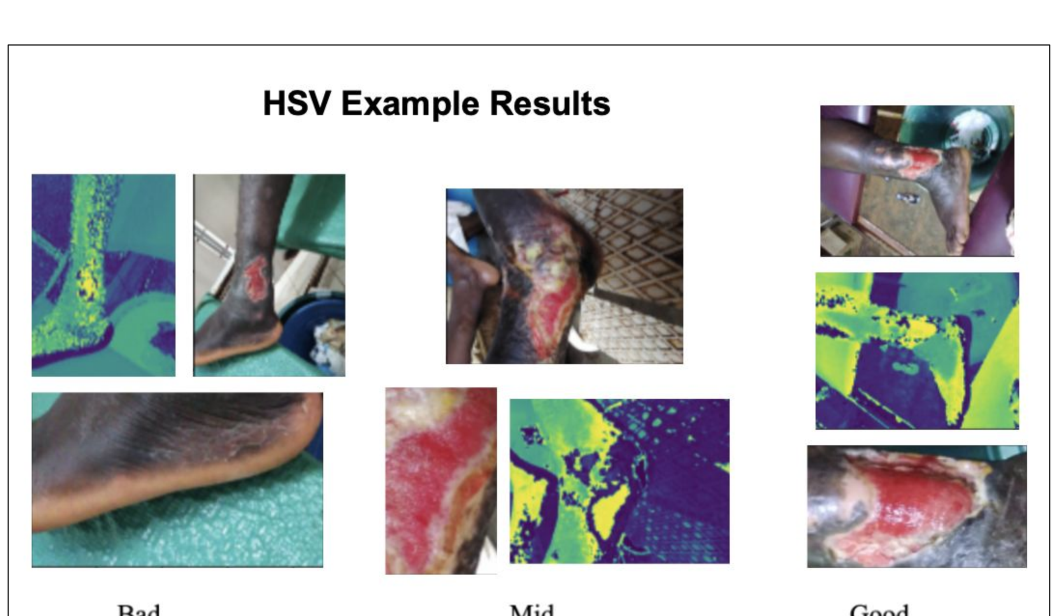
- High cost of medical care
- Diagnosis wait time → delayed diagnosis and treatment
- Bias and inadequate research on skin diseases in darker skin tones compared to white skin tones

Objective:

- Skin diseases focused on: Buruli Ulcer, Yaws, Mycetoma, Leprosy, Scabies in sub-Saharan African dataset
- Enhanced images using cropping, filtering, boundary boxes, and masks through Mask RCNN and Superpixel
- Goal to improve accuracy and reduce diagnosis wait times
- Aim to provide timely and effective treatment for skin diseases

METHODS/APPROACH





For this project, we ran three variations of region of interest detecting code to see which performed the best.

First we ran Mask RCNN, then we looked for the most red superpixel in the images, and finally we looked for the area with the most hue. To the left are examples of each rating (good, mid, and bad).

We rated these manually to see if the diseased area had been cropped to or had a mask adorned to it and if it had got the whole disease. If the crop/mask got both, then the result was rated good. If the crop/mask only got a portion of the disease then it got mid. Finally, if the crop/mask did not get the disease, then it got a bad rating.

The Mask RCNN code uses pytorch machine learning to identify region of interests.

The superpixel code compares the Euclidean distance from each superpixel to see which has the smallest distance from pure red.

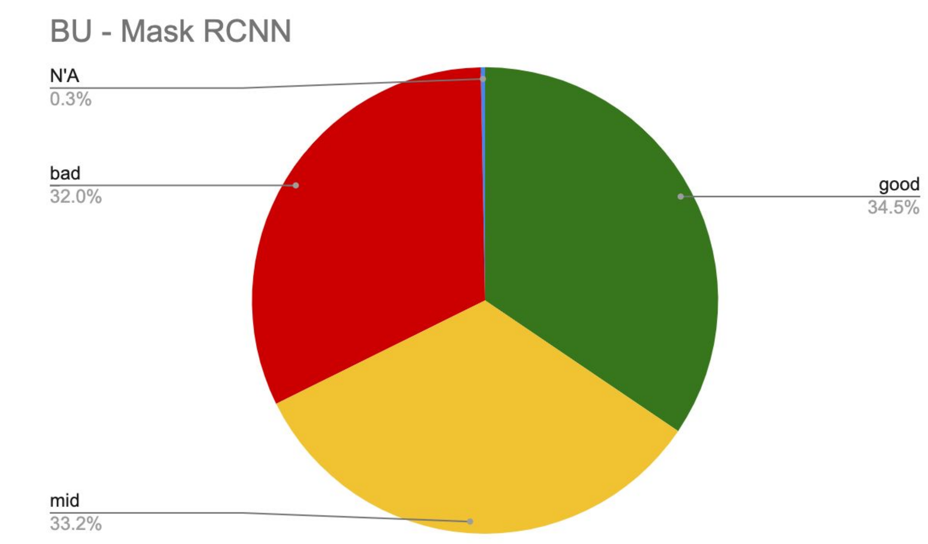
Lastly, the hue code identifies the superpixel with highest hue value as red is both the lowest and highest hue value.

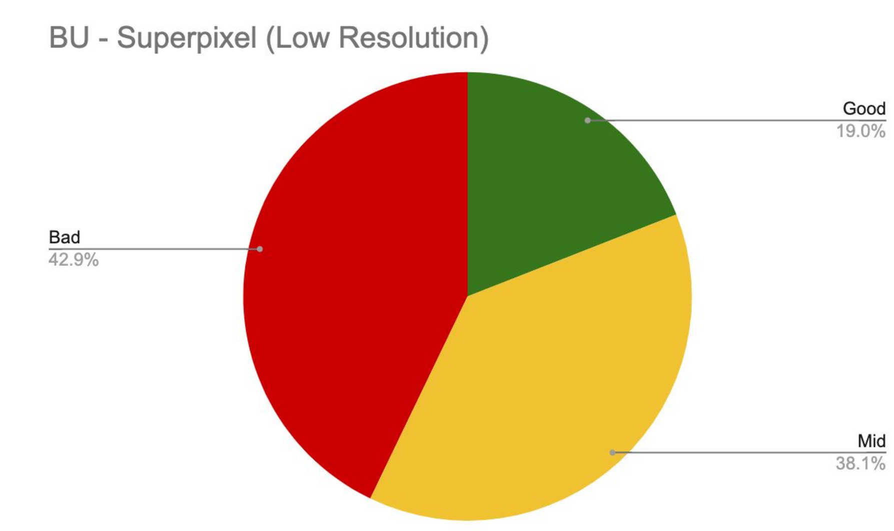
RESULTS

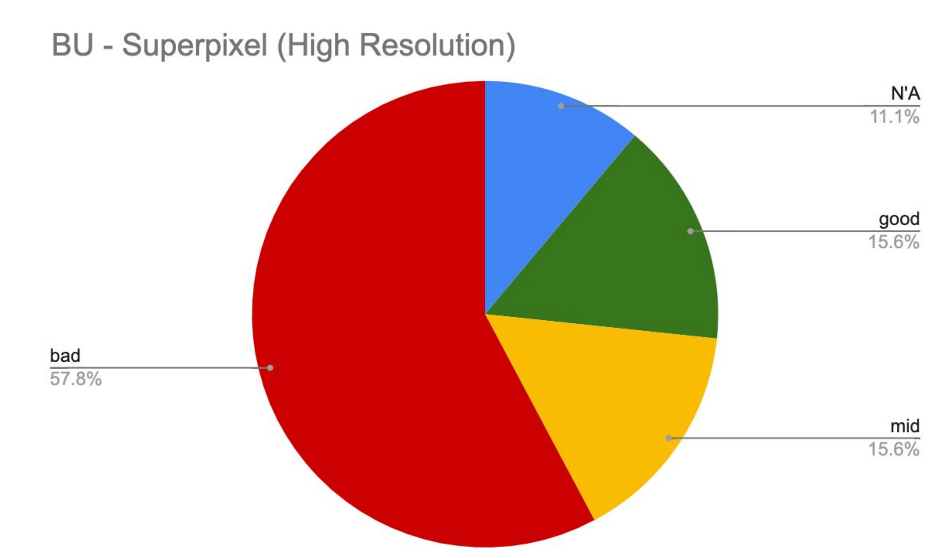
Although we had good results for Yaws and Leprosy using Mask RCNN, the results for Buruli Ulcer, as indicated on the right, were not as high.

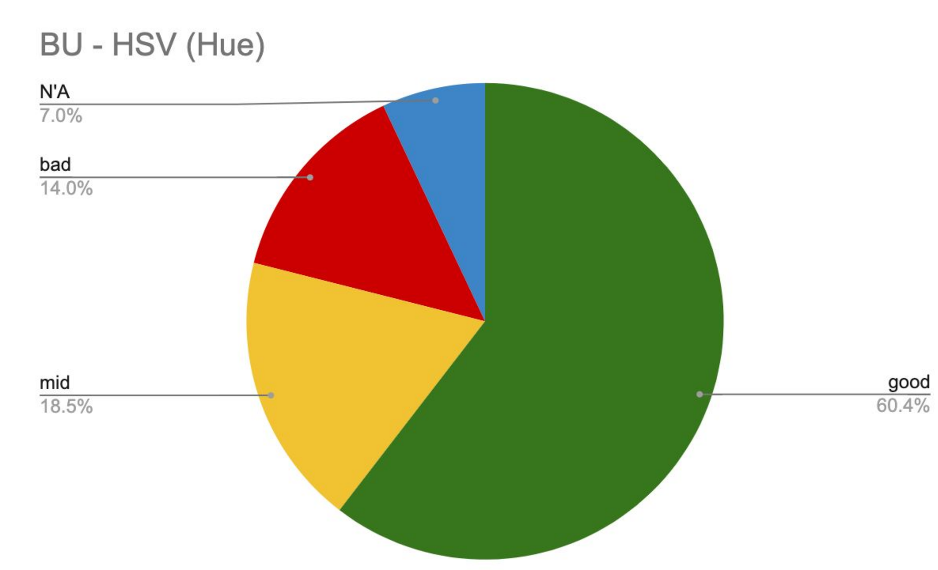
Therefore, we had tested two other codes to better the results for Buruli Ulcer. SInce Buruli Ulcer is a very visual disease, we decided to identify the superpixels associated with the disease. The color that is often indicative of Buruli Ulcer is red so we tested the good results from Mask RCNN using the superpixel code instead.

The results we got were less than satisfactory and even worse when the pictures were higher resolution. We concluded that although the code does search for the area with the "reddest" value, it does not leave out the green and blue values making brown and white superpixels just as likely to get picked as visually red ones.









CONCLUSIONS/DISCUSSIONS/FUTURE WORK

Results from Mask RCNN with Yaws and Leprosy were satisfactory as majority of the pictures used had been given a good rating. Due to the conflicting results with Buruli Ulcer, more work can be done to improve finding the region of interest. Nevertheless, the current dataset from these runs can be used to gauge a learning model for future work. The images that provided good results from our criteria can then be utilized in the diagnosis stage.

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