Fairness of Classifiers Across Skin Tones in Dermatology

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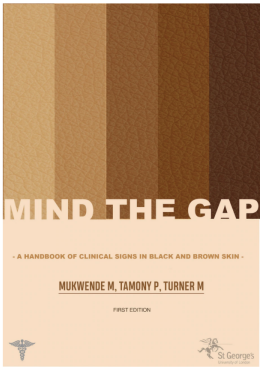
Background

Disparities with respect to ethnicity exist in dermatology, as in other medical fields

- In black population, melanoma is often diagnosed at an advanced stage with deeper tumors [MSL+17, WEK+11].
- 5 year survival rates for acral lentiginous melanoma (ALM) is 82.6% in whites, but only 77.2% in blacks [MCH15].
- The paucity of images of skin manifestations of COVID-19 in patients with darker skin is a problem, because it may make identification of COVID-19 presenting with cutaneous manifestations more difficult for both dermatologists and the public. [LJZ+20]

Machine learning systems may place certain groups of people at a systematic disadvantage due to dataset bias [BS16].



The cover of the "Mind the Gap" handbook, written by Malone Mukwende, with two of his lecturers, Peter Tamony and Margot Turner.

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Research Questions

1. Are standard **dermatology image datasets** used in ML tasks **biased with respect to skin tone**? Can we quantify this?
2. If so, does the dataset bias lead to **unequal performance** of downstream disease classification?

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Related Work

- Skin disease diagnosis using machine learning
  1. Benchmark model for melanoma diagnosis outperforms trained dermatologists [CNP+16]
  2. ISIC challenges (https://www.isic-archive.com/)
- Predictive inequity in computer vision with respect to skin type
  1. Automated face image analysis for gender classification [BG18]
  2. Pedestrian detection systems [WHM19]

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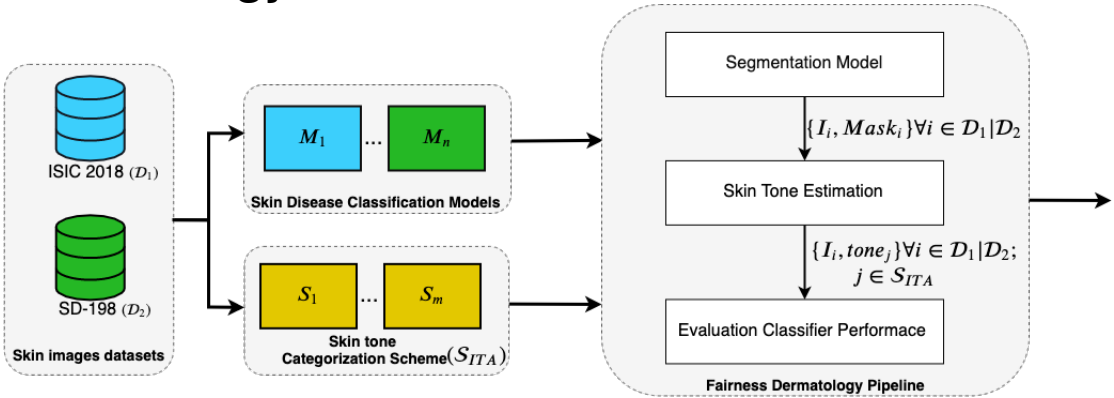
Methodology



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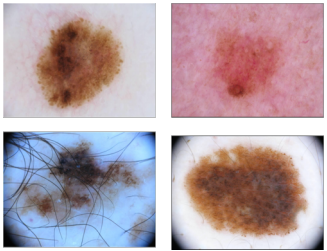
Datasets

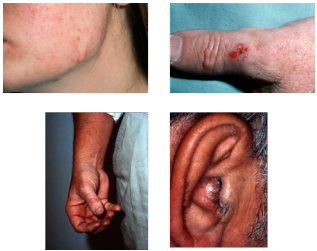
ISIC 2018

- 10015 dermoscopic images
- 7 disease classes
- 2594 images with ground truth segmentation masks for diseased area



SD-198

- 6548 clinical images
- 198 disease classes
- No segmentation data



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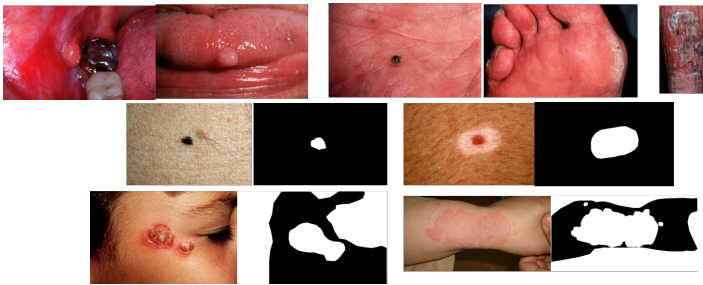
Pre-processing: Creating SD-136 Dataset

1. Manually remove:
   - Classes with images containing no observable non-diseased skin.
   - Images of palms, soles of the feet, inside of the mouth.
   - E.g., Fibroma, Arsenical Keratosis, Stasis Ulcer
   - Classes reduced from 198 to 136: SD-136
2. Manually segment a subset of 343 images to create segmentation masks.
3. Segment regions of non-diseased skin from other regions.



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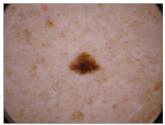
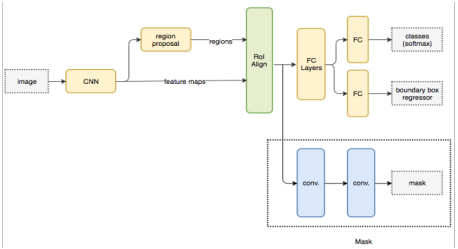
Segmentation to Obtain Non-Diseased Region

1. Finetune Mask R-CNN model [HGDG17]
   - Adjust pretrained classifier with a FastRCNNPredictor with 2 classes (background and mask)
   - Adjust mask predictor with new MaskRCNNPredictor with 2 classes and 512 hidden neurons
2. Further apply thresholding techniques on predicted grayscale mask including contour extraction for ISIC2018 and grid search for optimal binary thresholding for SD-136





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Skin Tone Metric of Non-Diseased Region

1. Given non-diseased pixels, characterize them with a skin tone metric
   1. Use individual typology angle (ITA) [WWdPR15], Highly correlated with melanin index
   2. $\text{ITA} = \tan^{-1}\left(\frac{L-50}{b}\right) \times \frac{180}{\pi}$ Where L is luminance and b quantifies amount of yellow.
   3. Use pixels with L and b values within 1 standard deviation to deal with outliers.
2. Bin into categories [CSD$^+$15]

ITA Range	Skin Tone Category	Abbreviation
ITA $> 55^\circ$	Very Light	very_lt
$48^\circ <$ ITA $\leq 55^\circ$	Light 2	lt2
$41^\circ <$ ITA $\leq 48^\circ$	Light 1	lt1
$34.5^\circ <$ ITA $\leq 41^\circ$	Intermediate 2	int2
$28^\circ <$ ITA $\leq 34.5^\circ$	Intermediate 1	int1
$19^\circ <$ ITA $\leq 28^\circ$	Tanned 2	tan2
$10^\circ <$ ITA $\leq 19^\circ$	Tanned 1	tan1
ITA $\leq 10^\circ$	Dark	dark

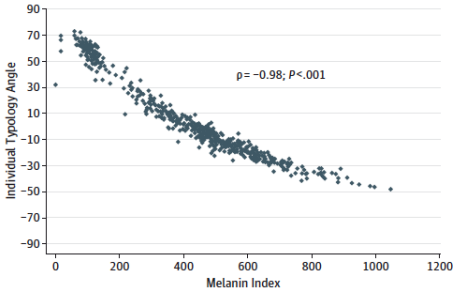

Figure from [WWdPR15].

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Classification of Skin Disease

We replicated state-of-the-art skin disease classification neural networks from ISIC2018:

1. Finetune Densenet 201 model pretrained on ImageNet [HLVDMW17].
2. Regularization methods: Dropout and early stopping.

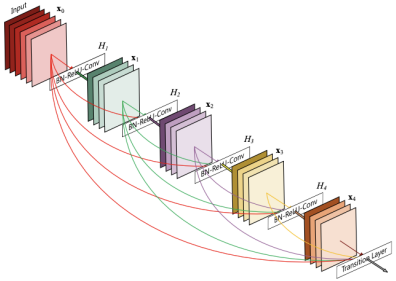

Figure from [HLVDMW17]

Overall accuracy on validation data

- ISIC2018: balanced accuracy 0.884 (benchmark model 0.885)
- SD-136: accuracy score 0.567 (benchmark model 0.52)

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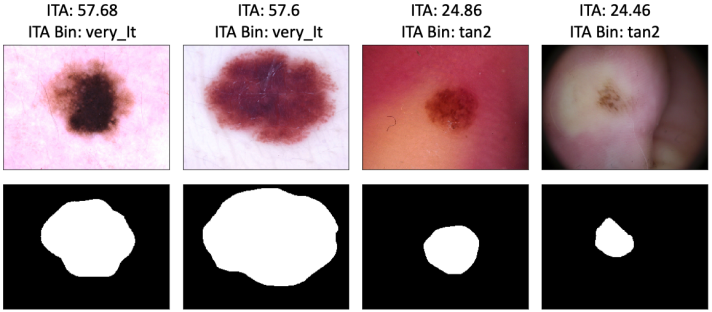
Results

Metrics for segmentation on ISIC 2018

The Mask R-CNN model yields an accuracy of **0.956**, a false negative rate of **0.024**, and a mean absolute error in ITA computation of **0.428** degrees. [KOC+19]



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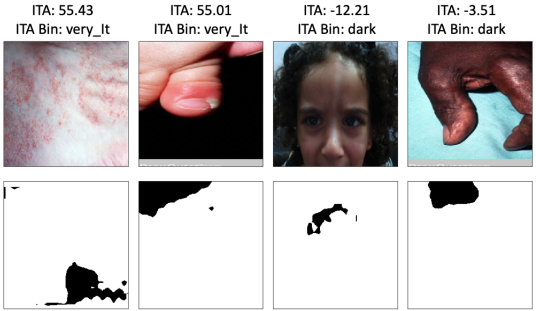
Results (Cont.)

Metrics for segmentation on SD-136

The segmentation model on the SD-136 dataset yield an accuracy of **0.802**, a false negative rate of **0.076**, and a mean absolute error in ITA computation of **3.572** degrees. [KOC+19]



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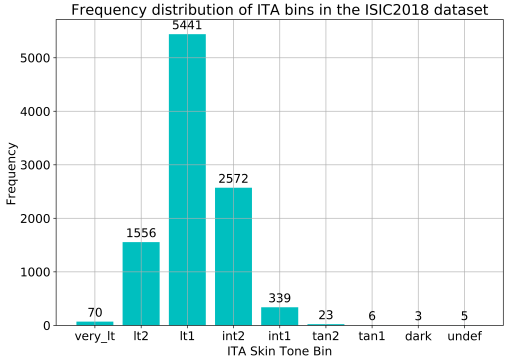
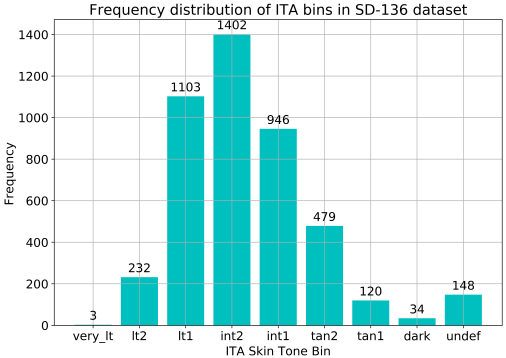
Results (Cont.)

Skin Tone Distribution

There is underrepresentation of darker skin tones in both datasets





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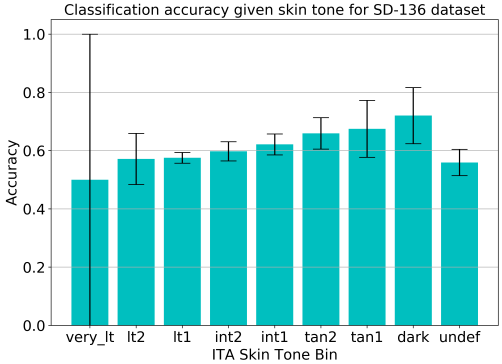
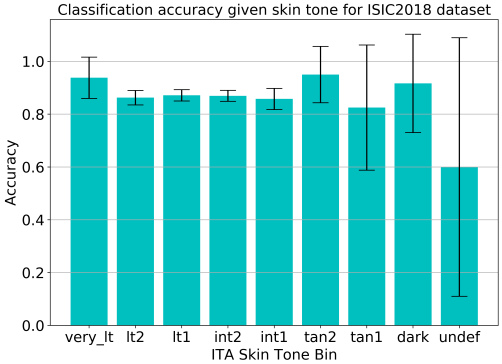
Results (cont.)

Accuracy by Skin Tone

There is no statistically significant pattern of unequal performance by skin tone





Conclusions & Future Work

- The two skin disease datasets are biased towards lighter skin with majority of the samples between ITA values $[34.5°, 48°]$.
- The bias in the datasets does not seem to affect the classification results for each skin tone category. Caveat: this conclusion is from datasets with significantly fewer dark-skinned samples.

We're currently working on:

1. Creation of datasets with more evenly distributed samples by skin tone categories.
2. Creation of ground truth segmentation masks for the entire SD-198 dataset.
3. Implementation of better segmentation models for clinical images.

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Asante, Thanks, Gracias!

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