An Evaluation of Self-Supervised Pre-Training for Skin-Lesion Analysis

   

Levy Chaves[1], Alceu Bissoto[1], Eduardo Valle[2], Sandra Avila[1]

[1]Institute of Computing [2]School of Electrical and Computing Engineering

Recod.ai, University of Campinas (UNICAMP), Brazil

Seventh ISIC Skin Image Analysis Workshop @ ECCV2022

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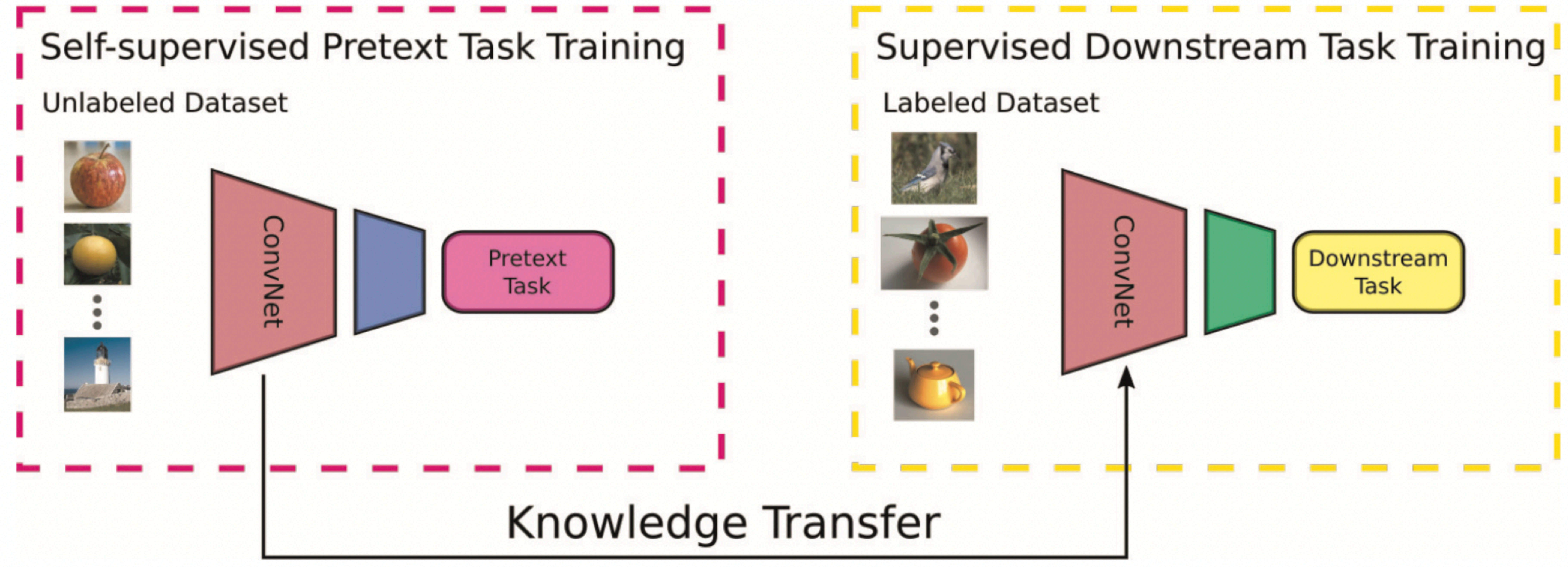
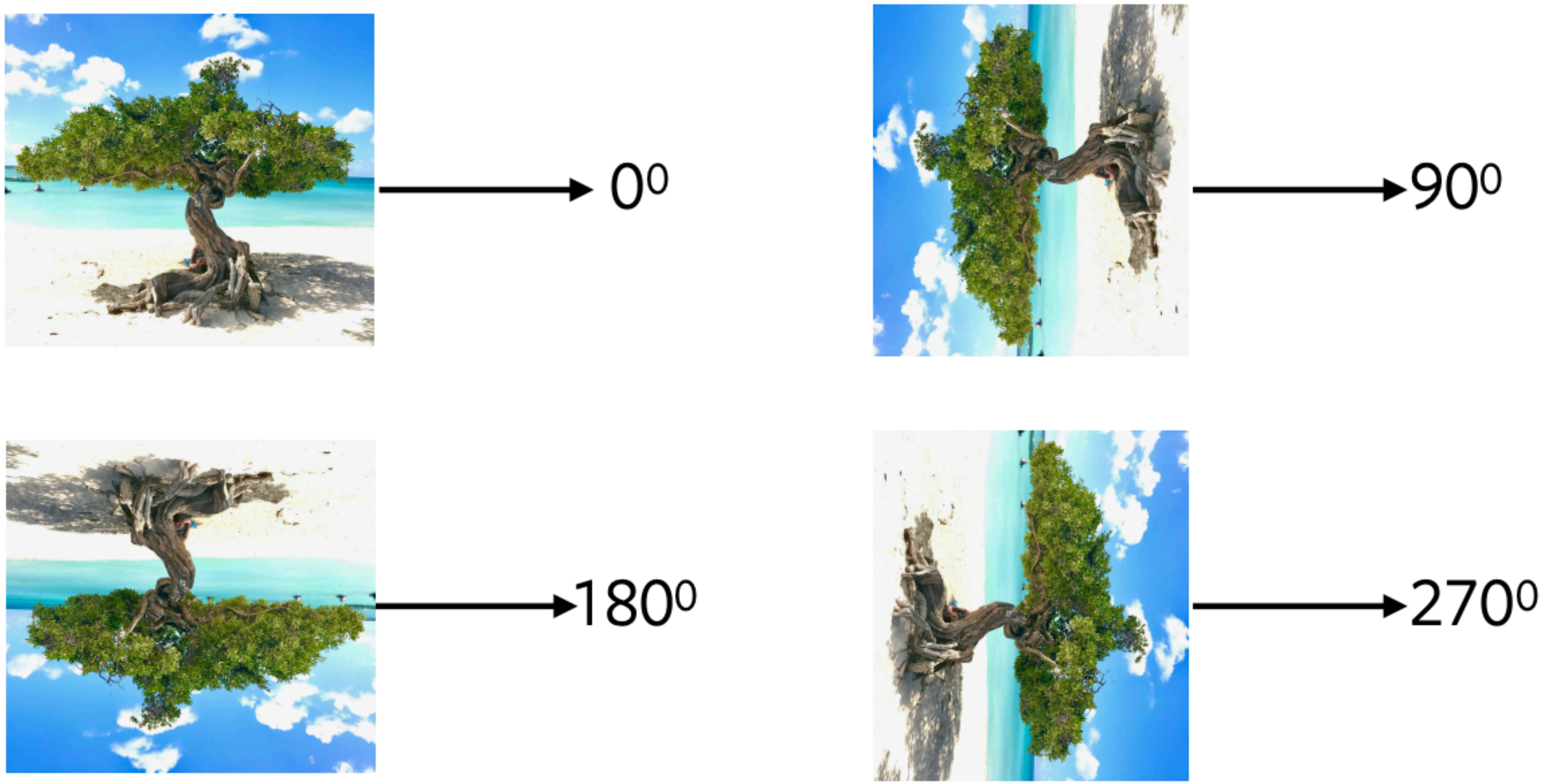
Self-Supervised Learning



Bastanlar, Yalin, and Semih Orhan. "Self-Supervised Contrastive Representation Learning in Computer Vision." (2022).

Pretext-task examples



Gidaris et al., 2018, Predicting Image Rotations

Pretext-task examples

Zhang, Richard, Phillip Isola, and Alexei A. Efros. "Colorful image colorization." *ECCV*. 2016.

How Transferable are Self-supervised Features in Medical Image Classification Tasks?

TUAN.TRUONG@BAYER.COM

SADEGH.MOHAMMADI@BAYER.COM

MATTHIAS.LENGA@BAYER.COM

Big Self-Supervised Models Advance Medical Image Classification

Shekoofeh Azizi, Basil Mustafa, Fiona Ryan*, Zachary Beaver, Jan Freyberg, Jonathan Deaton, Aaron Loh, Alan Karthikesalingam, Simon Kornblith, Ting Chen, Vivek Natarajan, Mohammad Norouzi

Google Research and Health†

Abstract

Self-supervised pretraining followed by supervised fine-tuning has seen success in image recognition, especially when labeled examples are scarce, but has received limited attention in medical image analysis. This paper studies the effectiveness of self-supervised learning as a pre-training strategy for medical image classification. We con-

(1) Self-supervised learning on **unlabeled** natural images

A Systematic Benchmarking Analysis of Transfer Learning for Medical Image Analysis

Mohammad Reza Hosseinzadeh Taher[1], Fatemeh Haghighi[1], Ruibin Feng[2], Michael B. Gotway[3], and Jianming Liang[1]

[1] Arizona State University, Tempe, AZ 85281, USA
{mhossei2,fhaghigh,jianming.liang}@asu.edu
[2] Stanford University, Stanford, California 94305, USA
ruibin@stanford.edu
[3] Mayo Clinic, Scottsdale, AZ 85259, USA
Gotway.Michael@mayo.edu

stract. Transfer learning from supervised ImageNet models has been quently used in medical image analysis. Yet, no large-scale evalua- has been conducted to benchmark the efficacy of newly-developed

ON THE IMPACT OF SELF-SUPERVISED LEARNING IN SKIN CANCER DIAGNOSIS

Maria Rita Verdelho and Catarina Barata

Institute for Systems and Robotics, Instituto Superior Técnico, Lisboa, Portugal

ABSTRACT

Deep neural networks (DNNs) are the standard approach for image classification. However, they require a large amount of data and corresponding annotations. Collecting

in medical image analysis [6]. Additionally, the color distribution of natural images is also very different from the medical ones [7], which can result in models that have difficulties in generalizing to the other data [6].

Self-supervised learning (SSL) has emerged as a strategy

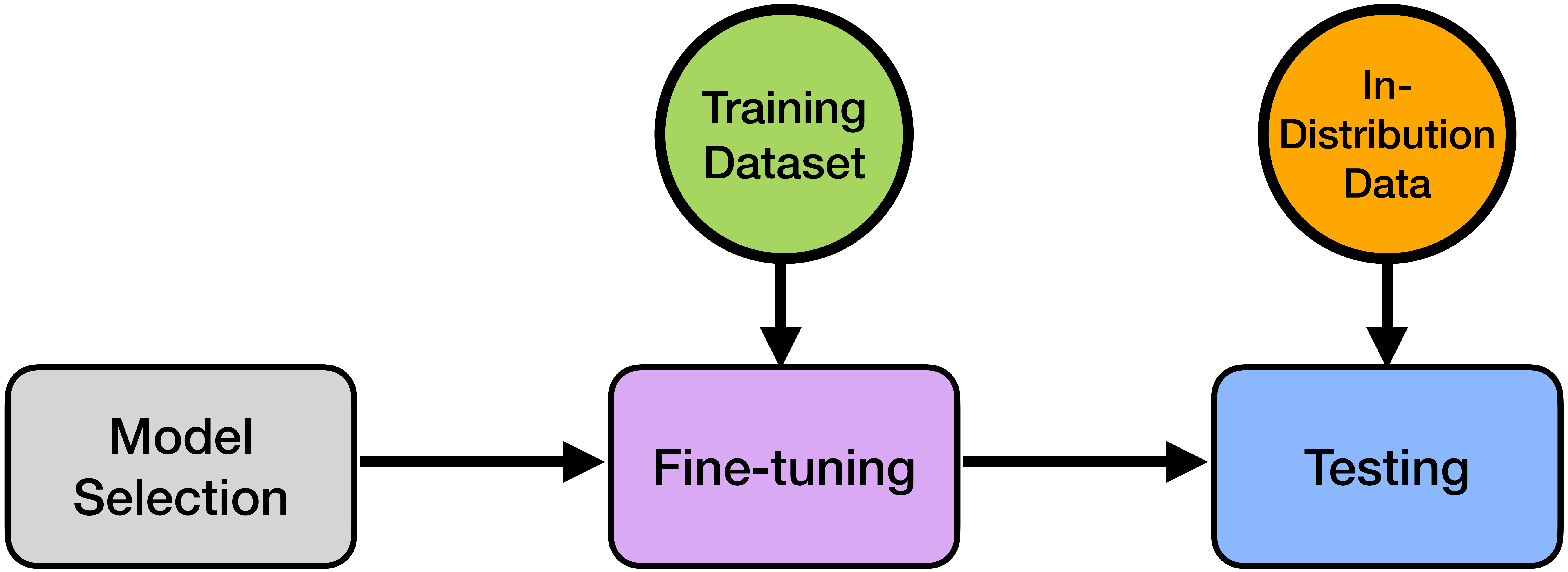
What were they missing?

Work *year*	Out-of-distribution Evaluation	Low-data Evaluation
Azizi et al. 2021	✗	✓
Hosseinzadeh et al. 2021	✗	✗
Truong et al. 2021	✗	✓
Verdelho et al. 2022	✗	✗
Ours 2022	✓	✓

Chaves et al., “An Evaluation of Self-Supervised Pre-Training for Skin-Lesion Analysis “, ISIC Workshop @ ECCV 2022

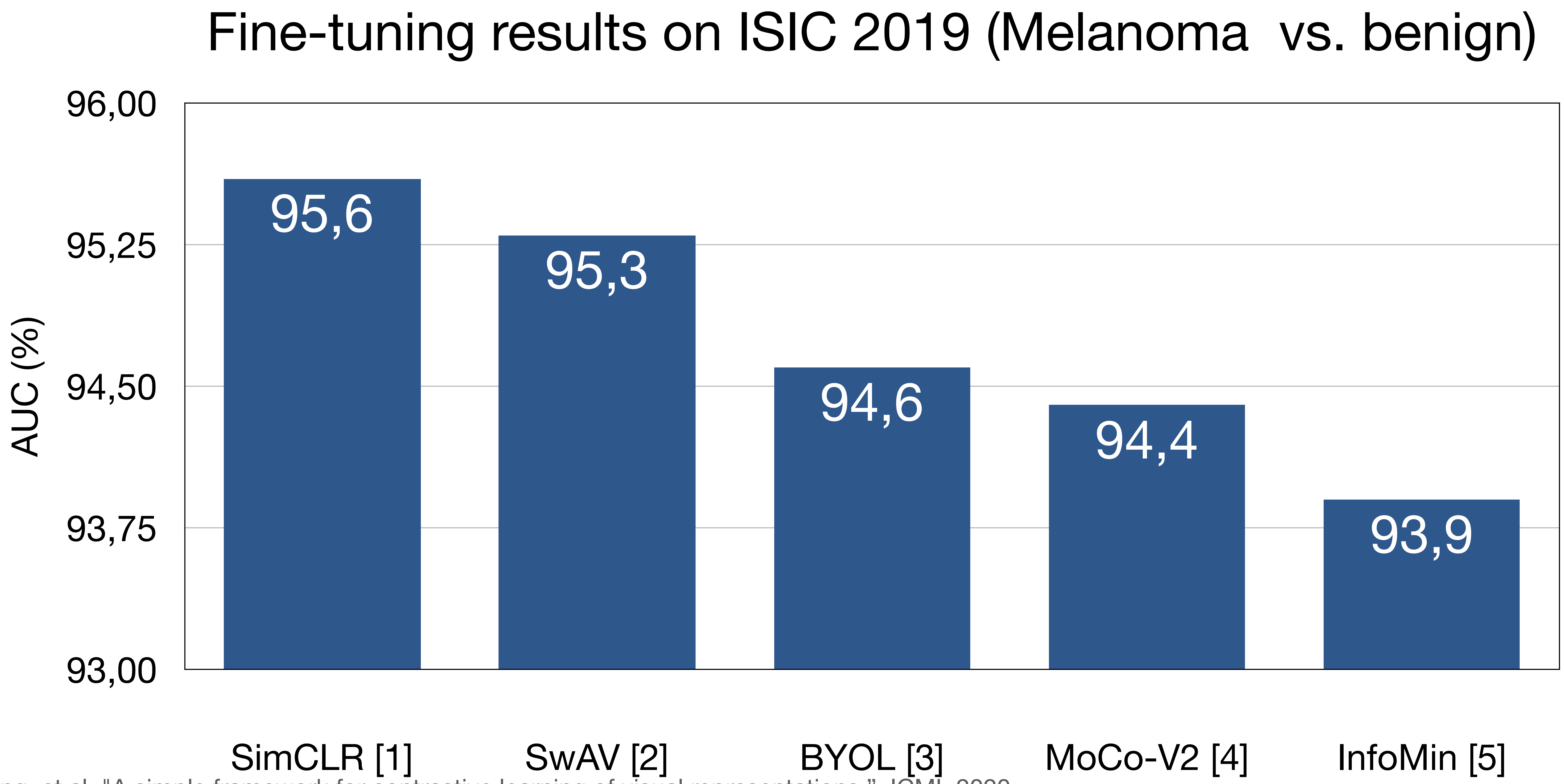
Experimental Design & Preliminary results

Standard Evaluation Protocol



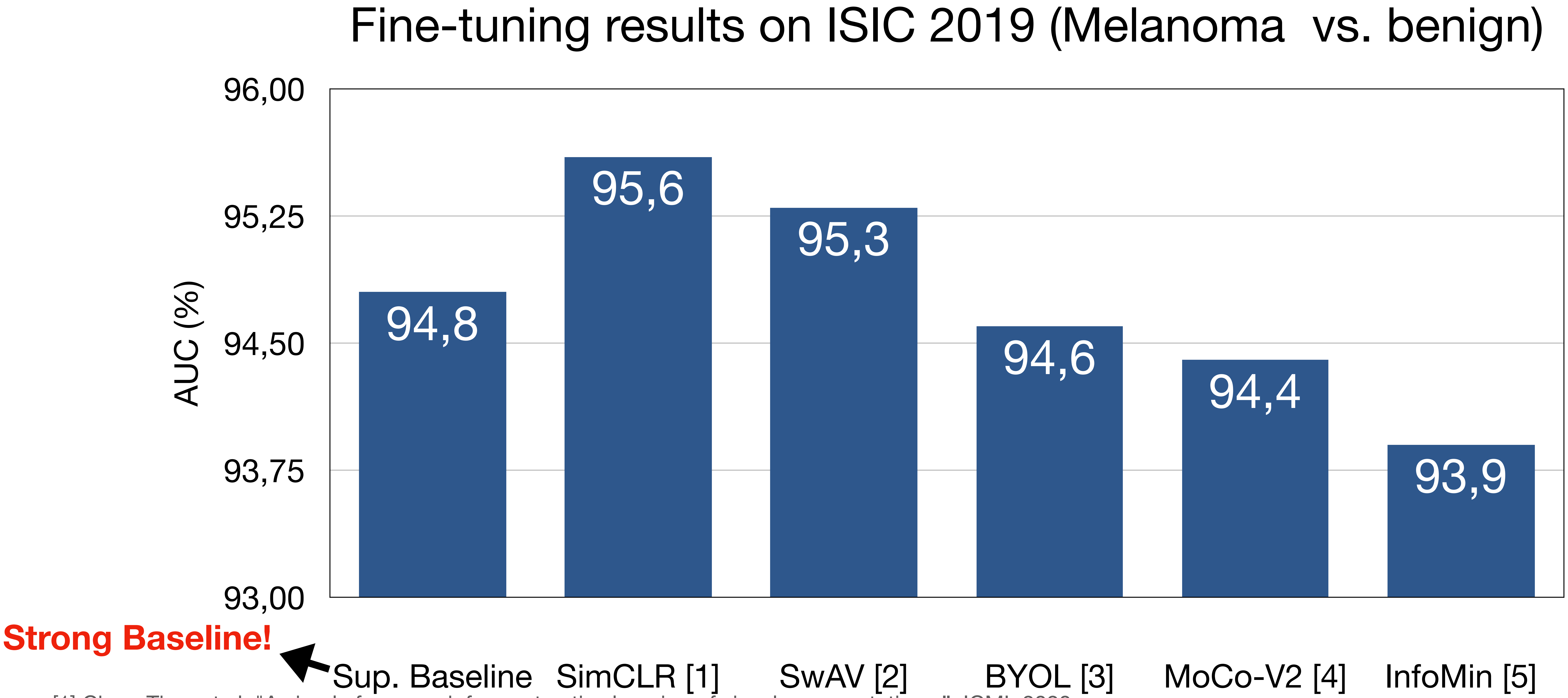
Supervised (baseline)
Self-supervised (5 candidates)

Evaluated self-supervised learning methods



[1] Chen, Ting, et al. "A simple framework for contrastive learning of visual representations.”. ICML 2020.
[2] Caron, Mathilde, et al. "Unsupervised learning of visual features by contrasting cluster assignments.”. NeurIPS 2020
[3] Grill, J. B, et al. Bootstrap your own latent-a new approach to self-supervised learning. NeurIPS. 2020
[4] Chen, Xinlei, et al. "Improved baselines with momentum contrastive learning." *arXiv preprint arXiv:2003.04297.* 2020.
[5] Tian, Yonglong, et al. "What makes for good views for contrastive learning?.”. *NeurIPS* 2020.

Evaluated self-supervised learning methods



[1] Chen, Ting, et al. "A simple framework for contrastive learning of visual representations.". ICML 2020.
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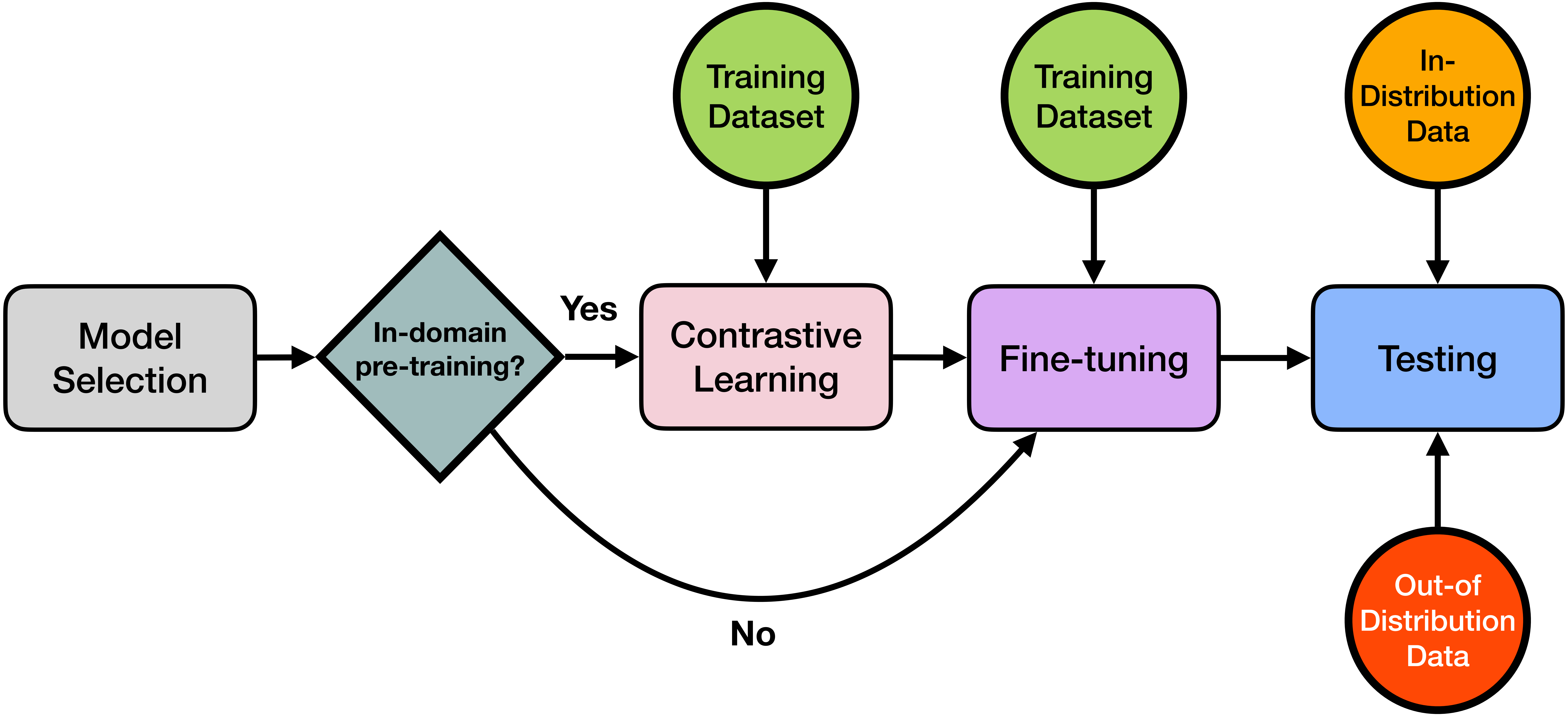
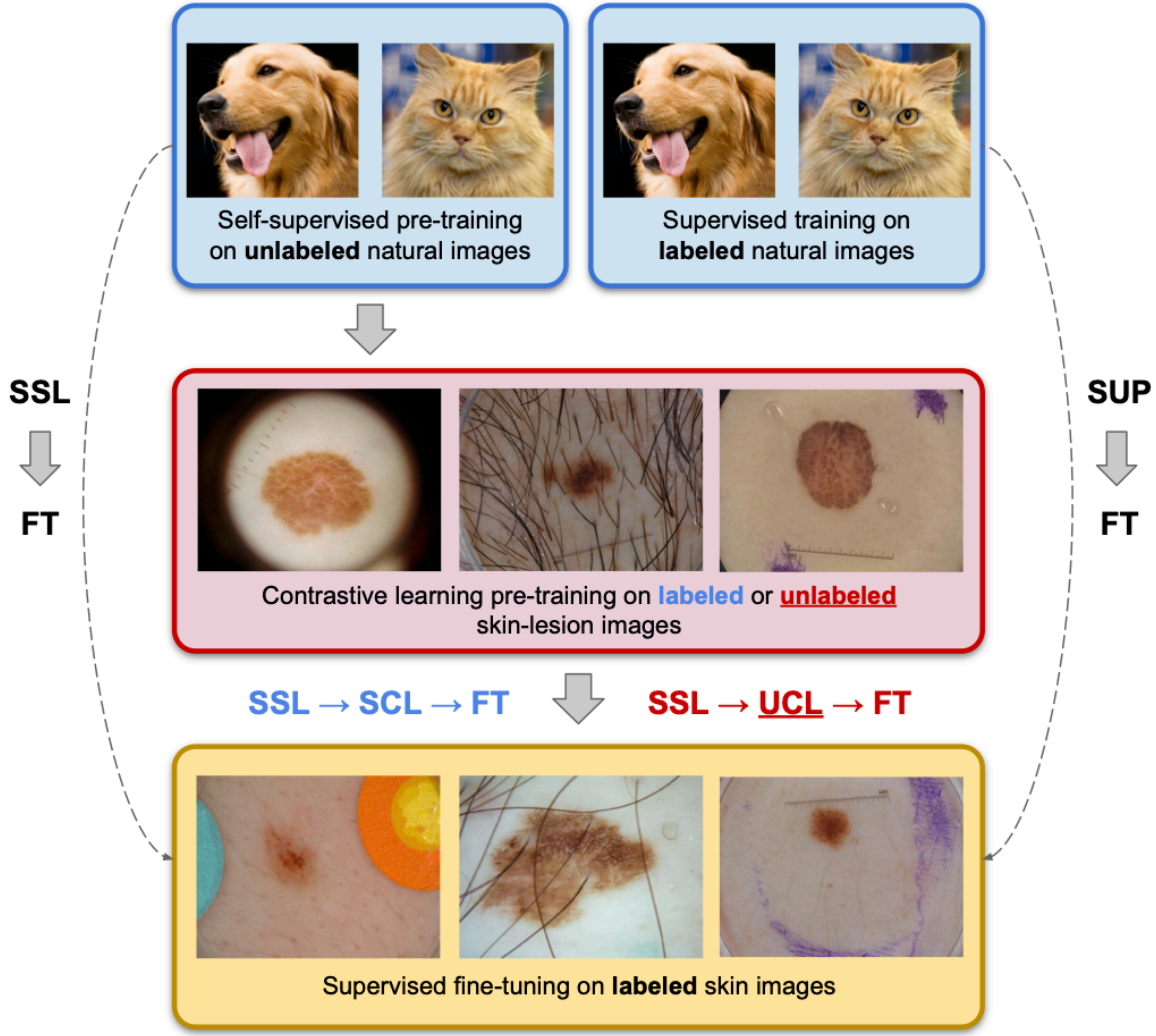
Our Evaluation Protocol



Our pipelines



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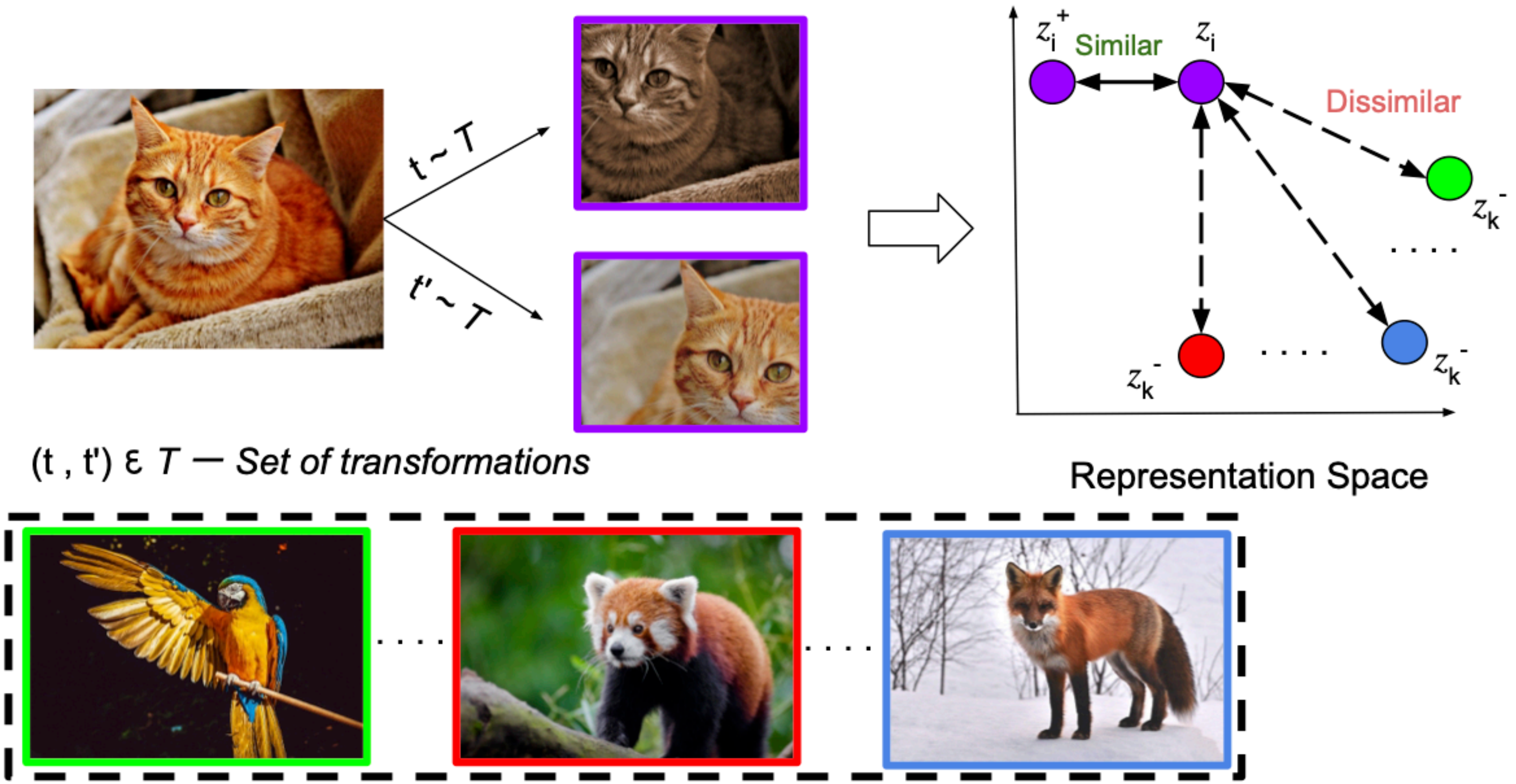
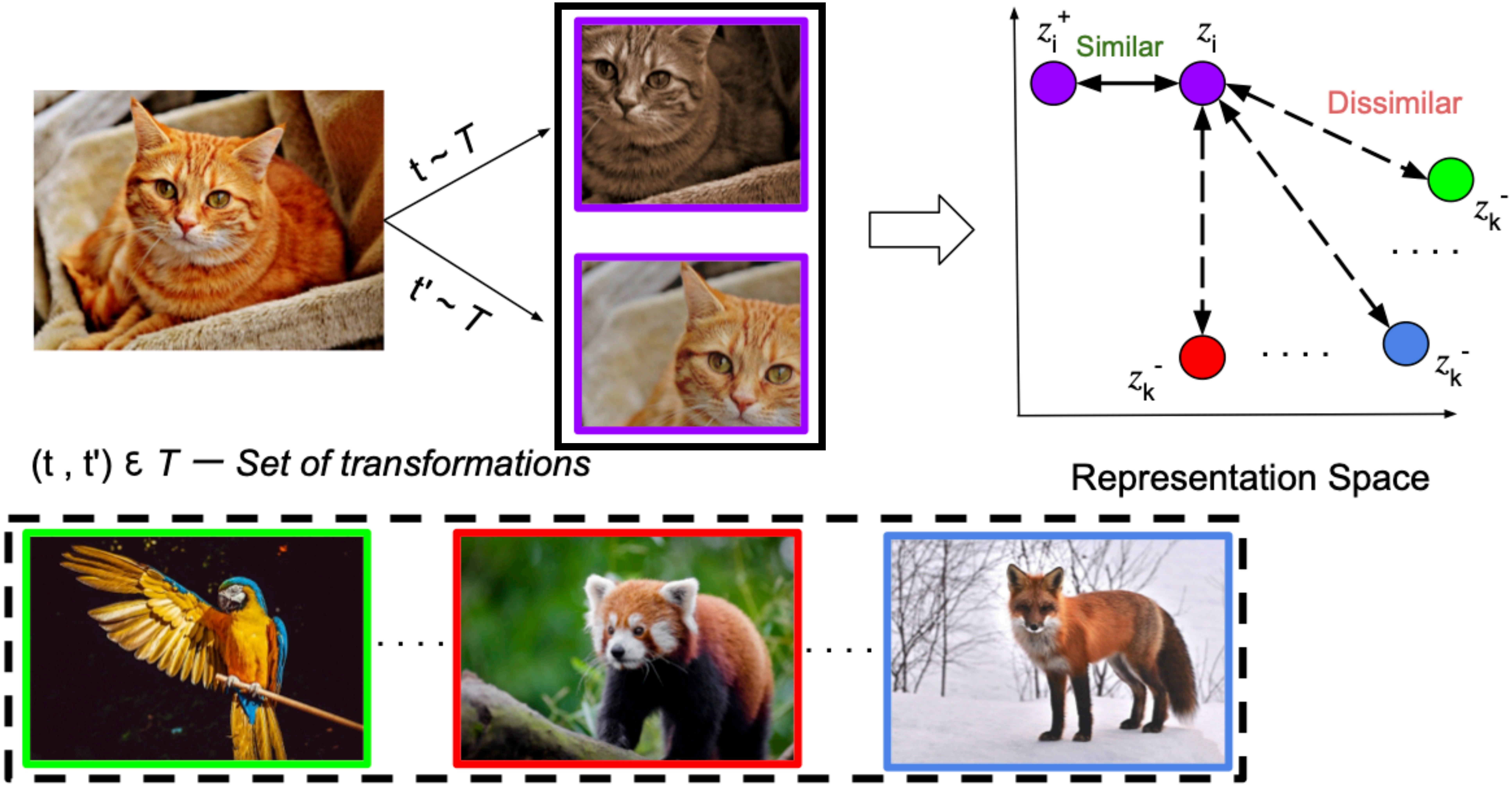
Contrastive Learning



Contrastive Learning

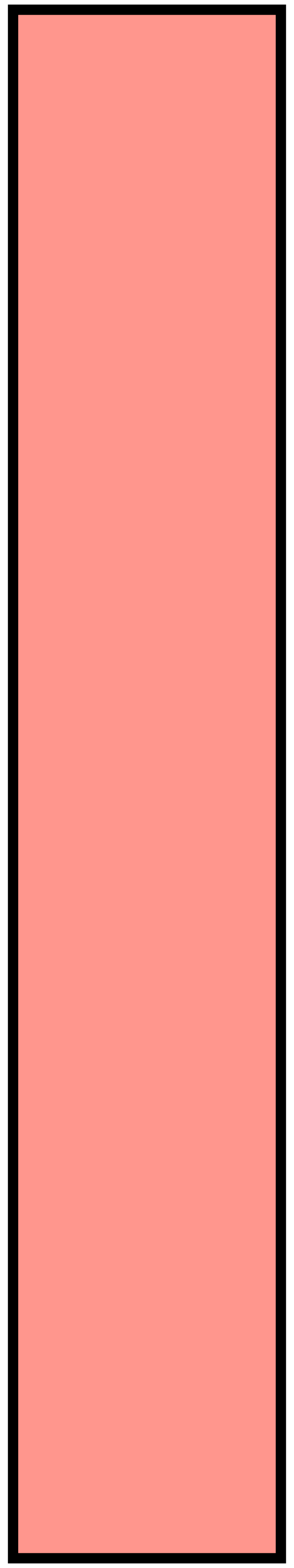


Unsupervised Contrastive Learning (UCL) -> Image augmentations to create positive views

Supervised Contrastive Learning (SCL) -> Label class to create positive views

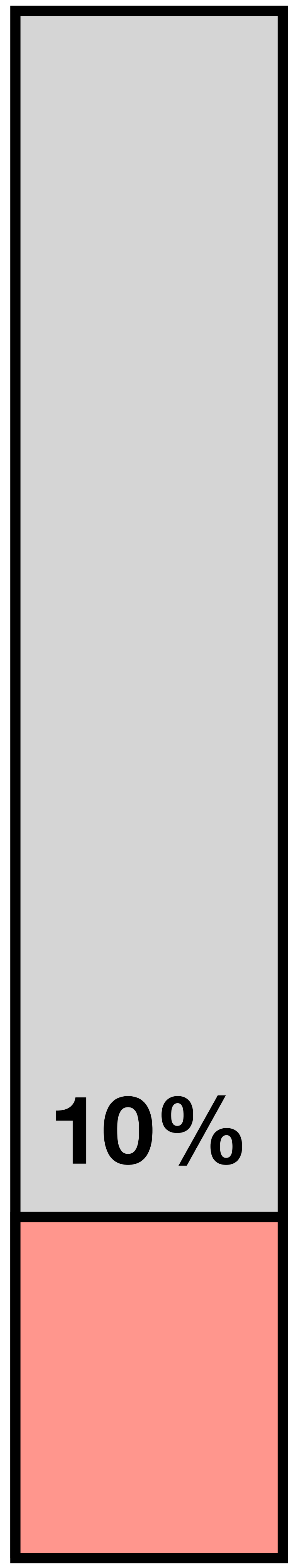
Full-data evaluation

Training Data
100 %



Low-data evaluation

Training Data

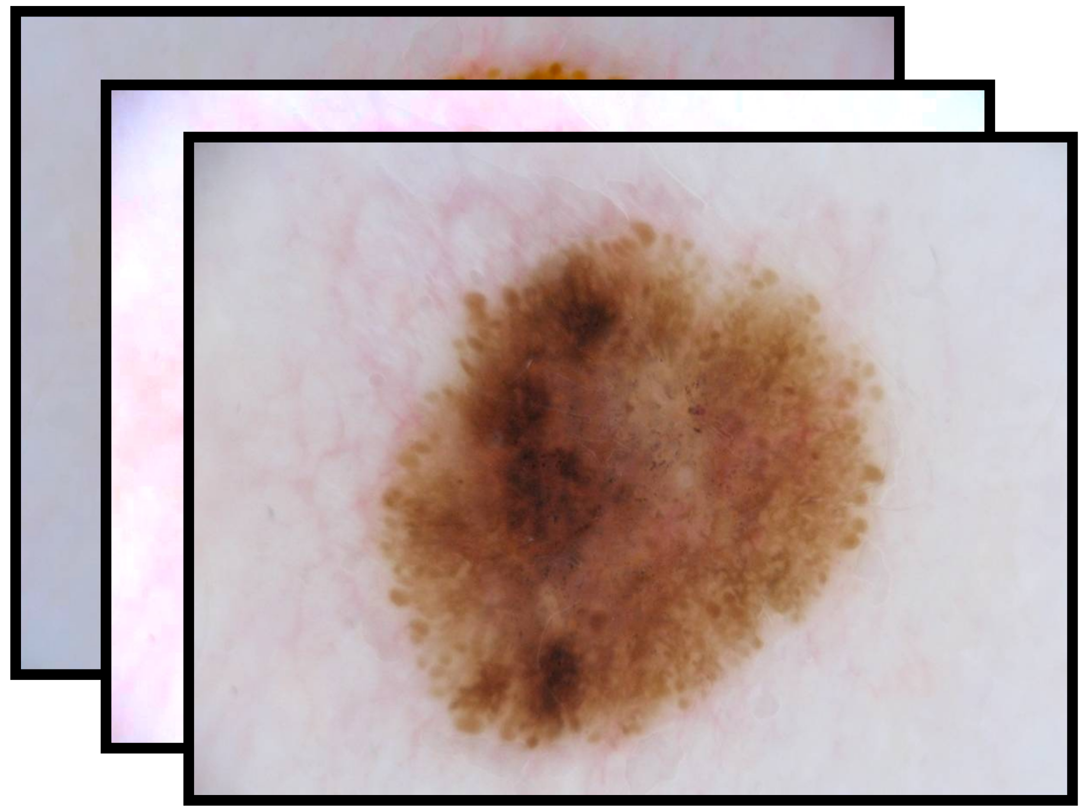


Low-data evaluation

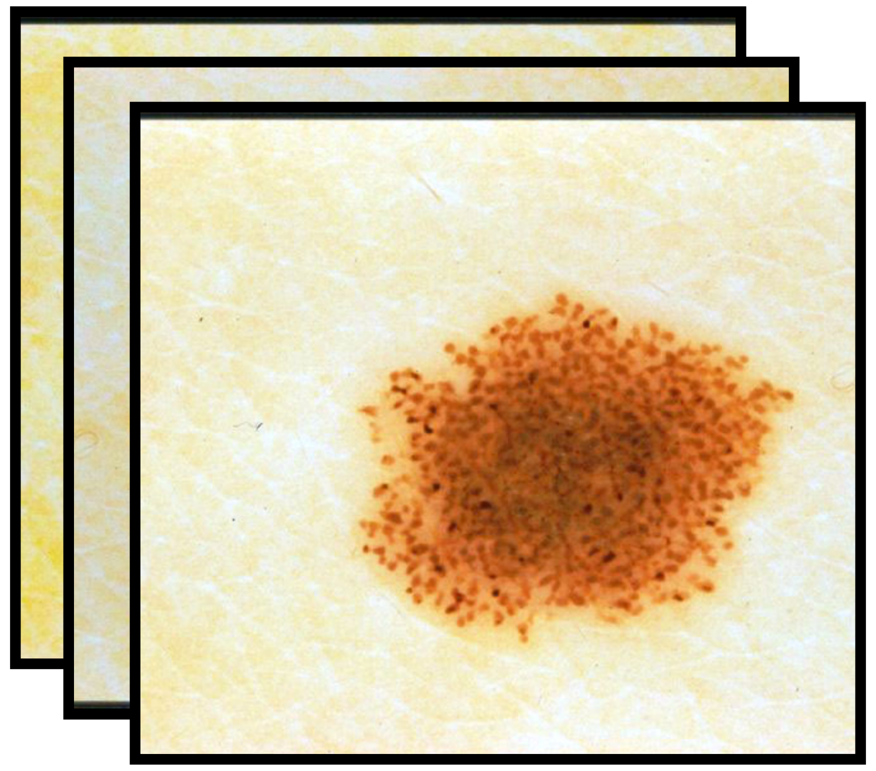
Out-of-Distribution Evaluation

Train | Test

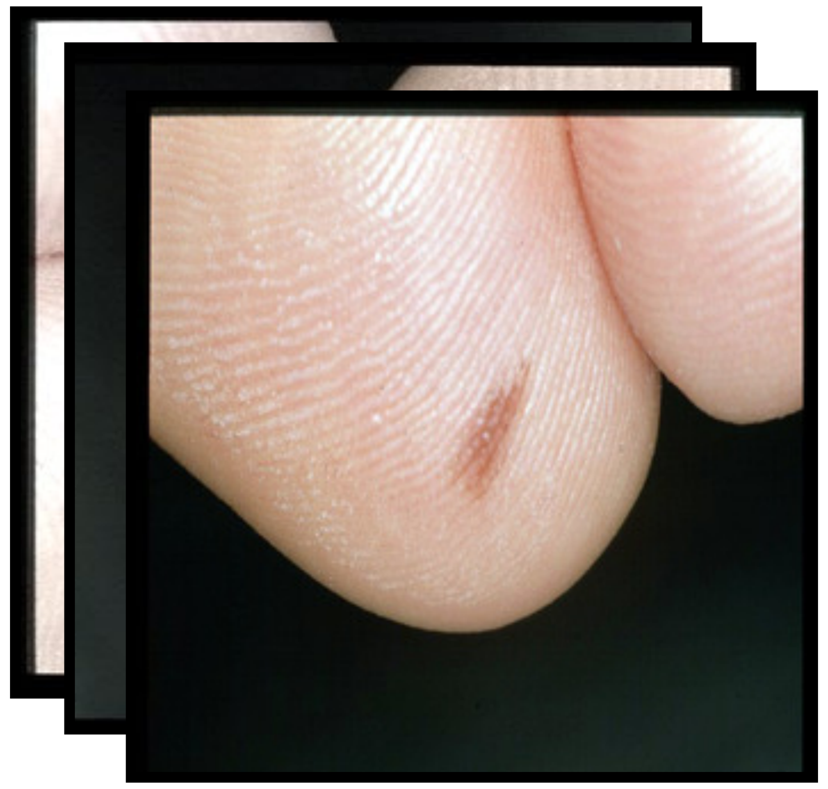
ISIC 2019



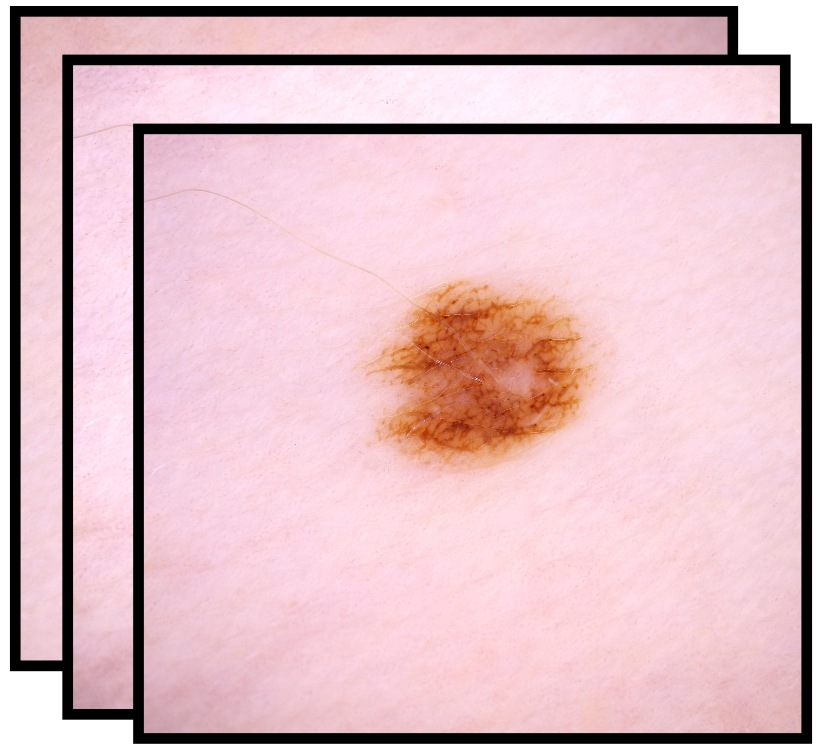
Derm7pt-dermato



Derm7pt-clinical

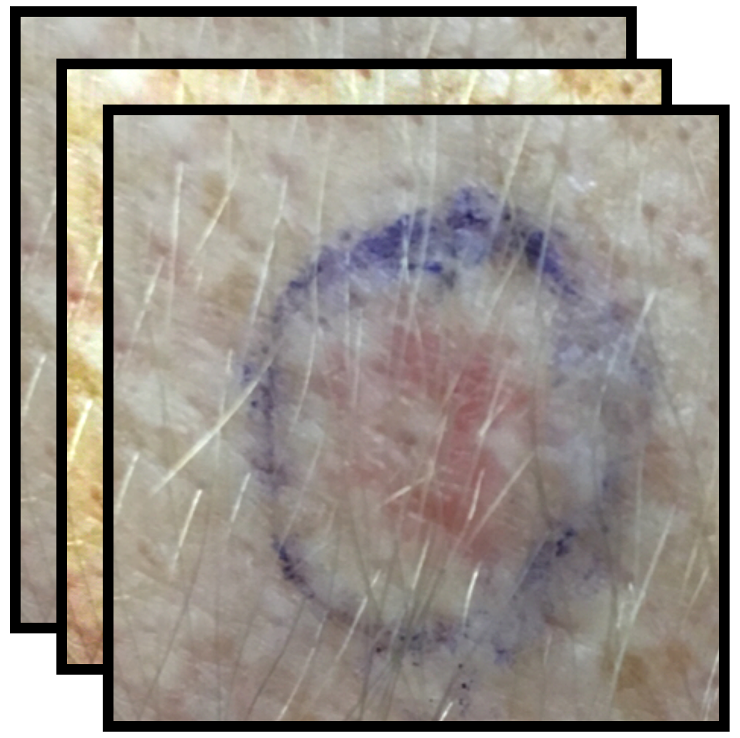


ISIC 2020



Additional benign Diagnosis

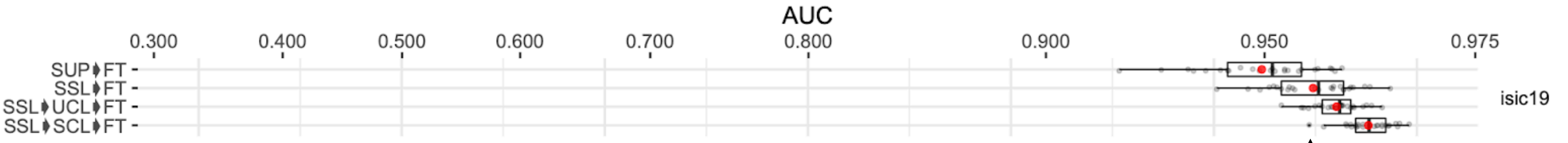
PAD-UFES-20



Additional benign Diagnosis

Results

Full data and out-of-distribution performance



Pipelines

Measurements (black dots) And Means (red dots)

Test Dataset

100% of training data — 14,805 samples

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Full data and out-of-distribution performance

100% of training data — 14,805 samples

Low-data and out-of-distribution performance

10% of training data — 1,480 samples

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Low-data and out-of-distribution performance

1% of training data — 148 samples

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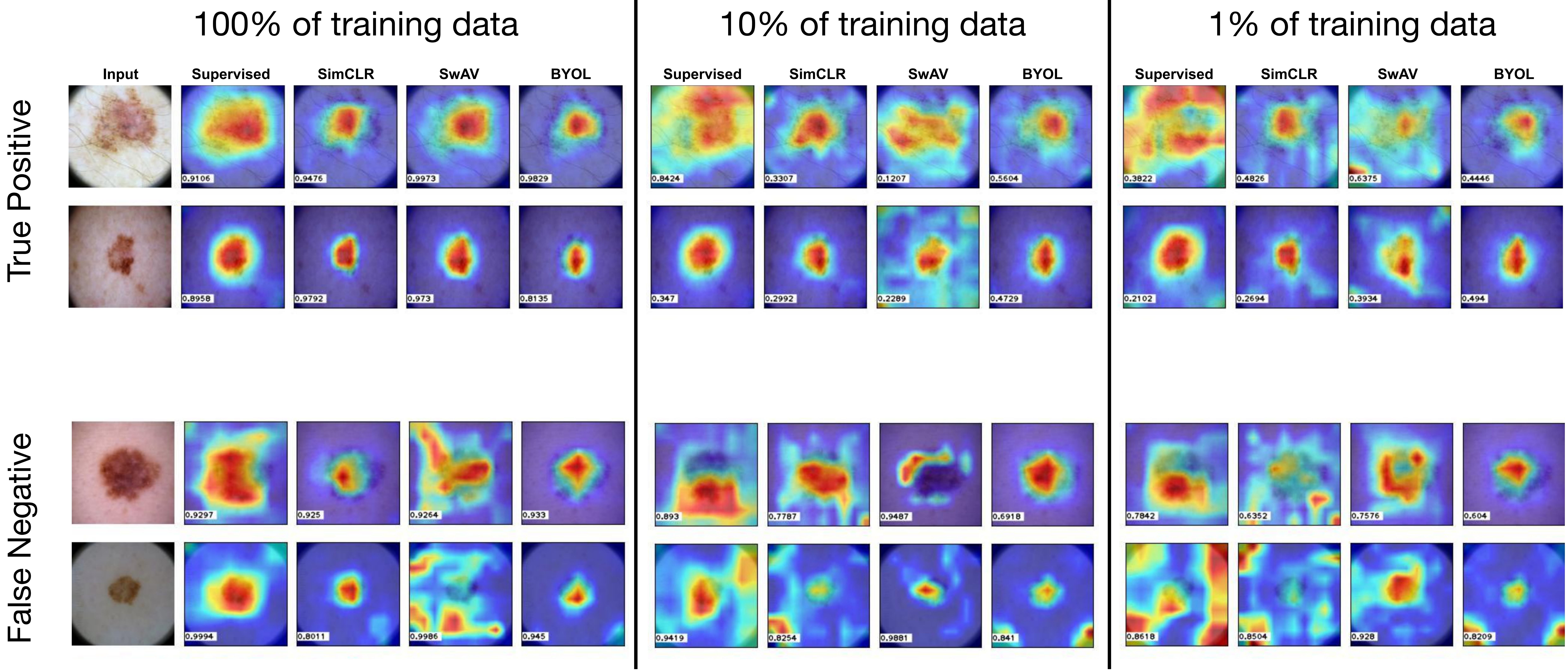
Qualitative Analysis



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Conclusion

- **The advantage of self-supervised pipelines was particularly positive in the low-data scenarios**

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- **Models pre-trained in a self-supervised manner felt easier to optimize**

Conclusion

- The advantage of self-supervised pipelines was particularly prominent in the low-data scenarios
- Models pre-trained in a self-supervised manner felt easier to optimize
- **Understanding what circumstances make self-supervised competitive from a theoretical perspective is a promising research area.**

Limitations

- Explored just one training dataset and model architecture

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- Explored just one training dataset and model architecture
- Extensive exploration is necessary to evaluate if self-supervised is reinforcing data biases

Code and data available on Github!
https://github.com/VirtualSpaceman/ssl-skin-lesions

Thank you!

Levy Chaves levy.chaves@ic.unicamp.br
Alceu Bissoto alceubissoto@ic.unicamp.br
Eduardo Valle dovalle@dca.fee.unicamp.br
Sandra Avila sandra@ic.unicamp.br

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