Ninth ISIC Skin Image Analysis Workshop @ MICCAI 2024

Lesion Elevation Prediction from Skin Images Improves Diagnosis

Kumar Abhishek   Ghassan Hamarneh

SIMON FRASER UNIVERSITY

Deep Learning for Skin Lesion Diagnosis

2017

nature

Letter | Published: 25 January 2017

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau & Sebastian Thrun

Nature 542, 115–118 (2017) | Cite this article

2018

Annals of Oncology
Volume 29, Issue 8, August 2018, Pages 1836-1842

Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists

H.A. Haenssle [1 †], C. Fink [1], R. Schneiderbauer [1], F. Toberer [1], T. Buhl [2], A. Blum [3], A. Kalloo [4], A. Ben Hadj Hassen [5], L. Thomas [6], A. Enk [1], L. Uhlmann [7], Reader study level-I and level-II Groups, Christina Alt, Monika Arenbergerova, Renato Bakos, Anne Baltzer, Ines Bertlich, Andreas Blum, Therezia Bokor-Billmann, Jonathan Bowling...Iris Zalaudek

2019

BJD
Volume 180, Issue 2
1 February 2019

JOURNAL ARTICLE

Deep-learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumour diagnosis

Y. Fujisawa, Y. Otomo, Y. Ogata, Y. Nakamura, R. Fujita, Y. Ishitsuka, R. Watanabe, N. Okiyama, K. Ohara, M. Fujimoto

British Journal of Dermatology, Volume 180, Issue 2, 1 February 2019, Pages 373–381,

European Journal of Cancer
Volume 113, May 2019, Pages 47-54

Original Research

Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task

Titus J. Brinker [a b], Achim Hekler [a], Alexander H. Enk [b], Joachim Klode [c], Axel Hauschild [d], Carola Berking [e], Bastian Schilling [f], Sebastian Haferkamp [g], Dirk Schadendorf [c], Tim Holland-Letz [h], Jochen S. Utikal [i j], Christof von Kalle [a], Collaborators[2]

European Journal of Cancer
Volume 119, September 2019, Pages 57-65

Original Research

Systematic outperformance of 112 dermatologists in multiclass skin cancer image classification by convolutional neural networks

Roman C. Maron [a 1], Michael Weichenthal [b 1], Jochen S. Utikal [c d], Achim Hekler [a], Carola Berking [e], Axel Hauschild [b], Alexander H. Enk [f], Sebastian Haferkamp [g], Joachim Klode [h], Dirk Schadendorf [h], Philipp Jansen [h], Tim Holland-Letz [i], Bastian Schilling [j], Christof von Kalle [a], Stefan Fröhling [a], Maria R. Gaiser [c d], Daniela Hartmann [e], Anja Gesierich [j], Katharina C. Kähler [b], Ulrike Wehkamp [b]...Alexander Thiem

European Journal of Cancer
Volume 118, September 2019, Pages 91-96

Original Research

Deep learning outperformed 11 pathologists in the classification of histopathological melanoma images

Achim Hekler [a], Jochen S. Utikal [b c], Alexander H. Enk [d], Wiebke Solass [e], Max Schmitt [a], Joachim Klode [f], Dirk Schadendorf [f], Wiebke Sondermann [f], Cindy Franklin [g], Felix Bestvater [h], Michael J. Flaig [i], Dieter Krahl [j], Christof von Kalle [a], Stefan Fröhling [a], Titus J. Brinker [a d]

2020

nature medicine

Article | Published: 18 May 2020

A deep learning system for differential diagnosis of skin diseases

Yuan Liu, Ayush Jain, Clara Eng, David H. Way, Kang Lee, Peggy Bui, Kimberly Kanada, Guilherme de Oliveira Marinho, Jessica Gallegos, Sara Gabriele, Vishakha Gupta, Nalini Singh, Vivek Natarajan, Rainer Hofmann-Wellenhof, Greg S. Corrado, Lily H. Peng, Dale R. Webster, Dennis Ai, Susan J. Huang, Yun Liu, R. Carter Dunn & David Coz

Nature Medicine 26, 900–908 (2020) | Cite this article

2024

nature medicine

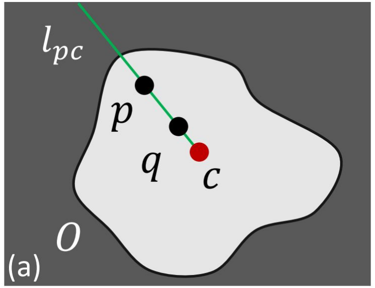
Article | Open access | Published: 05 February 2024

Deep learning-aided decision support for diagnosis of skin disease across skin tones

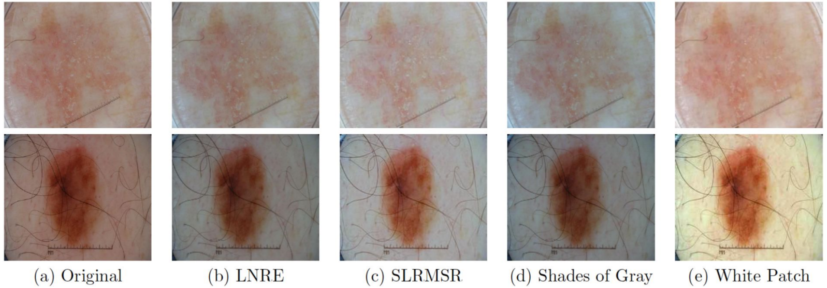
Matthew Groh, Omar Badri, Roxana Daneshjou, Arash Koochek, Caleb Harris, Luis R. Soenksen, P. Murali Doraiswamy & Rosalind Picard

Nature Medicine 30, 573–583 (2024) | Cite this article

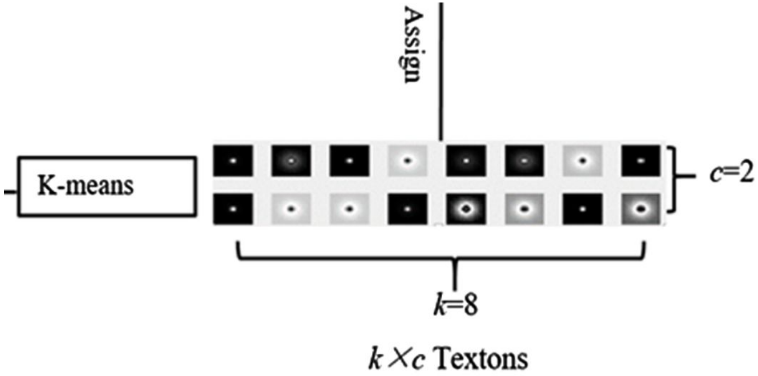
Additional Features Improve Skin Image Analysis



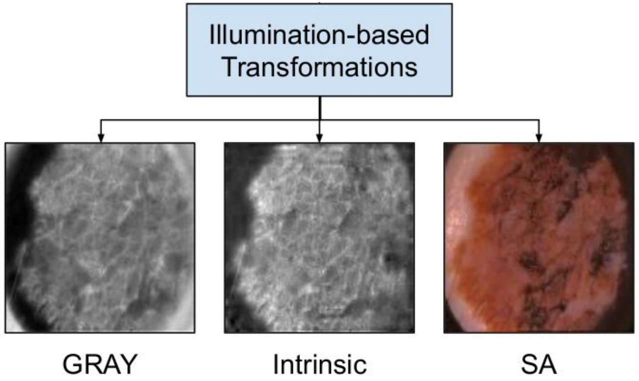
Shape prior [1]



Color constancy algorithms [2]



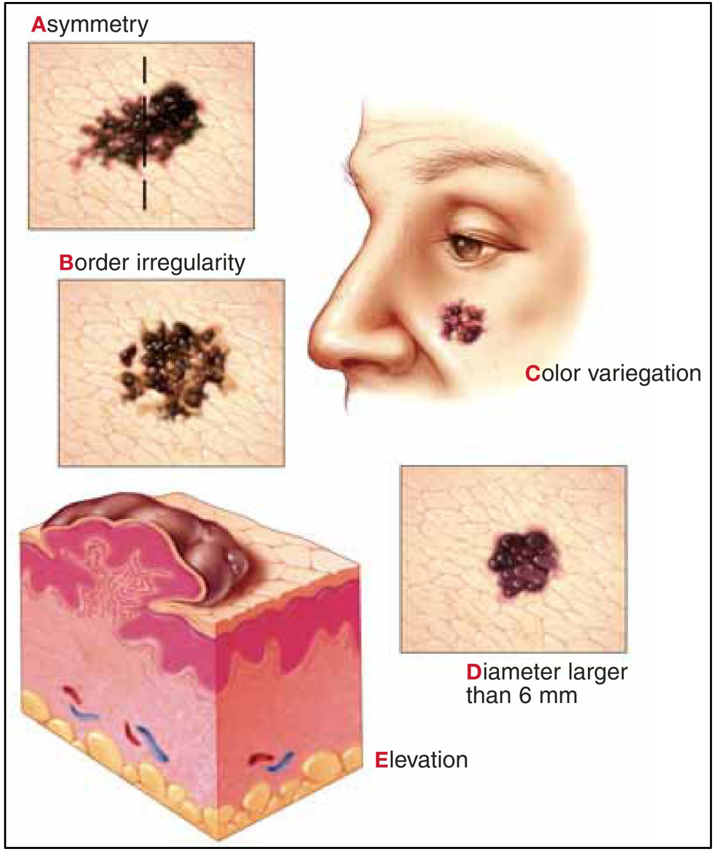
Lesion texture [3]



Illumination-based features [4]

Lesion Elevation in Clinical Practice

- Part of the American Cancer Society's ABCD**E** criteria.



[5] Strayer et al., 2003.

Lesion Elevation in Clinical Practice

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- The **palpation of skin** is an important step in lesion diagnosis, and is often one of the reasons for dermatologists' dissatisfaction with **teledermatology**.

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ELSEVIER

Journal of the American Academy of Dermatology
Volume 56, Issue 6, June 2007, Pages 949-951

Report

A literally blinded trial of palpation in dermatologic diagnosis

Neil H. Cox MD, BSc(Hons), FRCP(Lond & Edin)

RESULTS

In 14 of 16 cases, the correct diagnosis was chosen (P = .012, χ^2 test). The incorrect diagnoses were multiple small lesions of psoriasis that had been

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BJD British Journal of Dermatology
IMPROVING PATIENT OUTCOMES IN SKIN DISEASE WORLDWIDE

Full Access

Teledermatology: a review

D.J. Eedy, R. Wootton

First published: 22 August 2002 | https://doi.org/10.1046/j.1365-2133.2001.04124.x |

training per year.[23] By comparison, dermatologists' criticisms were usually concerned with picture quality, lack of rapport with patients, <u>inability to palpate lesions</u> or carry out diagnostic tests and that the systems were time-consuming and unsatisfying.[29,44,57] In a study using high

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JRSM
JOURNAL OF THE ROYAL SOCIETY OF MEDICINE

J R Soc Med. 2006 Dec; 99(12): 598–600. PMCID: PMC1676320
doi: 10.1258/jrsm.99.12.598 PMID: 17139058

Palpation of the skin—an important issue

Neil H Cox

adequately close to show fine detail. Also, <u>even good quality photos are two-dimensional</u>; raised lesions of urticaria, for example, <u>may be difficult to distinguish from flat lesions of a similar colour</u>, and quality of scaling can only be guessed at. Touching the skin is a modality that is omitted in teledermatology, but there are clearly situations where it can be important. Indeed, the inability to palpate lesions has also been given as a reason for dermatologists being less satisfied than primary care physicians with the results of teledermatology.[7] Even enthusiasts admit that this can be a problem.

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Lesion elevation information as a proxy for in-person palpation may **benefit teledermatology**.

Lesion Elevation in Deep Learning-based Methods

Skin Research & Technology
Forward Series

ORIGINAL ARTICLE | Open Access

A feature fusion system for basal cell carcinoma detection through data-driven feature learning and patient profile

P. Kharazmi, S. Kalia, H. Lui, Z. J. Wang, T. K. Lee

First published: 22 October 2017 | https://doi.org/10.1111/srt.12422 | Citations: 53

3.4 | Patient profile

Patient profile information consists of lesion location, lesion size, lesion elevation (a binary variable indicating whether the lesion is flat or elevated) along with age and gender of the patients. Figure 7 demon-

As it can be seen from Table 1, integrating the condensed feature maps with patient information increases the diagnosis accuracy of BCC. The BCC lesions of our dataset are mostly of the nodular type,

IEEE Journal of Biomedical and Health Informatics

Seven-Point Checklist and Skin Lesion Classification Using Multitask Multimodal Neural Nets

Publisher: IEEE Cite This PDF

Jeremy Kawahara ; Sara Daneshvar ; Giuseppe Argenziano ; Ghassan Hamarneh All Authors

2) Classify Using Image and Meta-Data: As the meta-data (gender, lesion location, and lesion elevation) is categorical, we one-hot encode the meta-data to produce a meta-data vector.

ible under dermoscopy. The classification layer that uses clinical, dermoscopic, and meta-data together yields the highest average accuracy. However, we note including clinical images

Lesion Elevation in Deep Learning-based Methods

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Computers in Biology and Medicine
Volume 116, January 2020, 103545

The impact of patient clinical information on automated skin cancer detection

Andre G.C. Pacheco [a], Renato A. Krohling [a b]

We summarize the presented analysis as follows:

- It is expected that these features improve the model performance for pigmented and non-pigmented lesions detection.
- Certain features, such as a change in the lesion pattern and elevation are important for MEL detection.

scientific reports

Article | Open access | Published: 08 April 2021

Predicting the clinical management of skin lesions using deep learning

Kumar Abhishek, Jeremy Kawahara & Ghassan Hamarneh

evaluate our prediction models. The dataset contains clinical and dermoscopic images of skin lesions, patient metadata (patient gender and the location and the elevation of the lesion), the corresponding seven-point criteria[32] for the dermoscopic images, and the diagnosis and the management labels for 1011 cases with mean [standard deviation] age of 28.08 [18.70] years; 489 males (48.37%); 294 malignant cases (29.08%); skin lesion diameter of 8.84 [5.39] mm.

3. *The inclusion of patient metadata may improve the management prediction accuracy.* When using only clinical images ('CM' versus 'C'), only dermoscopic image ('DM' versus 'D'), or both ('CDM' versus 'CD'), all but one metrics improved with the inclusion of metadata by $2.23 \pm 2.68\%$, with the most impactful contribution of metadata being in the 10.63%

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- Learning-based methods to predict lesion elevation.

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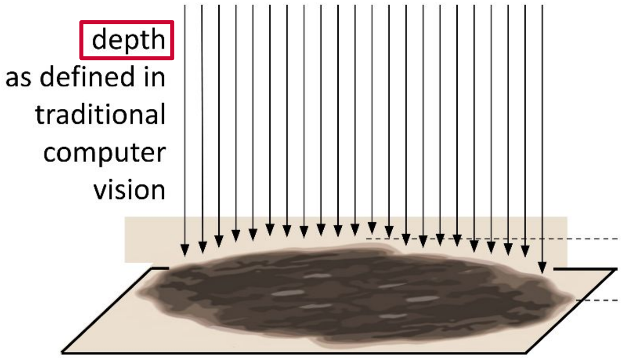
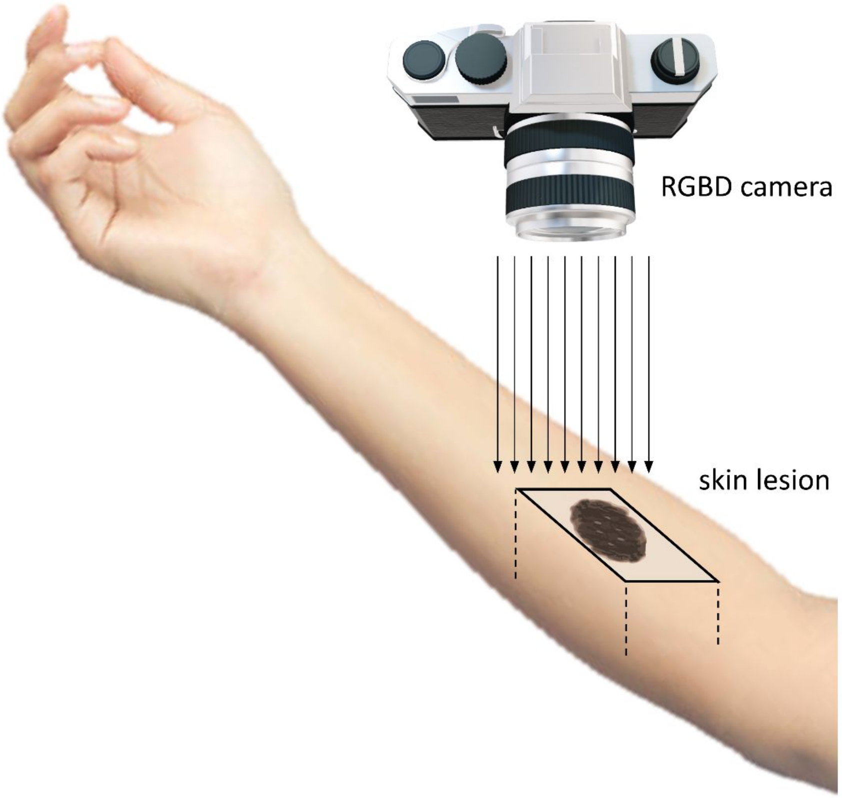
What's missing?

- Learning-based methods to predict lesion elevation.
- Assessing if elevation alone can improve lesion diagnosis performance.

Is elevation the same as depth?





Inset figure courtesy of Melanoma Institute Australia [6].

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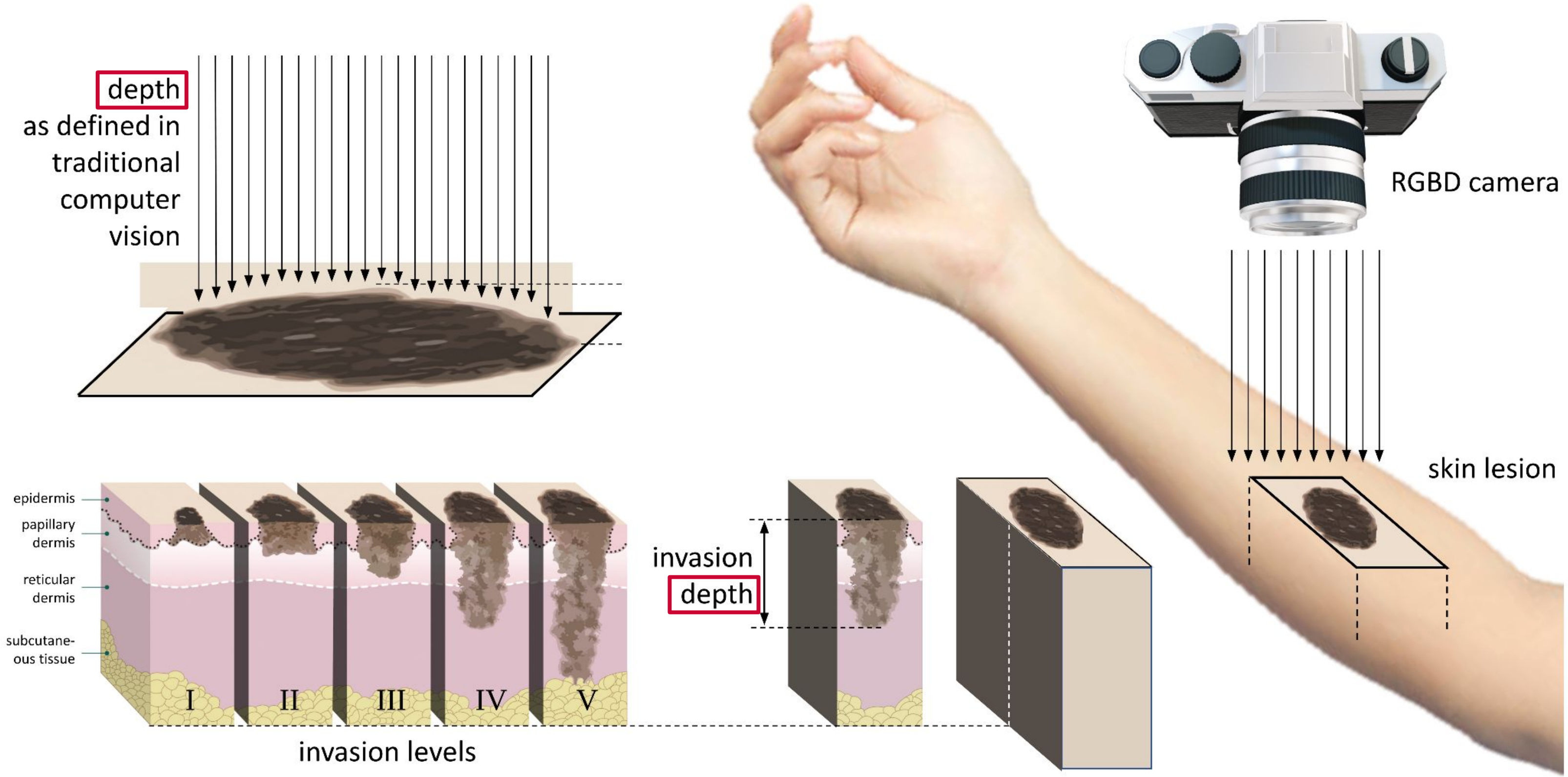

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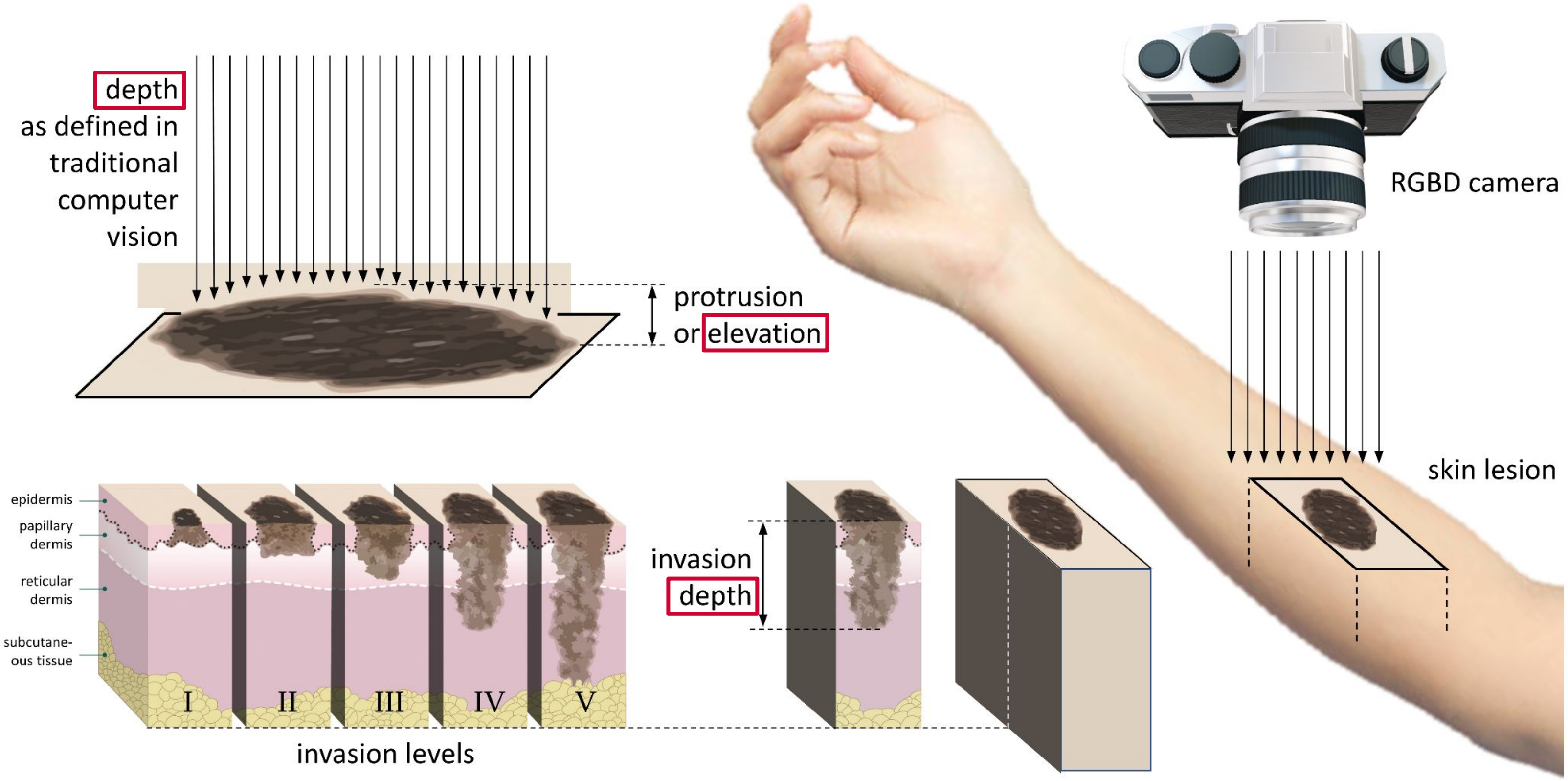

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This Work

We pose three questions:

☐ Can we estimate lesion elevation from skin lesion images alone?

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☐ Can we rely on estimated lesion elevation to improve diagnosis?

Can we use off-the-shelf depth prediction models trained on natural images?

[7] Ranftl et al., 2022.

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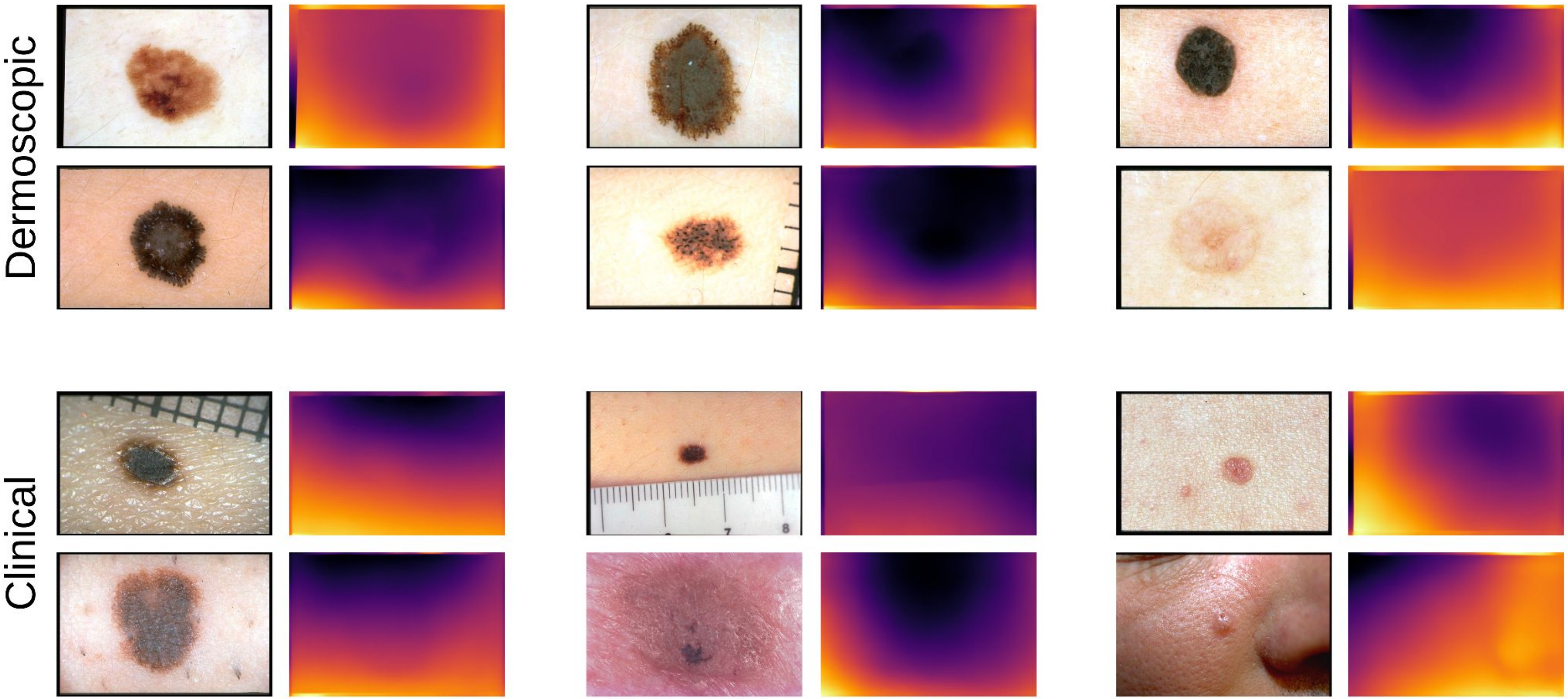

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Can we use off-the-shelf depth prediction models trained on natural images?

No, because:

- natural images scenes generally have a depth anisotropy.

- considerable difference in scale between natural images’ depths (typically in meters) and skin lesions’ elevations (typically in millimeters).

Lesion Elevation Datasets

PAD-UFES-20

- **Size:** 2,298 images.
- **1 modality:** Smartphone images.
- **2 elevation labels:** {“elevated”, “not elevated”}.

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derm7pt

- **Size:** 1,011 cases.
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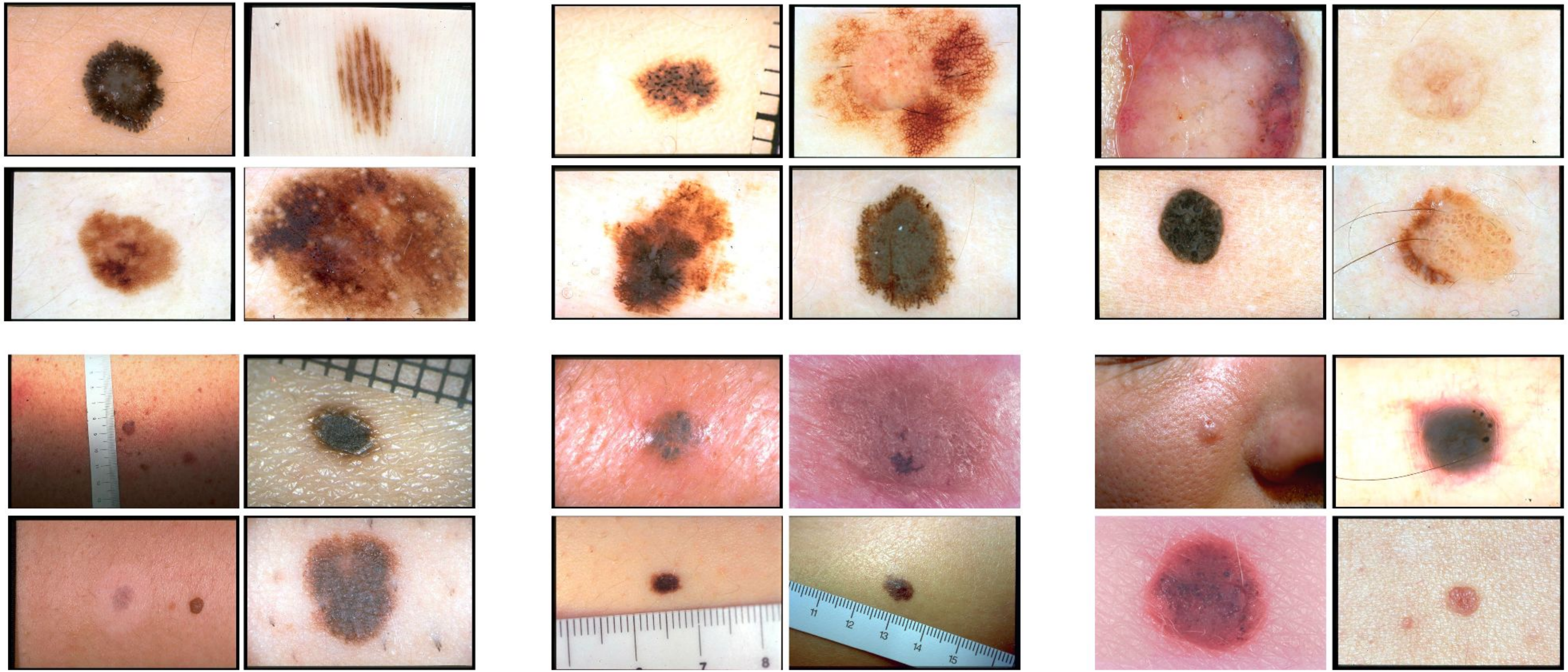
Elevation labels in derm7pt - Samples

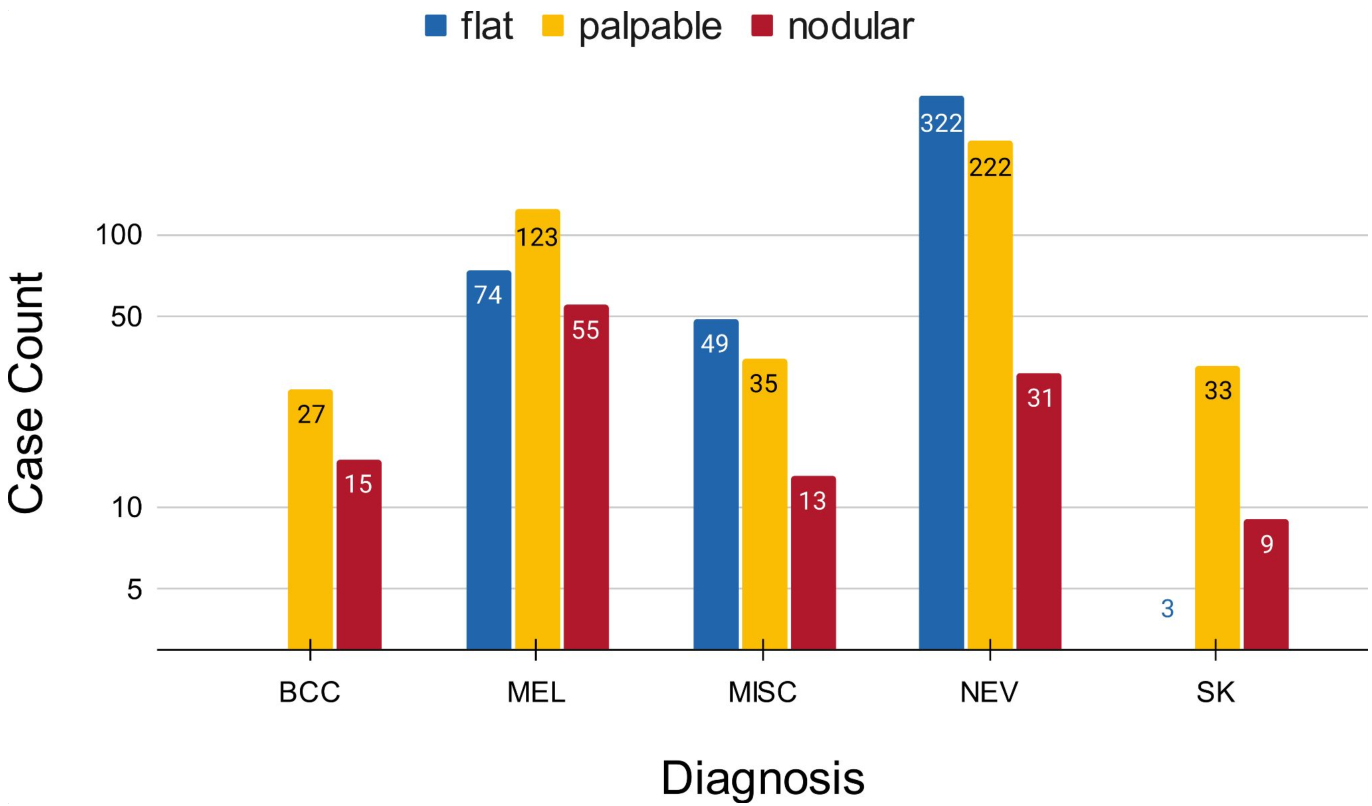
flat palpable nodular

Dermoscopic

Clinical



Elevation labels in derm7pt - Diagnosis-wise distribution



Can we predict skin lesion elevation labels from images alone?

$$\hat{E}_i = g(X_i; \phi)$$

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Lesion elevation prediction model

Probabilistic prediction of elevation label
[0.1, 0.3, 0.6]

Input image

Can we predict skin lesion elevation labels from images alone?

$$\hat{E}_i = g(X_i; \phi)$$

- MobileNetV2
- MobileNetV3L
- EfficientNet-B0
- EfficientNet-B1
- DenseNet-121
- VGG-16
- ResNet-18
- ResNet-50

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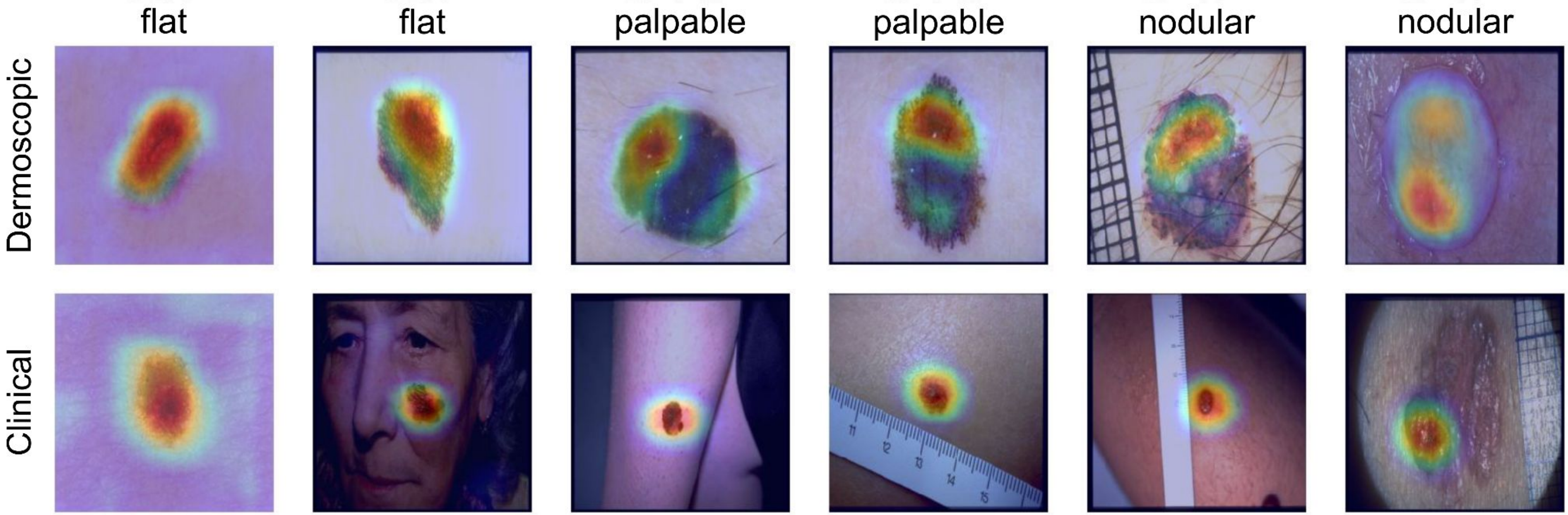
VGG-16	Accuracy	AUROC
Clinical Images	0.8543	0.8220
Dermoscopic Images	0.8475	0.8152

Can we predict skin lesion elevation labels from images alone?

Activation maps (GradCAM) localize the lesion well, despite artifacts.



Do ground truth elevation labels help improve diagnosis?

$$\hat{Y}_i = f_{DE}\left(X_i \oplus E_i; \Theta_{DE}\right)$$

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Diagnosis prediction model that leverages elevation

Predicted diagnosis

Ground truth elevation label
[0., 0., 1.]

Do ground truth elevation labels help improve diagnosis?

$$\hat{Y}_i = f_{DE}\left(X_i \oplus E_i; \Theta_{DE}\right)$$

VGG-16	**Clinical Images**		**Dermoscopic Images**	
	Accuracy	AUROC	Accuracy	AUROC
Without ground truth elevation	0.8464	0.6331	0.9137	0.8431
With ground truth elevation	0.8569	0.6820	0.9216	0.8703

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VGG-16	Clinical Images		Dermoscopic Images	
	Accuracy	AUROC	Accuracy	AUROC
Without ground truth elevation	0.8464	0.6331	0.9137	0.8431
With ground truth elevation	0.8569	0.6820	0.9216	0.8703
Improvement ⬆️	1.05%	4.89%	0.79%	2.72%

Can <u>inferred</u> elevation labels improve lesion diagnosis?

$$\hat{Y}_i = f_{D\hat{E}}(X_i \oplus \hat{E}_i; \Theta_{D\hat{E}})$$

Can inferred elevation labels improve lesion diagnosis?

$$\hat{Y}_i = f_{D\hat{E}}(X_i \oplus \hat{E}_i; \Theta_{D\hat{E}})$$

Diagnosis prediction model that leverages inferred elevation

Predicted diagnosis

Can inferred elevation labels improve lesion diagnosis?

$$\hat{Y}_i = f_{D\hat{E}}(X_i \oplus \hat{E}_i; \Theta_{D\hat{E}})$$

Diagnosis prediction model that leverages inferred elevation

Predicted diagnosis

Inferred elevation label

- Soft: [0.1, 0.7, 0.2]
- Discrete: [0., 1., 0.]

Can inferred elevation labels improve lesion diagnosis?

$$\hat{Y}_i = f_{D\hat{E}}(X_i \oplus \hat{E}_i; \Theta_{D\hat{E}})$$

Clinical Image Datasets

- DermoFit

Dermoscopic Image Datasets

- MSK
- ISIC 2016
- ISIC 2017
- ISIC 2018

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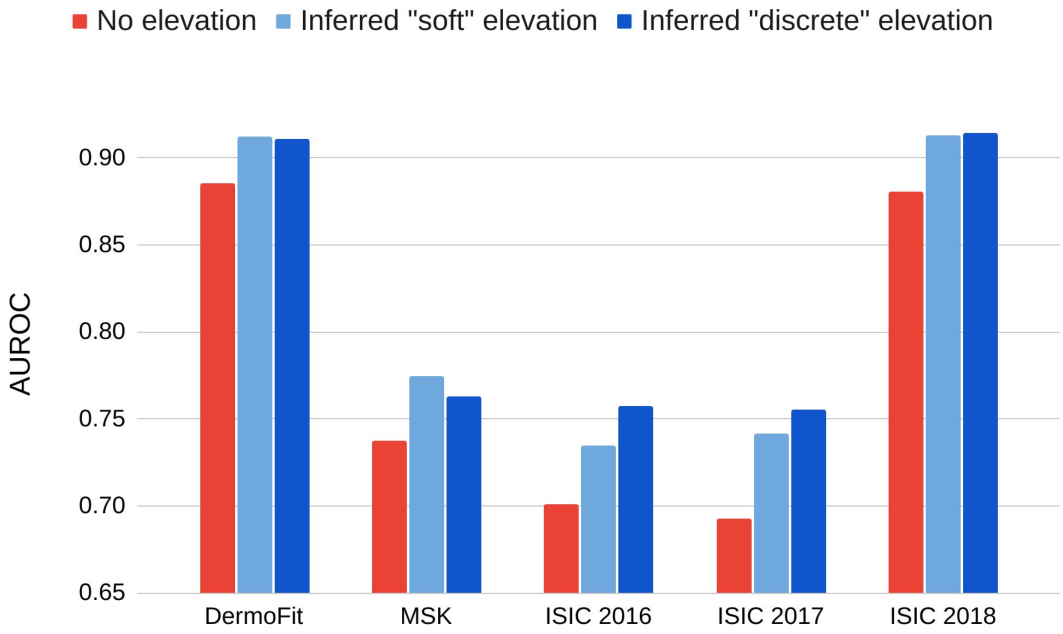

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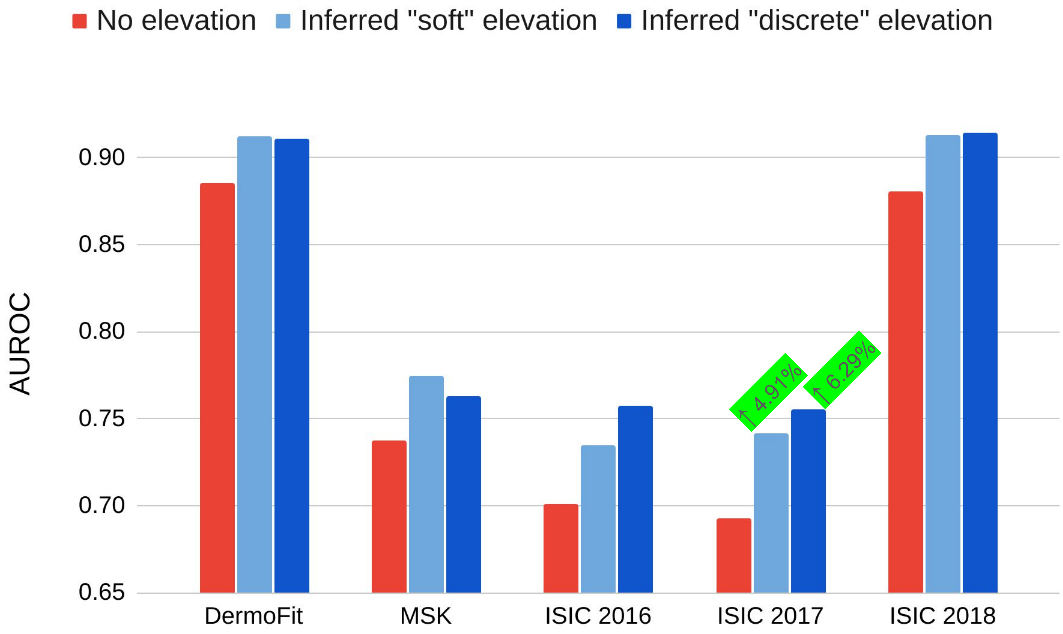

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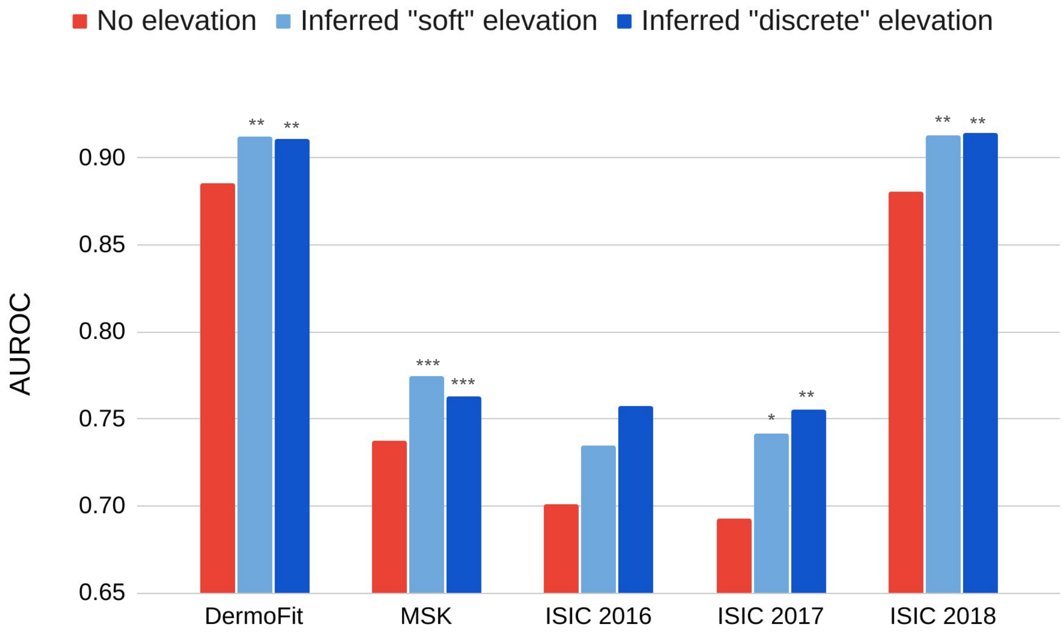

Statistical Significance Tests:

- McNemar's mid-p: AUROC improvements **stat. sig. (*p* < 0.05)** for all datasets except ISIC 2016.
- Cohen's *d*: "small" effect size for ISIC 2016, **"huge" effect sizes** for all other datasets.

Conclusion

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It is **possible to predict** image-level **skin lesion elevation labels** directly from **2D RGB images** with sufficient accuracy.

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✅ Can we rely on estimated lesion elevation to improve diagnosis?

On datasets without ground truth elevation labels, **estimated elevation labels** may help **improve lesion diagnosis**.

Conclusion

✅ Can we estimate lesion elevation from skin lesion images alone?

✅ Can ground truth lesion elevation alone, as a meta-data, improve diagnosis?

✅ Can we rely on estimated lesion elevation to improve diagnosis?

The ability to predict and leverage elevation from 2D images may offer the potential to **improve teledermatology consultations** by offering previously unavailable clinical information.

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Thank you.

Questions?

kabhishe@sfu.ca

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