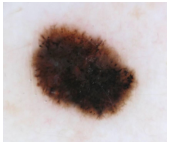
CVPR SEATTLE WASHINGTON JUNE 16-18 2020



ISIC Skin Image Analysis Workshop

MIAL Medical Image Analysis Lab

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Illumination-based Transformations Improve Skin Lesion Segmentation in Dermoscopic Images

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Introduction

Clinical motivation

- Cancer is the second leading cause of death globally.
  - 1 out of every 6 deaths is cancer-related.
- Skin cancer is the most prevalent cancer globally.
  - Estimated 5 million cases will be diagnosed in 2020 in USA alone.
- Incidence rate of skin cancer increasing in the past decades [WHO, 2020].
- The early detection, diagnosis, and treatment of skin cancers is extremely important.
  - The estimated five-year survival rate of skin cancers with early detection is about **99%** [Siegel et al., Cancer Statistics, 2020].

Computer Aided Diagnosis of Skin Lesions

Advantages:

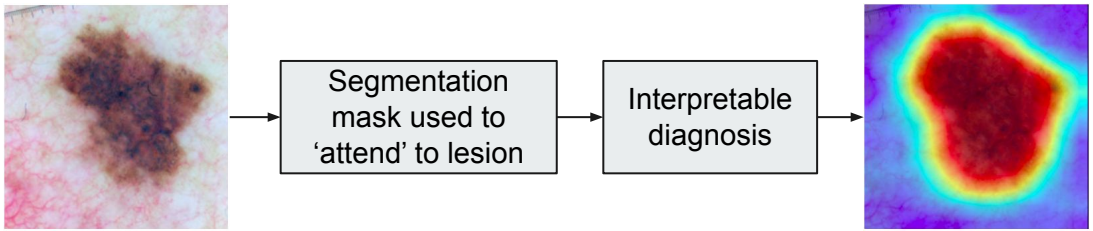
- Quick, robust, and reproducible results to assist dermatological diagnoses.
  - Able to serve as the source of a second opinion.
- Reduced diagnostic costs.
- Alleviate the lack of dermatological expertise in underserved communities through teledermatology.

Skin Lesion Segmentation

Localizing the lesion is often the first step in diagnosis.

Segmentation provides an added sense of trust in automated diagnosis algorithms.

Lesion segmentation localizes region for information extraction.



Courtesy: Yan et al., IPMI 2019

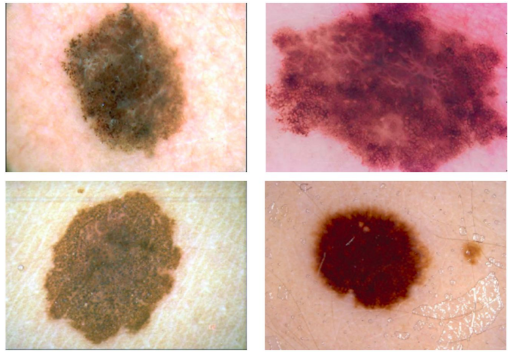
Motivation

Deep learning based segmentation approaches usually ignore illumination and color based knowledge.

"changes in the acquisition setup can **alter the colors of an image**. … The human brain is able to **compensate for this variability**, but the same cannot be said of a CAD system" [Barata et al., ICIP 2014]

Melanoma

Benign Lesions



Courtesy: Argenziano et al., 2000

Motivation

Very few works have explored color constancy algorithms and used multiple color space representations for skin lesion segmentation.

Goal: Leverage knowledge about illumination and skin imaging in a deep learning-based segmentation model.

Method

Selecting Color Channels

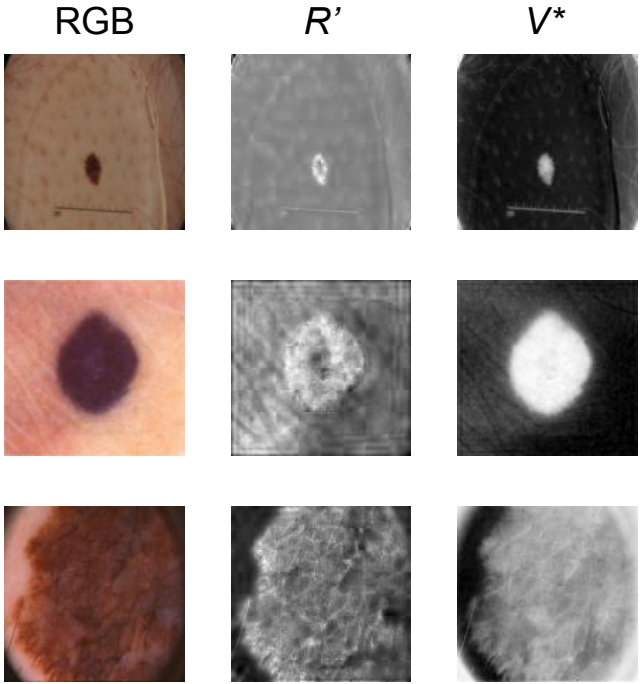
"the normalized RGB space eliminates the effect of varying intensities due to uneven illumination and it is free from shadow and shading effects" [Guarracino et al., JBHI 2019]

Two color channels selected:

- Red channel from normalized RGB image (denoted by ***R'***)
- Complement of value channel (V) from HSV color space representation (denoted by ***V****).

$$R' = \frac{R}{R+G+B} \qquad V^* = 1 - V \qquad V = max\ (\frac{R}{M}, \frac{G}{M}, \frac{B}{M})$$

Selecting Color Channels: Results

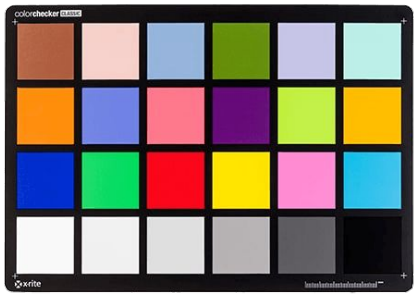


Intrinsic Images

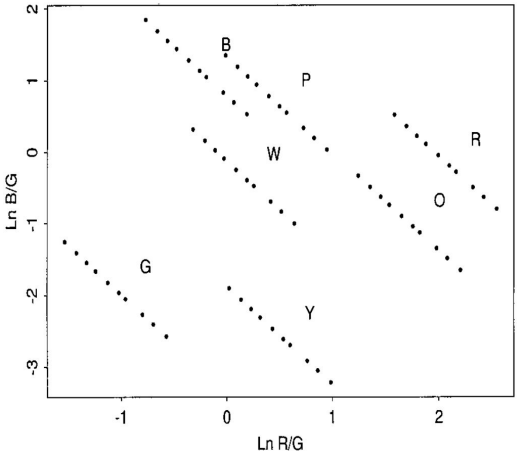
Motivation: Shadows in images can cause automated algorithms (including segmentation methods) to fail.

Goal: Find an illumination-invariant ‘intrinsic’ image of a scene that depends only on the reflectance properties.

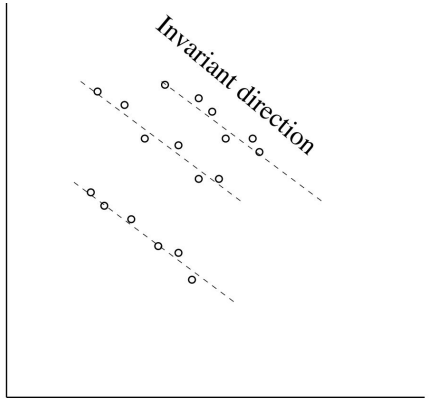
Intrinsic Images Using Camera Calibration



Color checker



2D log chromaticity plots for 7 patches imaged under 10 illuminants



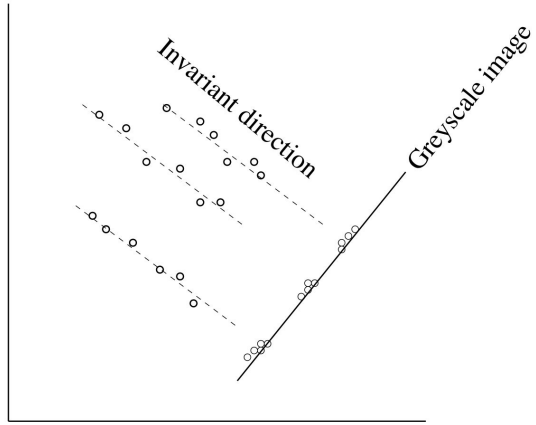
Finding the invariant direction

Intrinsic Images

This process is camera dependent.

Goal: Find the invariant direction without imaging the scene with more than one illuminant.

Invariant direction = direction along which the projected image has minimum entropy.

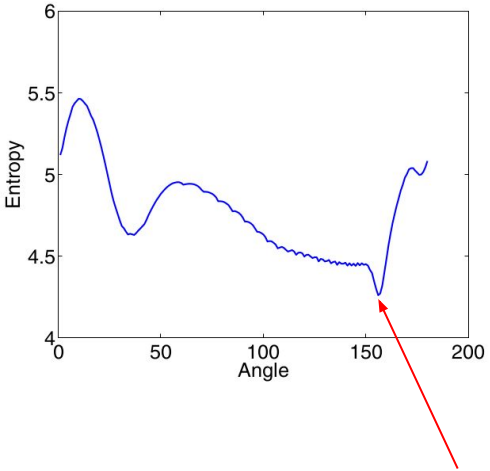


Intrinsic Images: Overview

RGB Image

2D log chromaticity

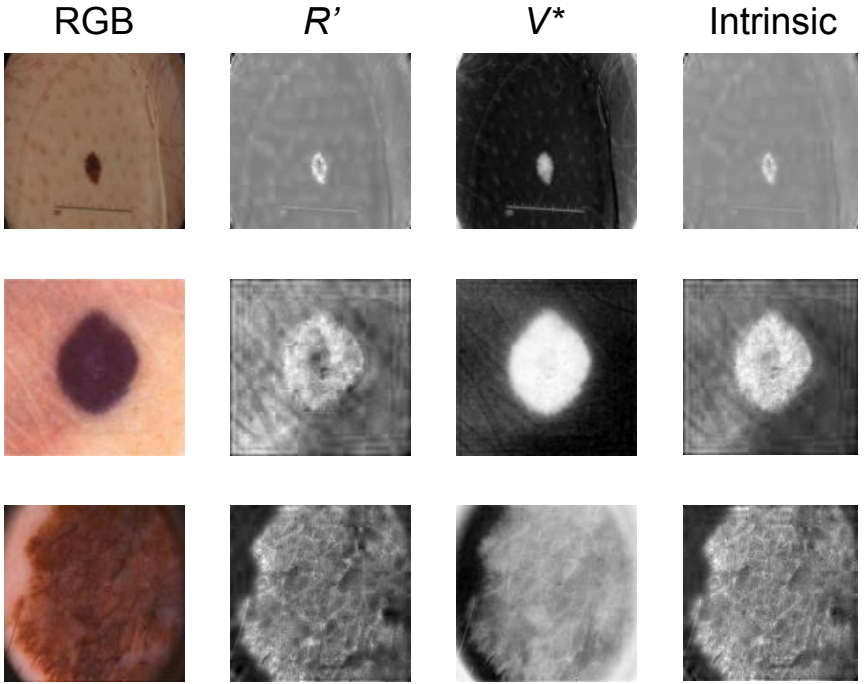
Calculate entropy for angles from 0° to 180°



Intrinsic Image

Courtesy: Finlayson et al., ECCV 2004

Intrinsic Images: Results



Grayscale Images of Skin Lesions

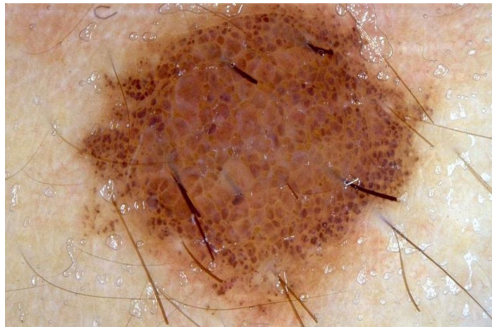
Goal: Find a single channel (grayscale) representation of the skin lesion image based on optics of the human skin.

Consider the optical density space: [-log R, -log G, -log B].

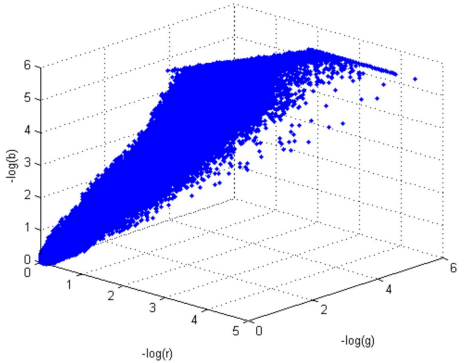
In this space, RGB value triplets for pixels in skin images reside on a plane [Tsumura et al., JOSAA 1999].

"by carrying PCA, eigenvalues indicate that the data is **distributed mostly along a vector** (rather than a plane)" [Madooei et al., CIC 2012].

Grayscale Images of Skin Lesions



Skin lesion RGB image



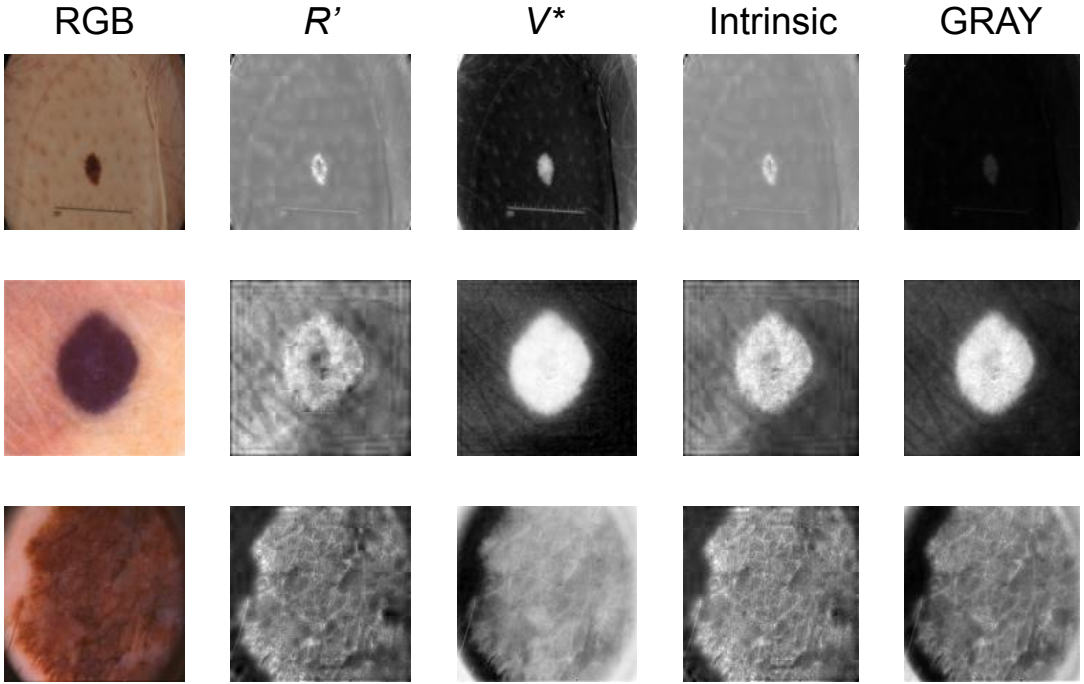
Optical density space representation

PCA

98.3% total variance explained by 1st principal component

Courtesy: Madooei et al., CIC 2012

Grayscale Images of Skin Lesions: Results



Shading-attenuated Images

Motivation: Imaging non-flat skin surfaces, especially lesions, can induce shading in dermoscopic images, which can degrade the segmentation.

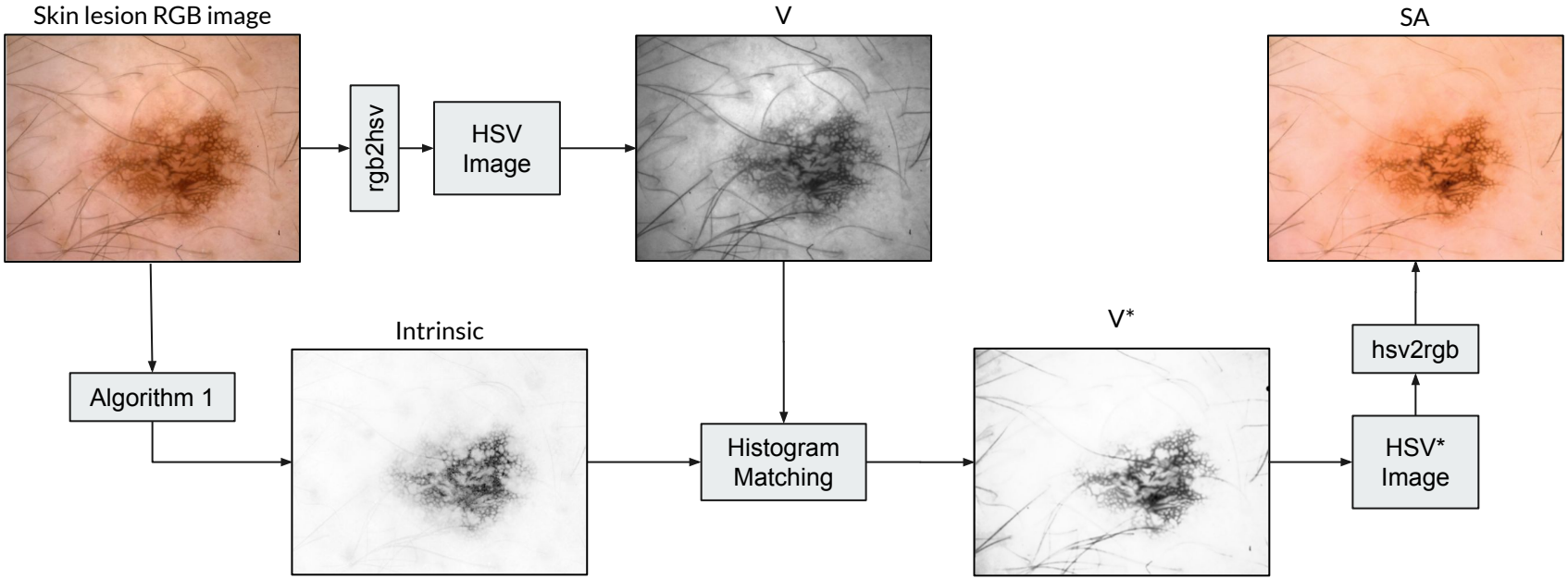
Goal: Attenuate shading in dermoscopic images.

Normalize illumination w.r.t the intrinsic image [Madooei et al., CIC 2012]

Illumination: V channel from HSV color space representation.

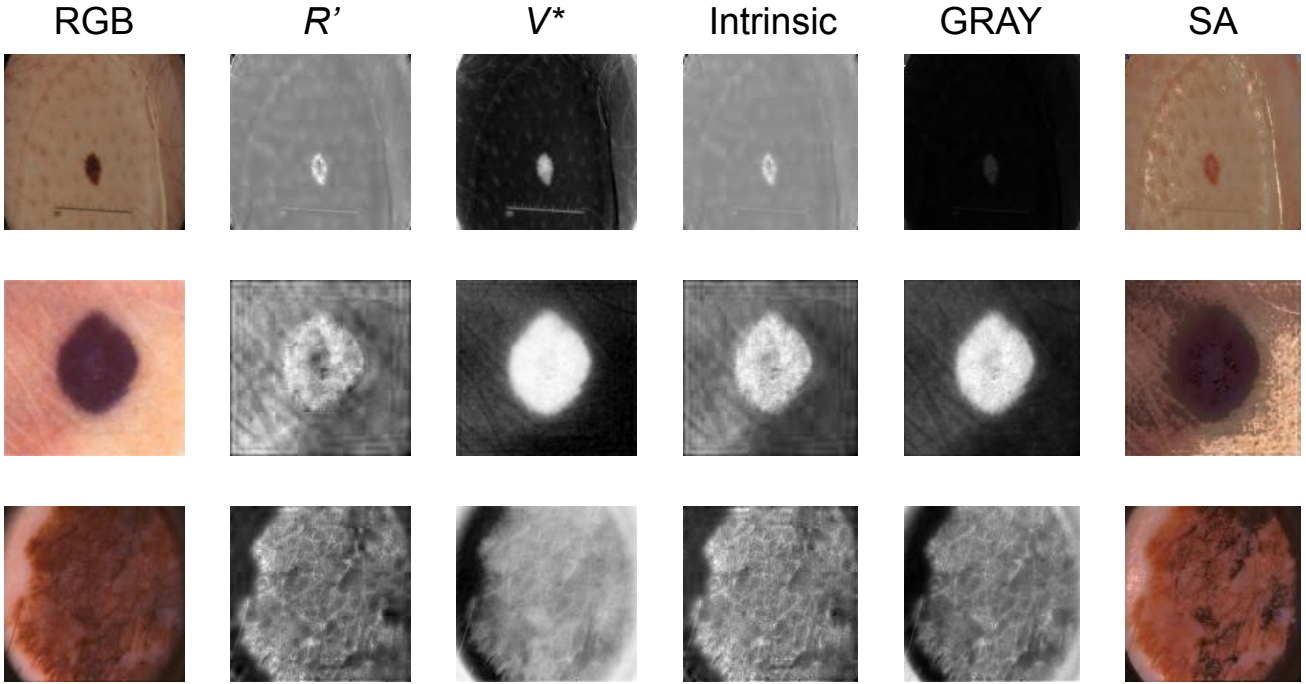
The shading effects are visible in the V channel [Soille et al., 1999]

Shading-attenuated Images: Overview

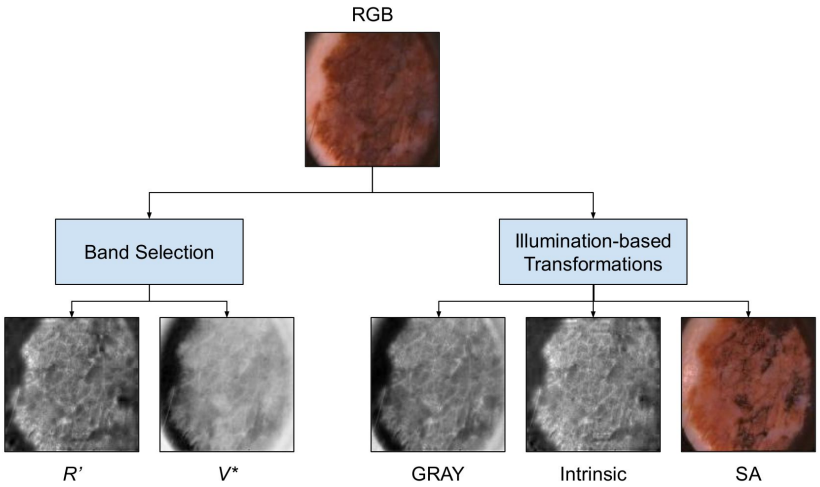


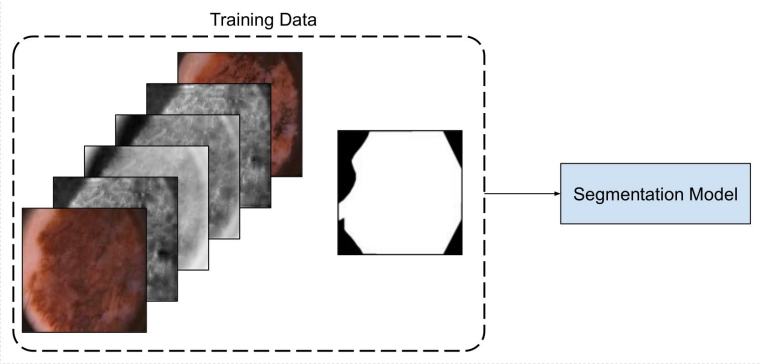
Courtesy: Madooei et al., CIC 2012

Shading-attenuated Images: Results



Method Overview





Datasets, Experiments, and Results

Datasets

3 datasets used

DermoFit split into training:validation:testing partitions in 60:10:30 ratio.

PH2 used entirely for testing.

Split / **Dataset**	Training	Validation	Testing
ISIC 2017	2000	150	600
DermoFit	1300	-	-
PH2	200	-	-

Evaluation: Ablation Study

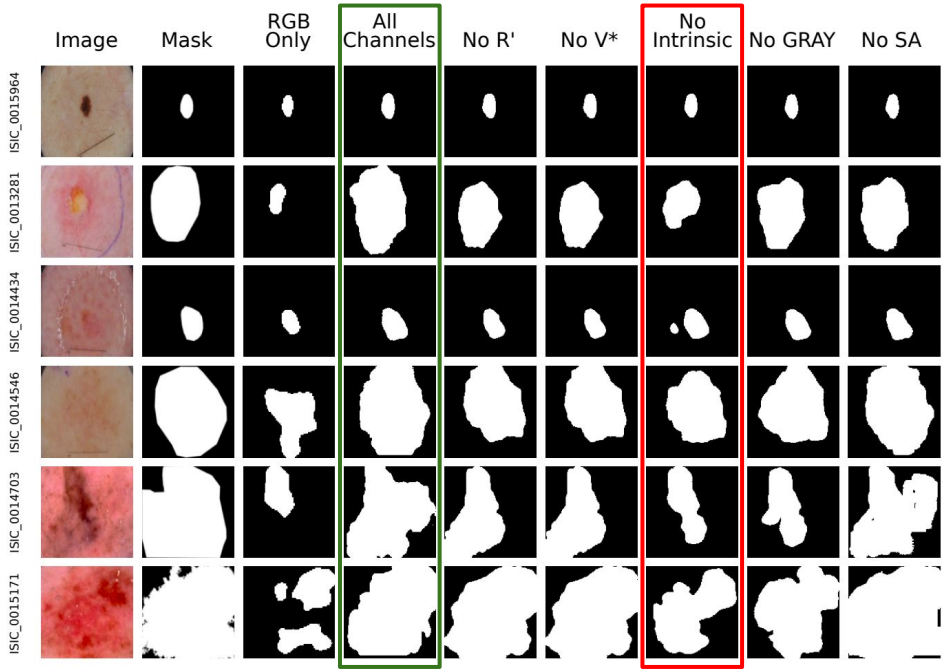
7 models trained and evaluated on the ISIC 2017 dataset with the following inputs to the networks:

- RGB images only ('RGB Only')
- RGB + all transformation based channels ('All Channels')
- Drop one transformation at a time from 'All Channels':
  - Call it 'No x', where x ϵ {*R'*, *V**, Intrinsic, GRAY, SA}
  - 5 such models.

Ablation Study: Quantitative Results

Method	Accuracy	Dice Coefficient	Jaccard Index	Sensitivity	Specificity
RGB Only	0.9029 ± 0.0053	0.7781 ± 0.0086	0.6758 ± 0.0095	0.7471 ± 0.0091	0.9683 ± 0.0031
All Channels	$\mathbf{0.9220 \pm 0.0045}$	$\mathbf{0.8386 \pm 0.0078}$	$\mathbf{0.7570 \pm 0.0089}$	$\mathbf{0.8706 \pm 0.0077}$	0.9516 ± 0.0037
No R'	0.9185 ± 0.0046	0.8243 ± 0.0078	0.7363 ± 0.0090	0.7949 ± 0.0085	0.9735 ± 0.0030
No V^*	0.9189 ± 0.0049	0.8263 ± 0.0077	0.7381 ± 0.0089	0.7892 ± 0.0087	0.9786 ± 0.0025
No Intrinsic	0.9092 ± 0.0056	0.7997 ± 0.0094	0.7139 ± 0.0103	0.7662 ± 0.0104	$\mathbf{0.9803 \pm 0.0024}$
No GRAY	0.9116 ± 0.0052	0.8163 ± 0.0080	0.7260 ± 0.0091	0.8041 ± 0.0090	0.9643 ± 0.0033
No SA	0.9198 ± 0.0050	0.8274 ± 0.0083	0.7445 ± 0.0093	0.8137 ± 0.0088	0.9603 ± 0.0044

Ablation Study: Qualitative Results



Evaluation on other datasets: DermoFit and PH2

2 models trained on the DermoFit dataset with the following inputs to the networks:

- RGB Only
- No SA

No SA used because SA images do not contribute much to performance improvement and are somewhat computationally expensive.

Both models evaluated on DermoFit and PH2 datasets.

Quantitative Results

Dataset	Method	Accuracy	Dice Coefficient	Jaccard Index	Sensitivity	Specificity
DermoFit	RGB Only	0.9024 ± 0.0038	0.8437 ± 0.0053	0.7418 ± 0.0069	0.8080 ± 0.0078	$\mathbf{0.9534 \pm 0.0030}$
	No SA	$\mathbf{0.9124 \pm 0.0030}$	$\mathbf{0.8674 \pm 0.0042}$	$\mathbf{0.7737 \pm 0.0055}$	$\mathbf{0.8721 \pm 0.0053}$	0.9347 ± 0.0032
PH2	RGB Only	0.8546 ± 0.0133	0.7989 ± 0.0128	0.6944 ± 0.0140	0.8032 ± 0.0166	0.9543 ± 0.0031
	No SA	$\mathbf{0.8926 \pm 0.0091}$	$\mathbf{0.8537 \pm 0.0071}$	$\mathbf{0.7559 \pm 0.0091}$	$\mathbf{0.8442 \pm 0.0110}$	$\mathbf{0.9607 \pm 0.0022}$

Summary

- Motivated by information from illumination and skin imaging, we proposed a segmentation framework to incorporate certain color bands and illumination-based transformations.
- Our experiments on multiple datasets show the potential value of using such information to improve segmentation.
- An ablation study demonstrates the relative importance of various transformations.
- It is unclear why the deep segmentation model trained on RGB images only cannot learn to generate these transformations.
    - Future work: attempt to learn to estimate these illumination-based transformations in a deep learning setting.

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Thank you.

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