

Optimized Image Classification Models on Dark Skin Lesions

Problem Statement

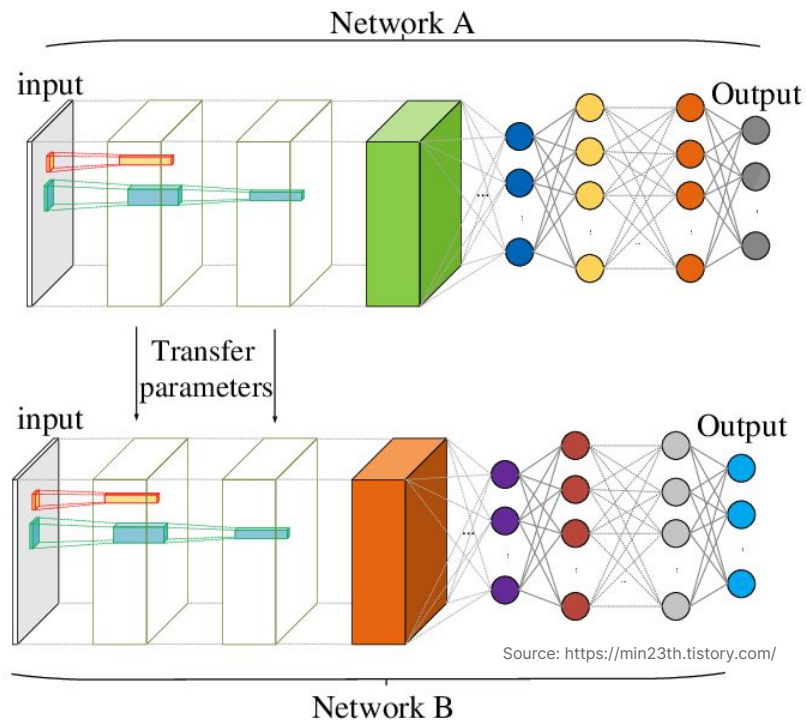
- ▣ Skin diseases
 - 1 in 4 Americans impacted by skin diseases
 - \$75B USD spent annually
 - Only 1 in 3 Americans with skin diseases seen by a dermatologist
- ▣ Underserved groups, including ethnic minorities, have poorer melanoma and nonmelanoma skin cancer outcomes. This is mostly due to lack of adequate awareness and general apathy towards proactive care. Providing non-intrusive early triage could help spur them to action (seeing a dermatologist).

Background Research

- Previous research demonstrates that images of skin lesions on dark skin are a significant problem for image classifiers and publishes datasets to address that.
 - Uses various techniques to correct that bias within a single model
 - Pruning parts of the model that would only work for one skin type or another
 - Segmenting skin disease images beforehand
 - Resampling dataset to be more balanced

Materials

- ▣ Trained on Kaggle Notebooks platform
- ▣ Used Python, TensorFlow, and Keras



Design Execution

- ▣ **Independent variable:** whether or not an image modification algorithm is used
- ▣ **Dependent variable:** ROC-AUC metric
- ▣ **Controls:** dataset subsets used for trials
- ▣ **Images split by their measurement on Fitzpatrick scale**
 - Fitzpatrick type values 1-3 were placed in Group 1 & 4-6 in Group 2
- ▣ **Optimized image modification layers:**
 - focused on Group 2, fine-tuned image layers to maximize accuracy

Performed hyper-parameter optimization on the image modification layers using Optuna

Created 3 subsets for cross-validating the data

Ran 24 trials, models trained and tested for each subset

Used a model based on EfficientNet-B1

Modification Layers Deployed

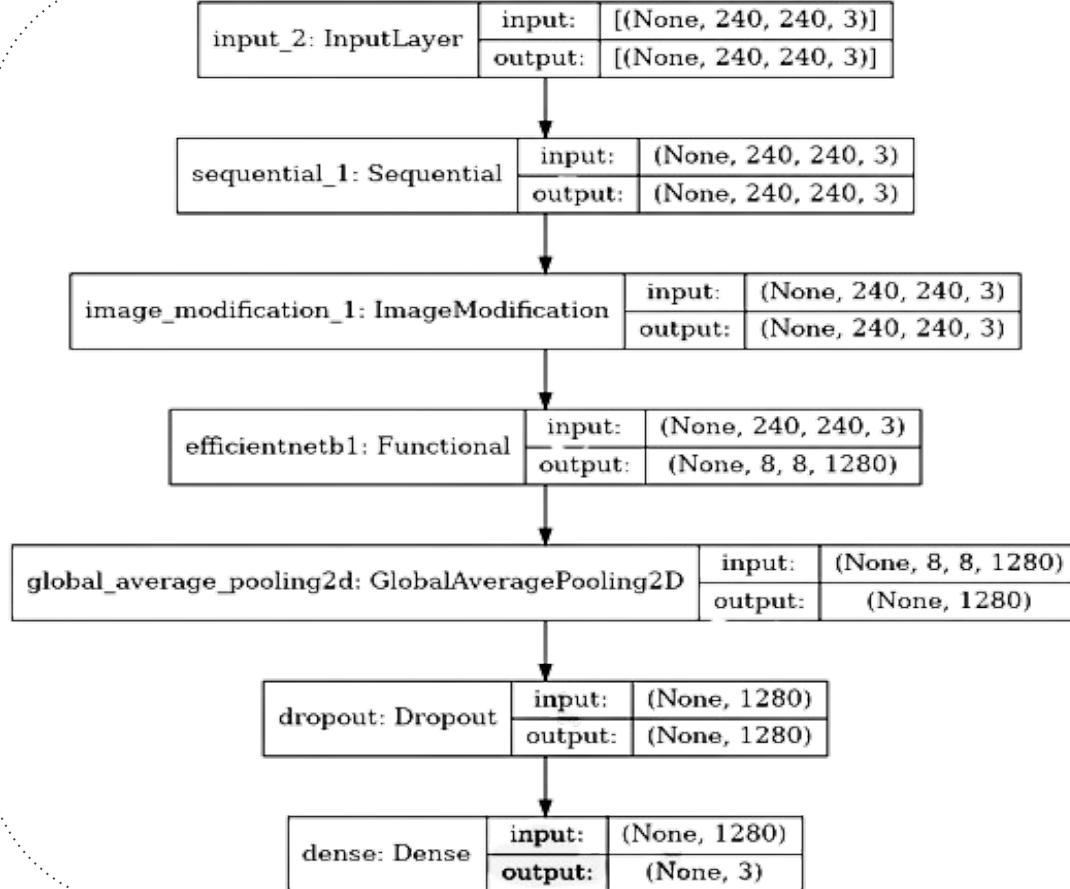


Image Modification Layer

Contrast Modifier

Brightness Modifier

Image Saturation Modifier

Findings

	Control	With Image Modifications
Trial 0	0.791	0.907
Trial 1	0.818	0.913
Trial 2	0.832	0.852
Average	0.814	0.891
Standard Deviation	0.021	0.034

Dataset

- Fitzpatrick 17k dataset has 17000 images from 2 datasets
- Fitzpatrick describes skin tones: 1 lightest & 6 darkest
- Skin type assessed through human annotation
- It has three classifications:
 - Non-neoplastic growth
(growth or changes in tissue not caused by abnormal cell growth)
 - Benign growth
(non-cancerous growths or changes in tissue)
 - Malignant growth
(cancerous growths or changes in tissue)

	Non-Neoplastic	Benign	Malignant
# Images	12,080	2,234	2,263
Type 1	17.0%	19.9%	20.2%
Type 2	28.1%	30.0%	32.8%
Type 3	19.7%	21.2%	20.2%
Type 4	17.5%	16.4%	13.3%
Type 5	10.1%	7.1%	6.5%
Type 6	4.4%	2.0%	2.7%
Unknown	3.2%	3.3%	4.6%

Table 1. Distribution of skin conditions in *Fitzpatrick 17k* by Fitzpatrick skin type and high level skin condition categorization.

The Fitzpatrick Scale



TYPE I

Light,
pale white

Always burns,
never tans



TYPE II

White, fair

Usually burns,
tans with difficulty



TYPE III

Medium,
white to olive

Sometimes mild burn,
gradually tans to olive



TYPE IV

Olive,
moderate brown

Rarely burns, tans with
ease to a moderate brown



TYPE V

Brown,
dark brown

Very rarely burns,
tans very easily



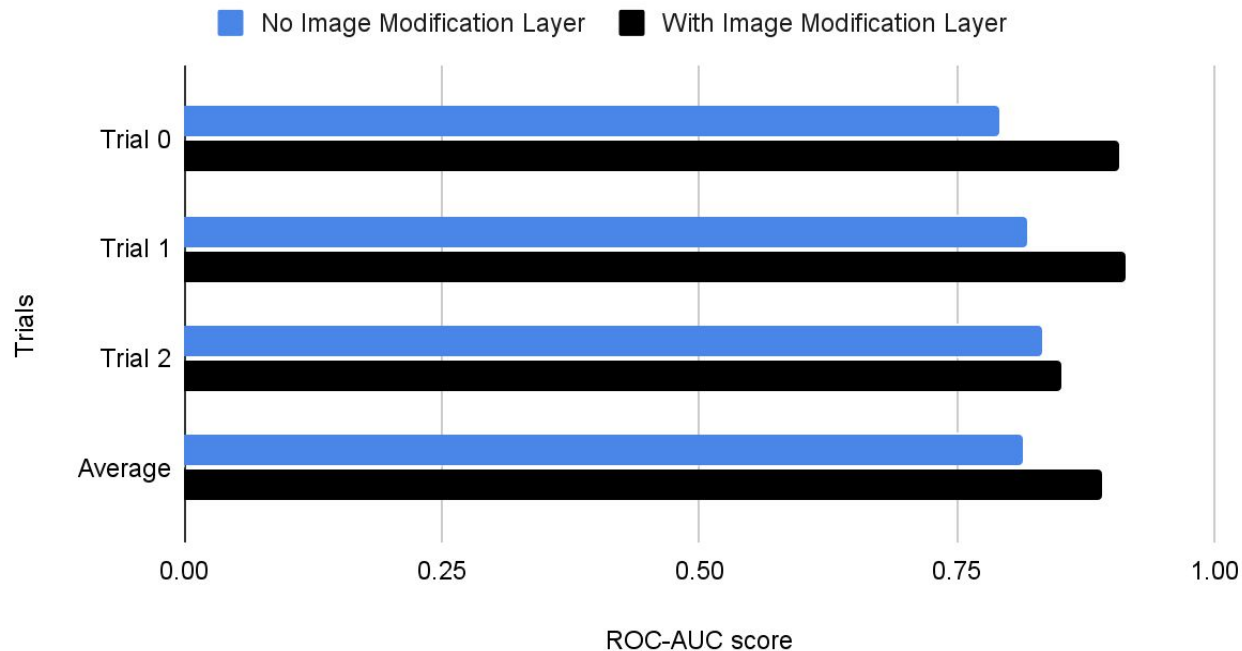
TYPE VI

Black, very dark
brown to black

Never burns, tans very
easily, deeply pigmented

Performance Overview

Results



This graph shows a comparison of the performance of the models depending on whether or not there is an image modification layer.

Conclusions

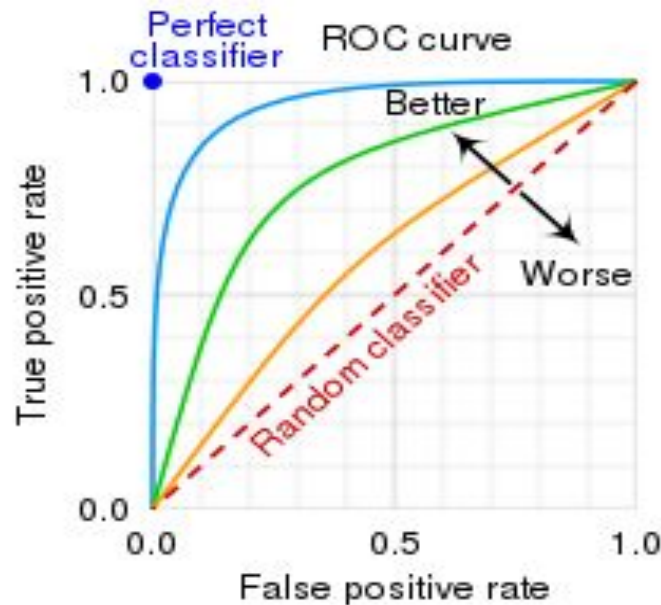
- ▣ Image classifier model accuracy can be enhanced by segmenting data based on visual aspects and using image modification layers
 - Multiple similar models can be combined to create highly accurate ensemble-based classifications tailored for an individual.
- ▣ Can be used by medical professionals with limited experience with certain disease pairs, especially in diverse countries where training materials are comparatively homogeneous.

Results

- ▣ This novel approach of optimizing image preprocessing is an effective way to increase model performance for datasets with similar types of images.

7.7%

increase in ROC-AUC score,
on average



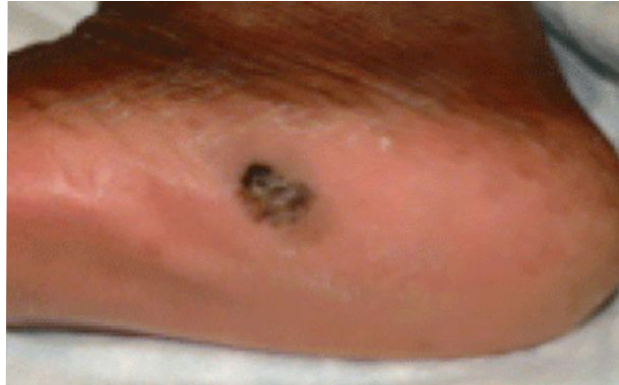
Skin Cancer on Lighter Skin Tones

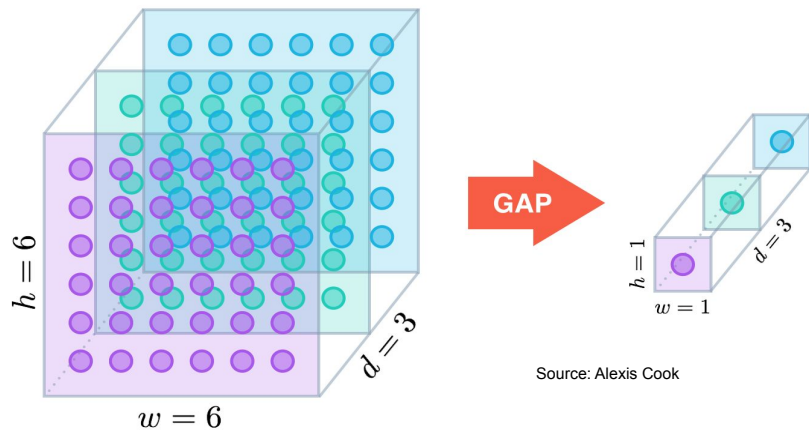


Image from Healthline

ADAM

Skin Cancer on Darker Skin Tones





Source: Alexis Cook

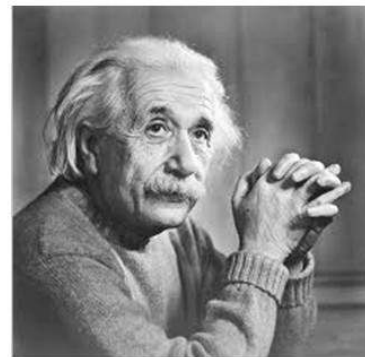
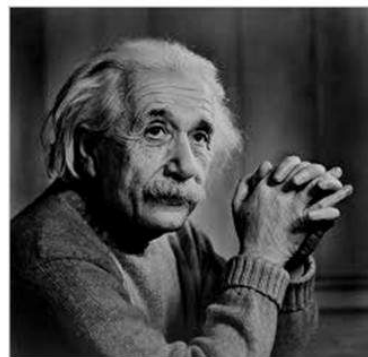


-80



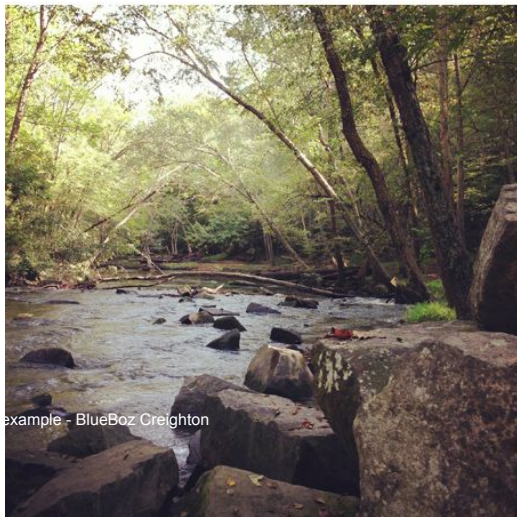
+80

Saturation example - Adobe Support



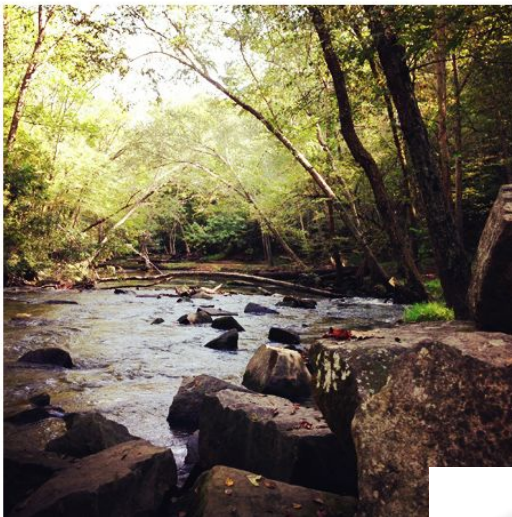
Brightness example - Tutorialspoint

Original image



example - BlueBoz Creighton

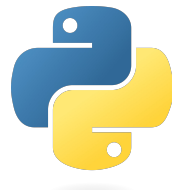
Increased contrast



O P T U N A



Keras



The Fitzpatrick Scale



TYPE I

Light,
pale white

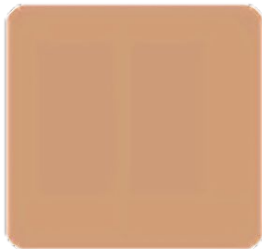
Always burns,
never tans



TYPE II

White, fair

Usually burns,
tans with difficulty



TYPE III

Medium,
white to olive

Sometimes mild burn,
gradually tans to olive



TYPE IV

Olive,
moderate brown

Rarely burns, tans with
ease to a moderate brown



TYPE V

Brown,
dark brown

Very rarely burns,
tans very easily



TYPE VI

Black, very dark
brown to black

Never burns, tans very
easily, deeply pigmented