Ninth ISIC Skin Image Analysis Workshop @ MICCAI 2024

Segmentation Style Discovery: Application to Skin Lesion Images

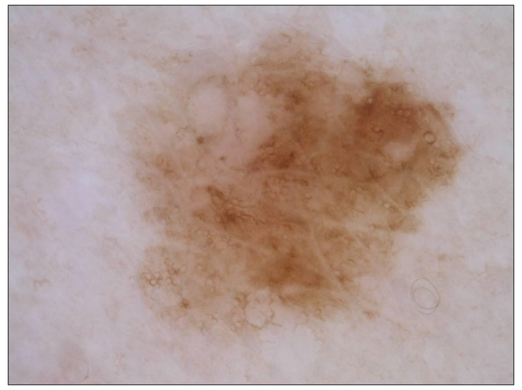


Kumar Abhishek[†] Jeremy Kawahara[‡] Ghassan Hamarneh[†]

[†] SFU Simon Fraser University

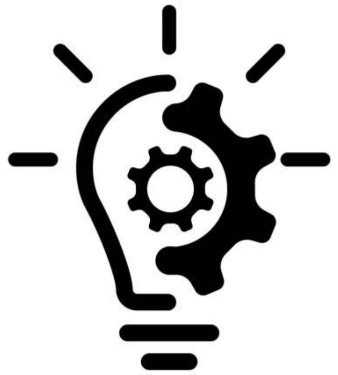
[‡] AIP LABS®

Variability in Medical Image Segmentation



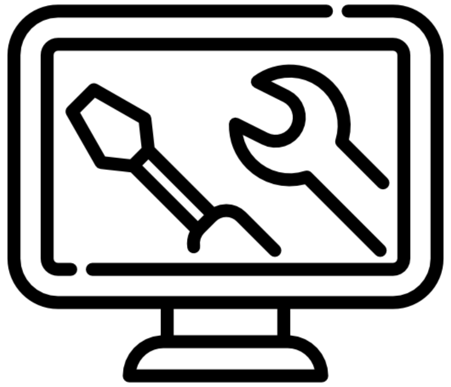
Ambiguous object boundaries

Annotators' personal preferences



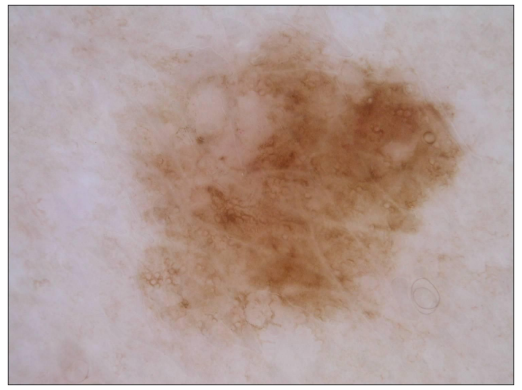
Annotators' skill levels

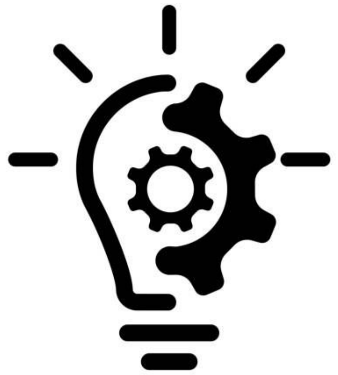
Segmentation criteria

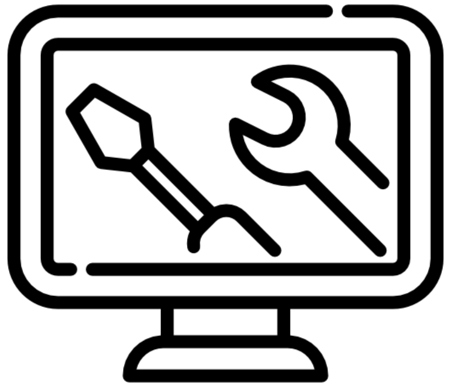


Segmentation tools

Variability in Medical Image Segmentation







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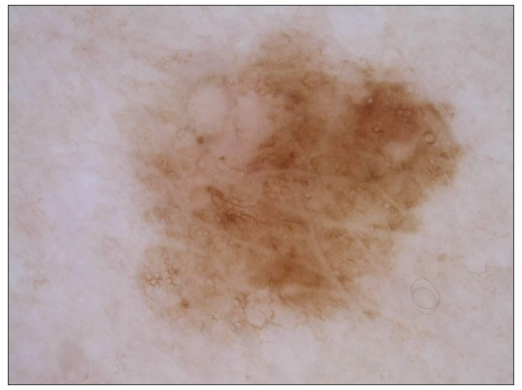

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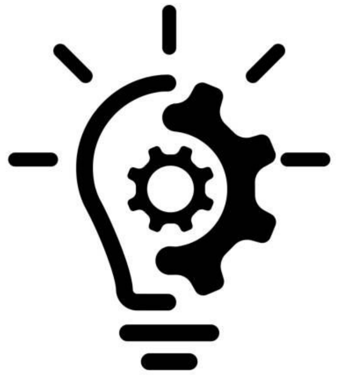

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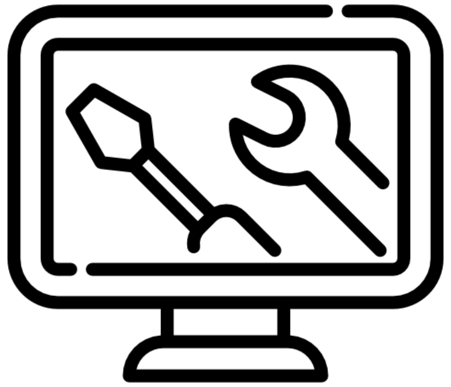

Segmentation tools

Latent factors

Different annotation segmentation preferences or "**styles**"

Methods for Learning from Multiple Annotations

$\mathbb{SS}\mathbf{eg}$ **methods** model and learn to predict a single “gold standard” segmentation.

[1] Silletti et al., 2009

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***Abstract*— In a double blind evaluation of 60 digital dermatoscopic images by 4 “junior”, 4 “senior” and 4 “expert” dermatologists (dermatoscopy training respectively less than 1 year, between 1 and 5 years, and more than 5 years), a significant inter-operator variability was observed in melanocytic lesion border identification (with a disagreement of the order of $10-20\%$ of the area of the lesions). Expert dermatologists**

dard operative definition. For example, if even experienced dermatologists disagree on how to classify 5% of the area of an image, no automated system can be expected to classify “correctly” more than 95% of the area of that image.

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Dataset requirement:
multi-annotator segmentations containing image-mask pairs with annotator-segmentation correspondence.

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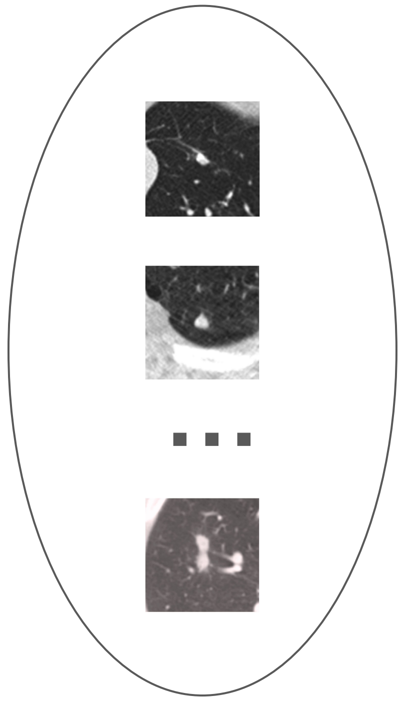
Multi-Annotator Medical Image Segmentation Datasets



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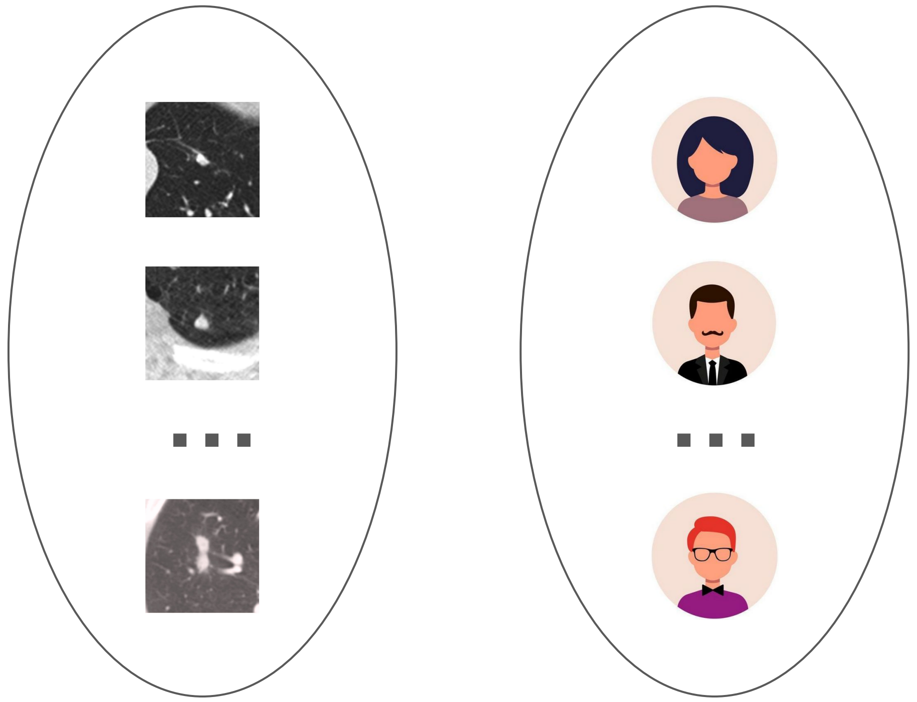

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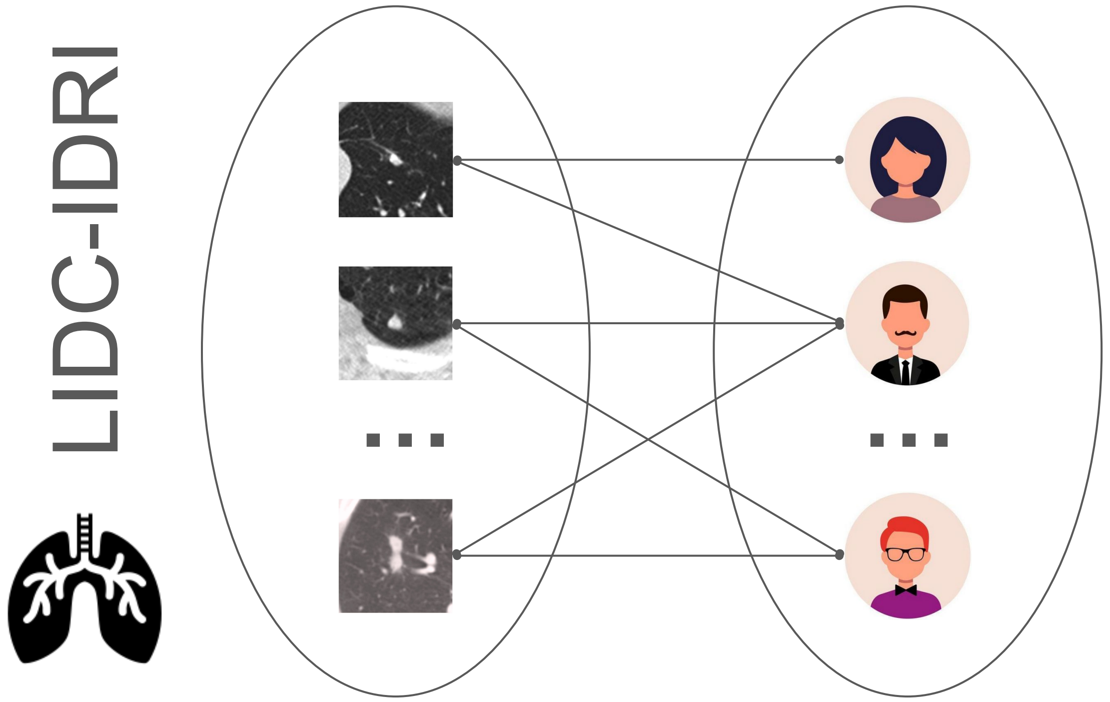
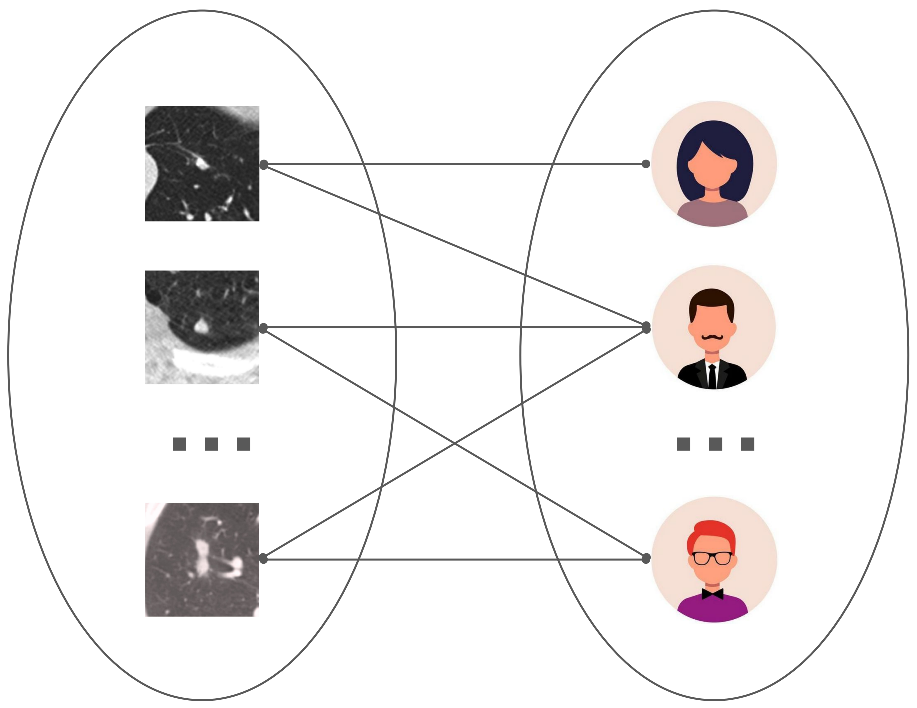


Bipartite graph

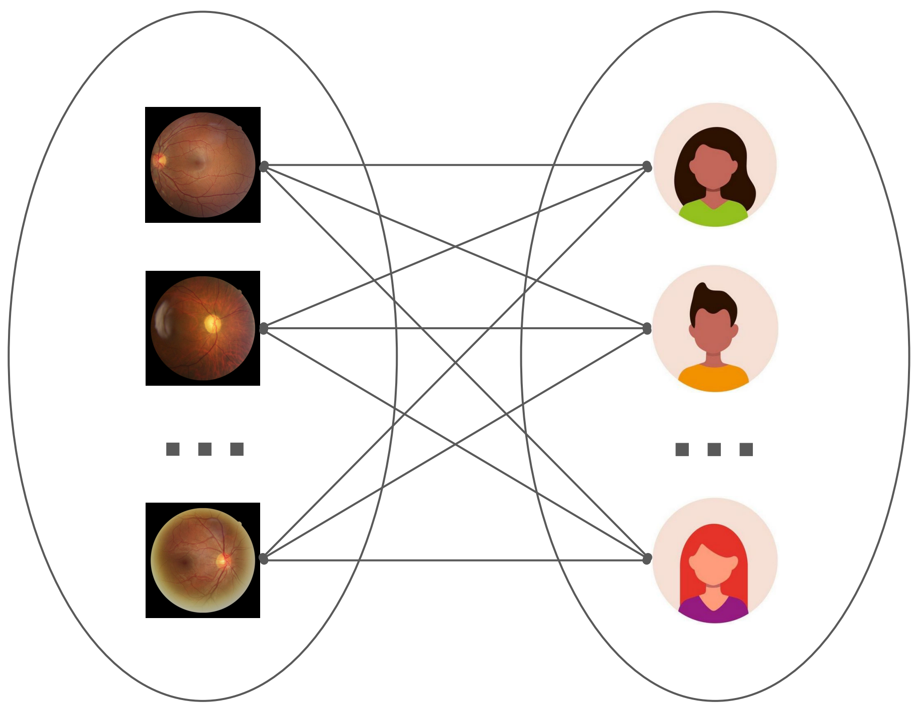
Multi-Annotator Medical Image Segmentation Datasets

LIDC-IDRI



Bipartite graph

RIGA



<u>Complete</u> bipartite graph

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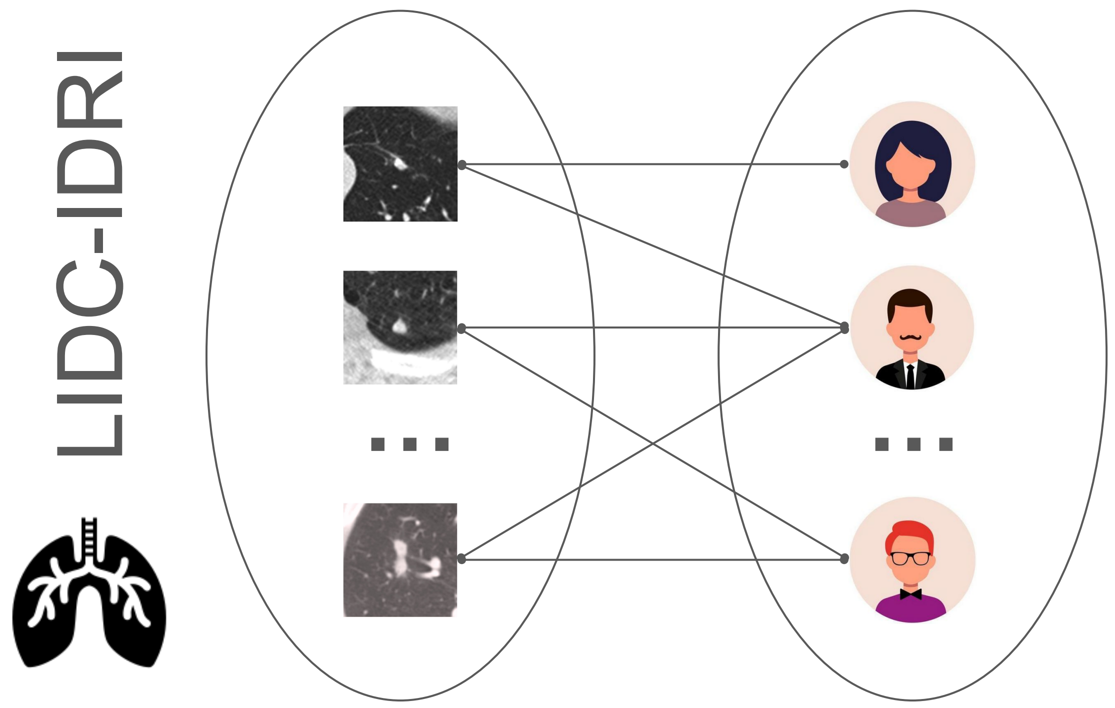

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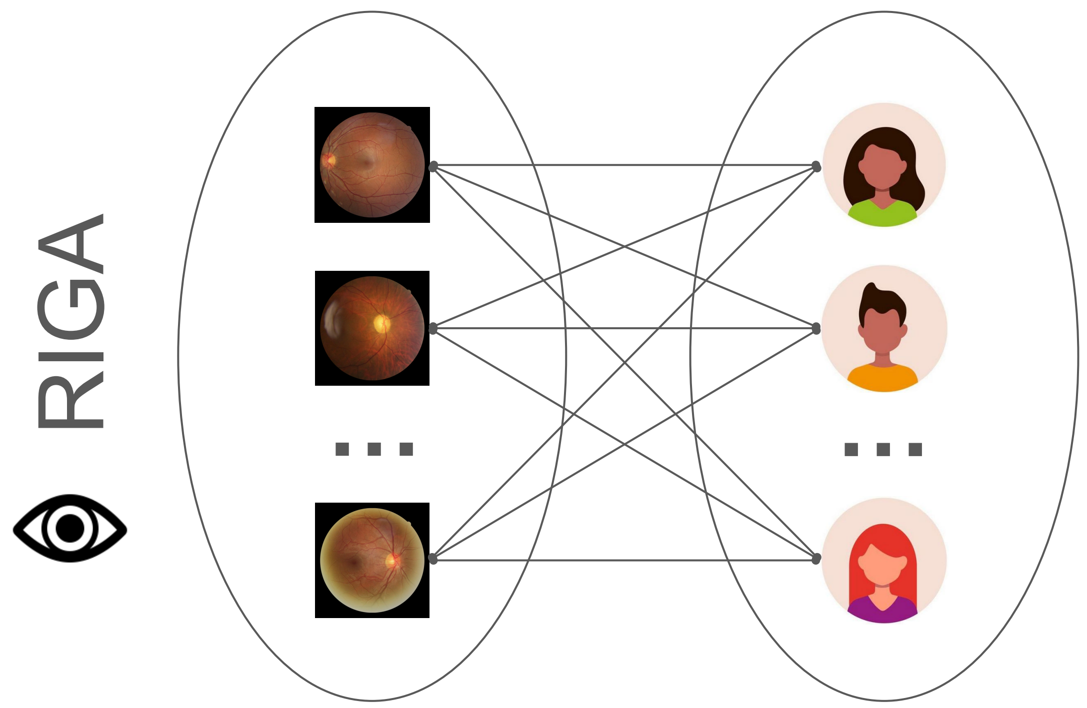

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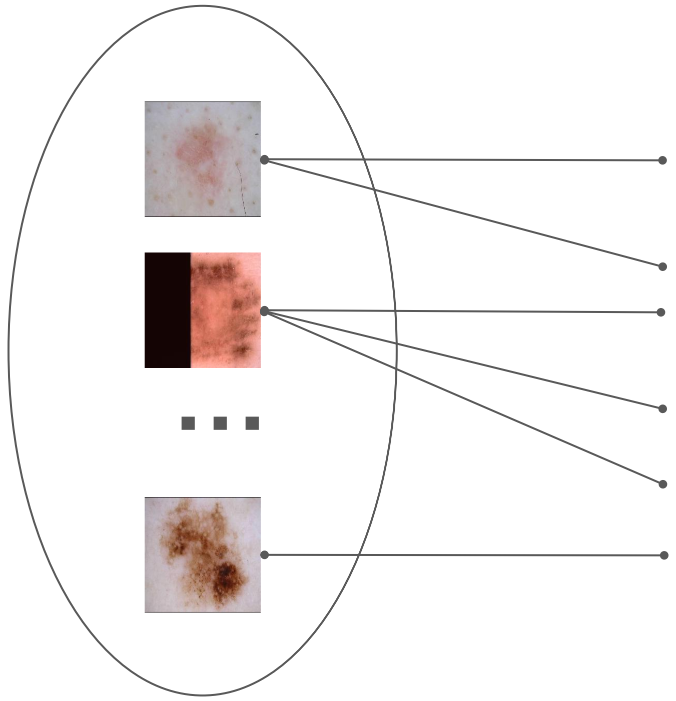

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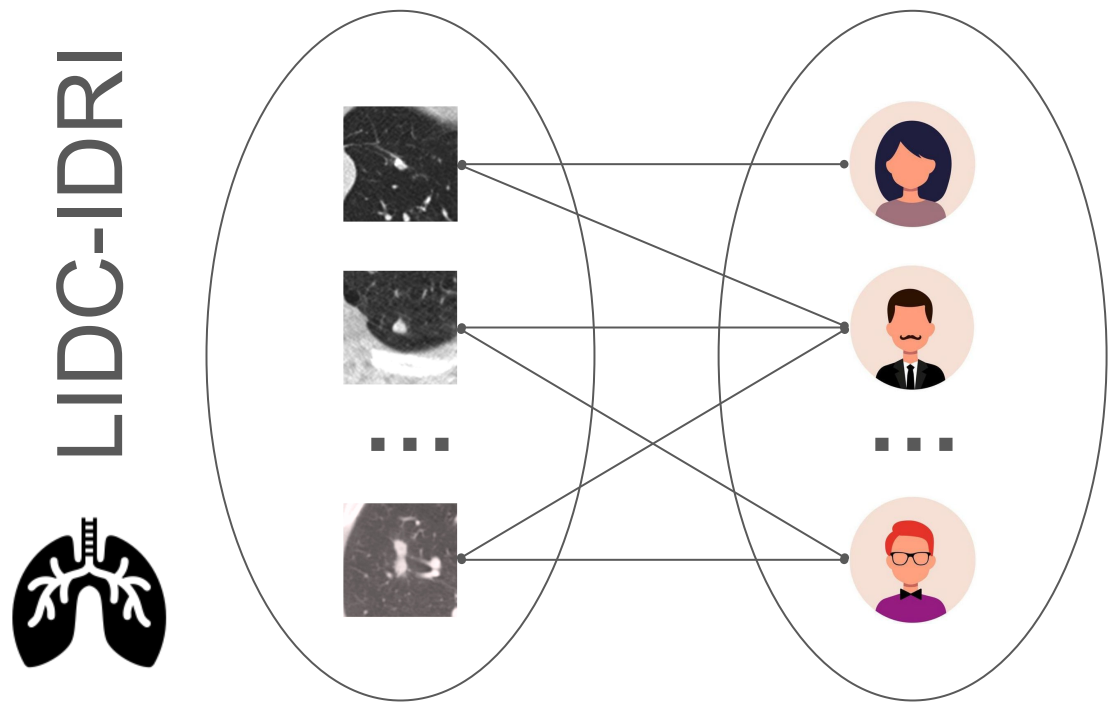

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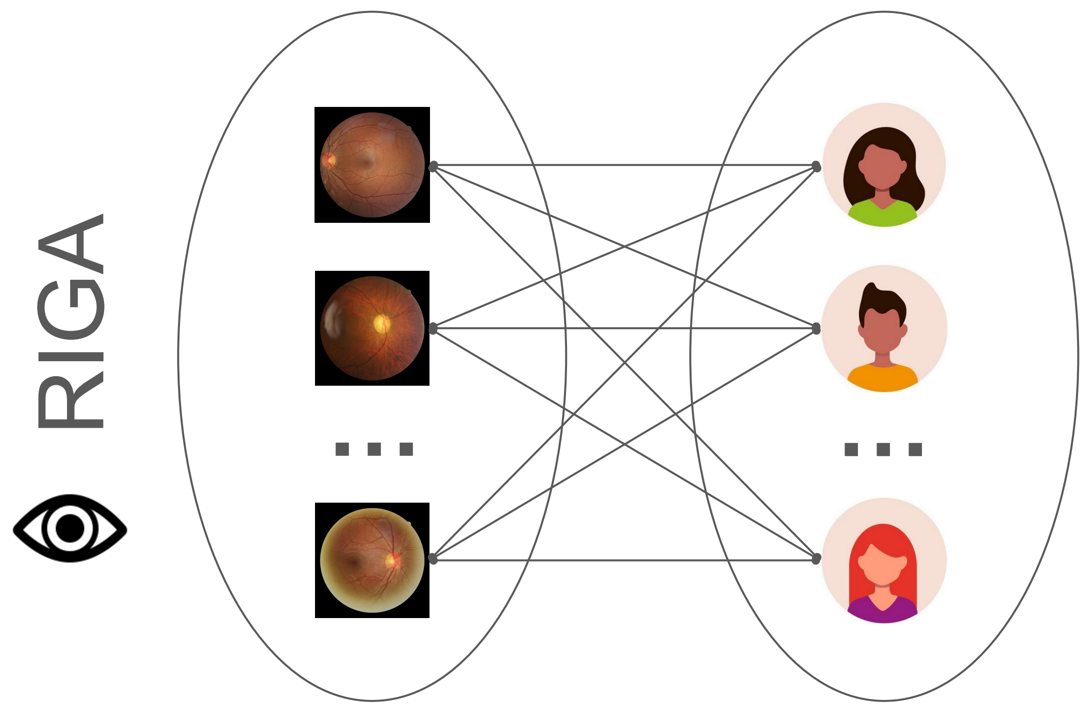

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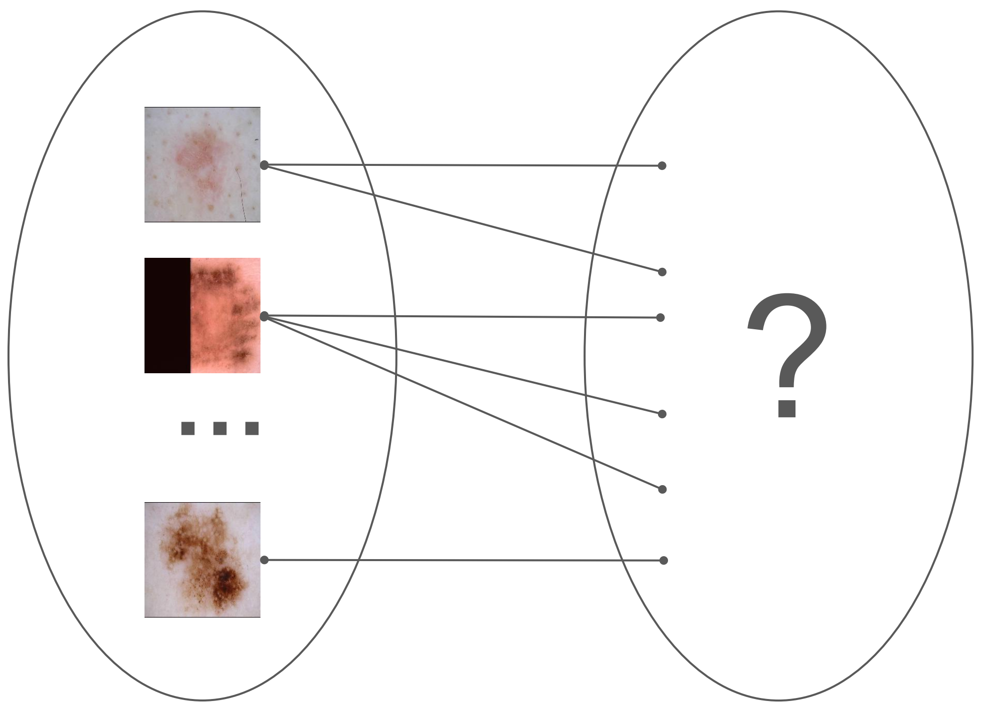

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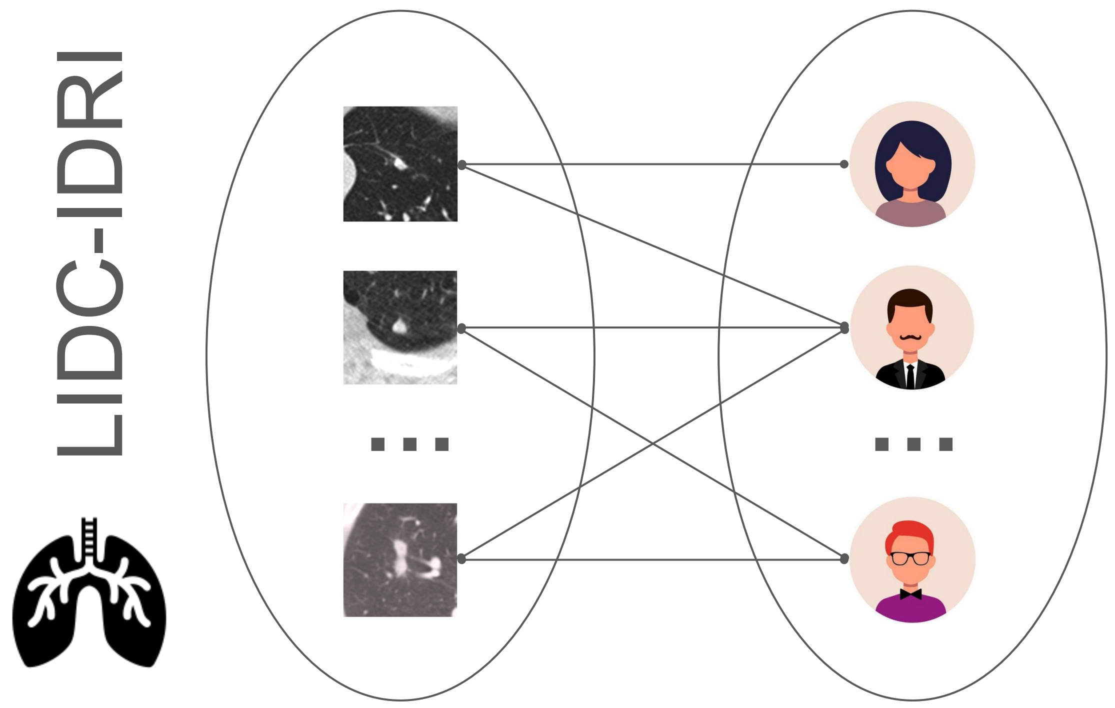

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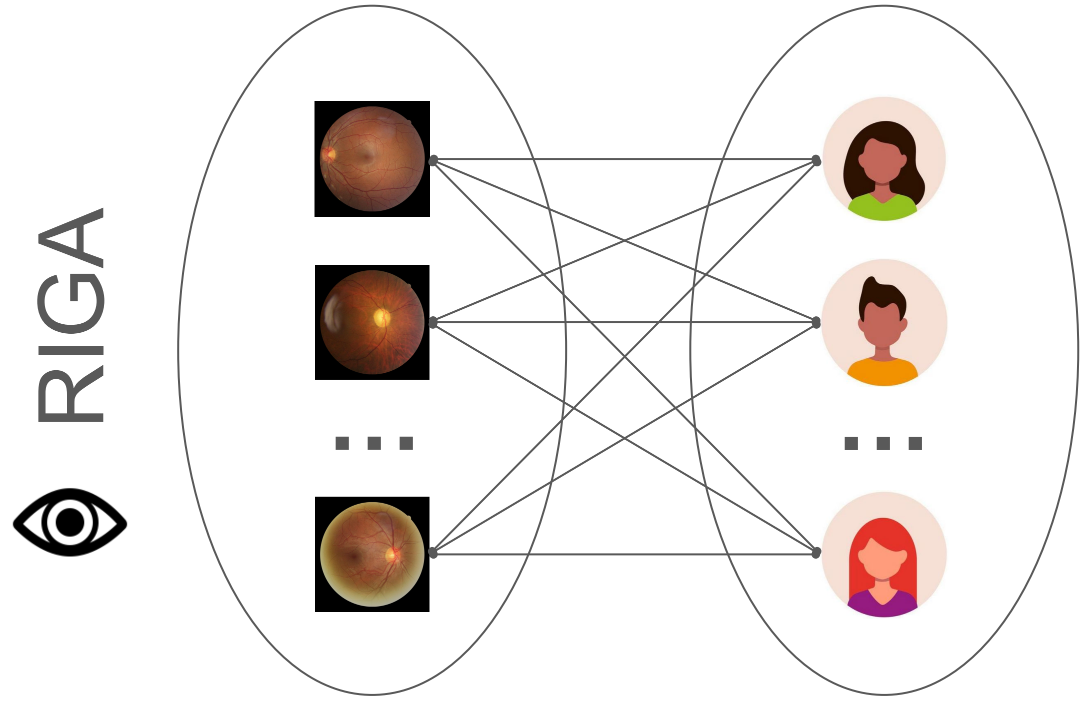

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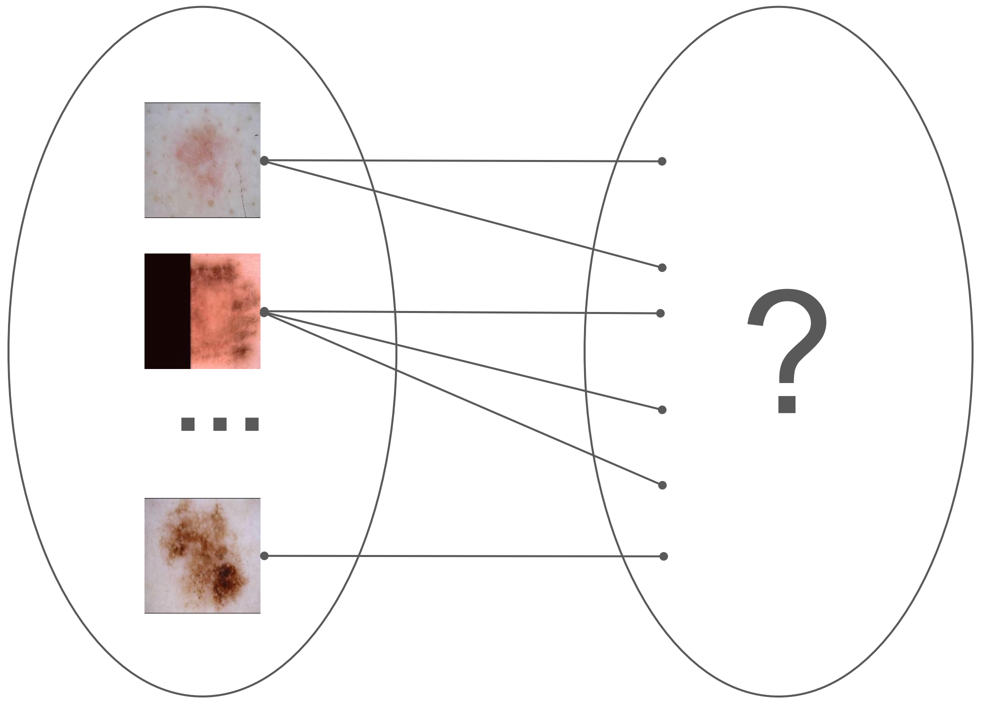

Latent factors unknown ⇒ difficult to define a segmentation “**style**”.

Segmentations in ISIC Archive and their Variability

2,261 images with more than 1 “ground truth” segmentation mask
⇒ 4,704 training image-mask pairs for skin lesion segmentation (**SLS**).

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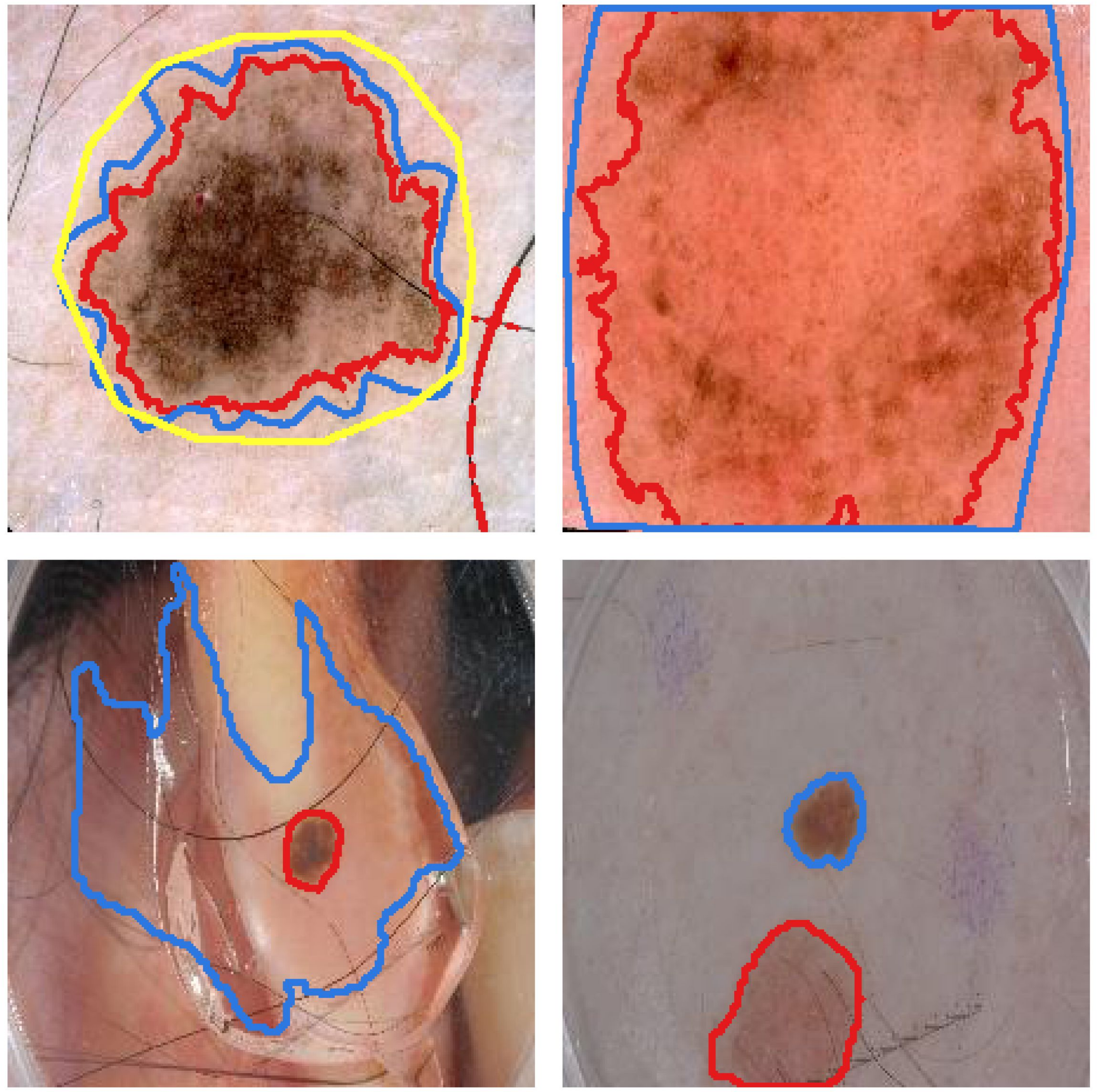

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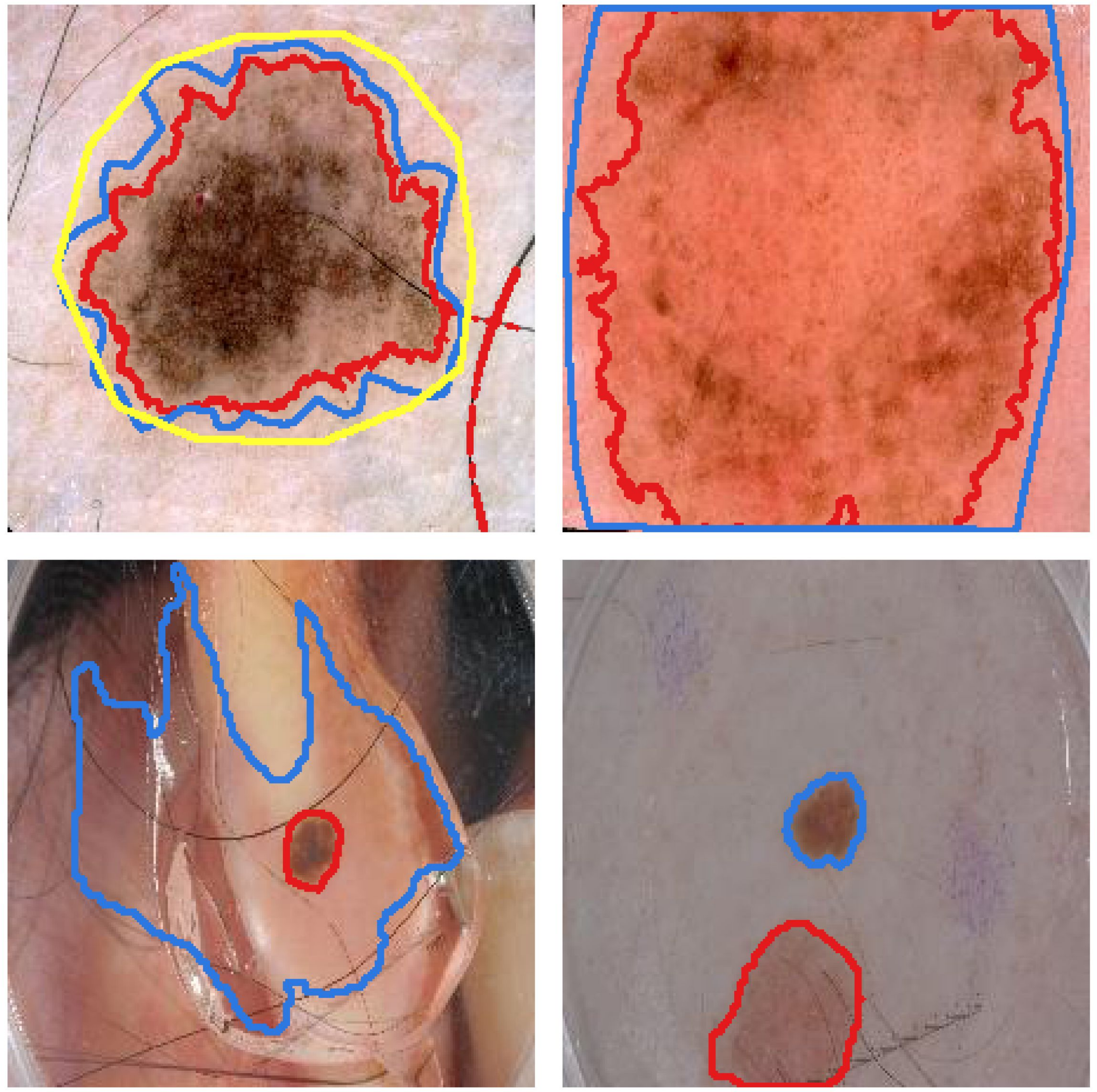

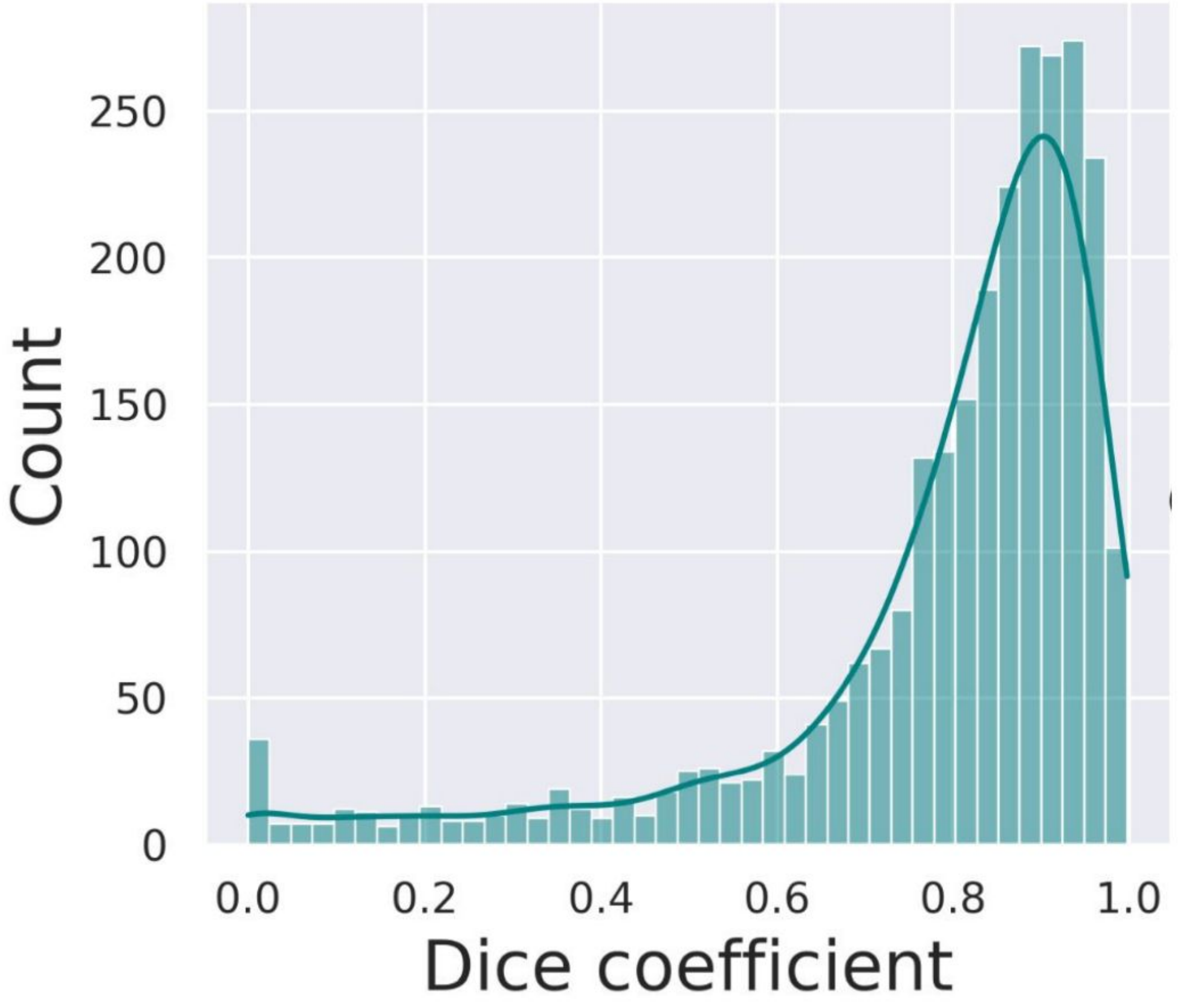

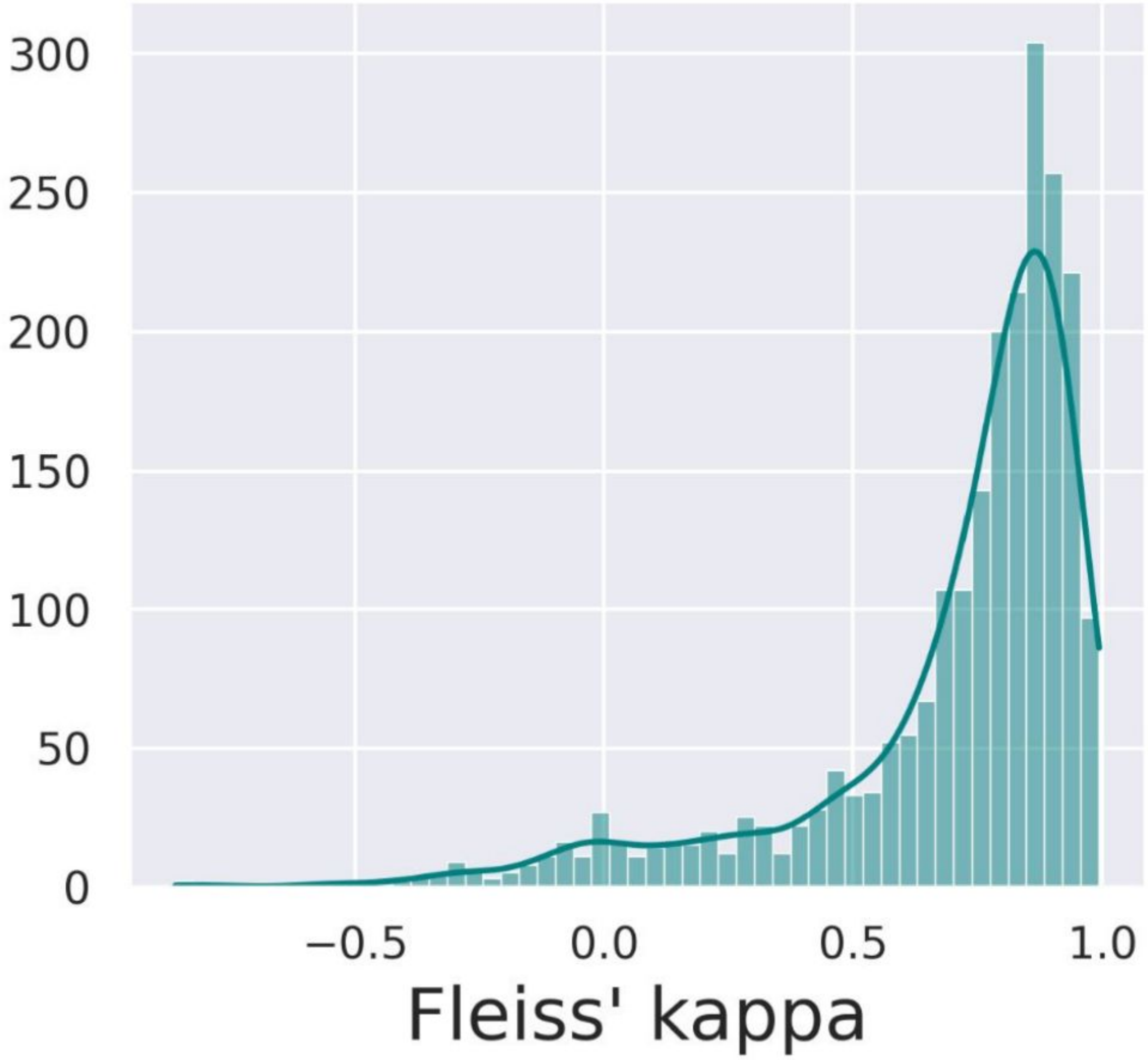

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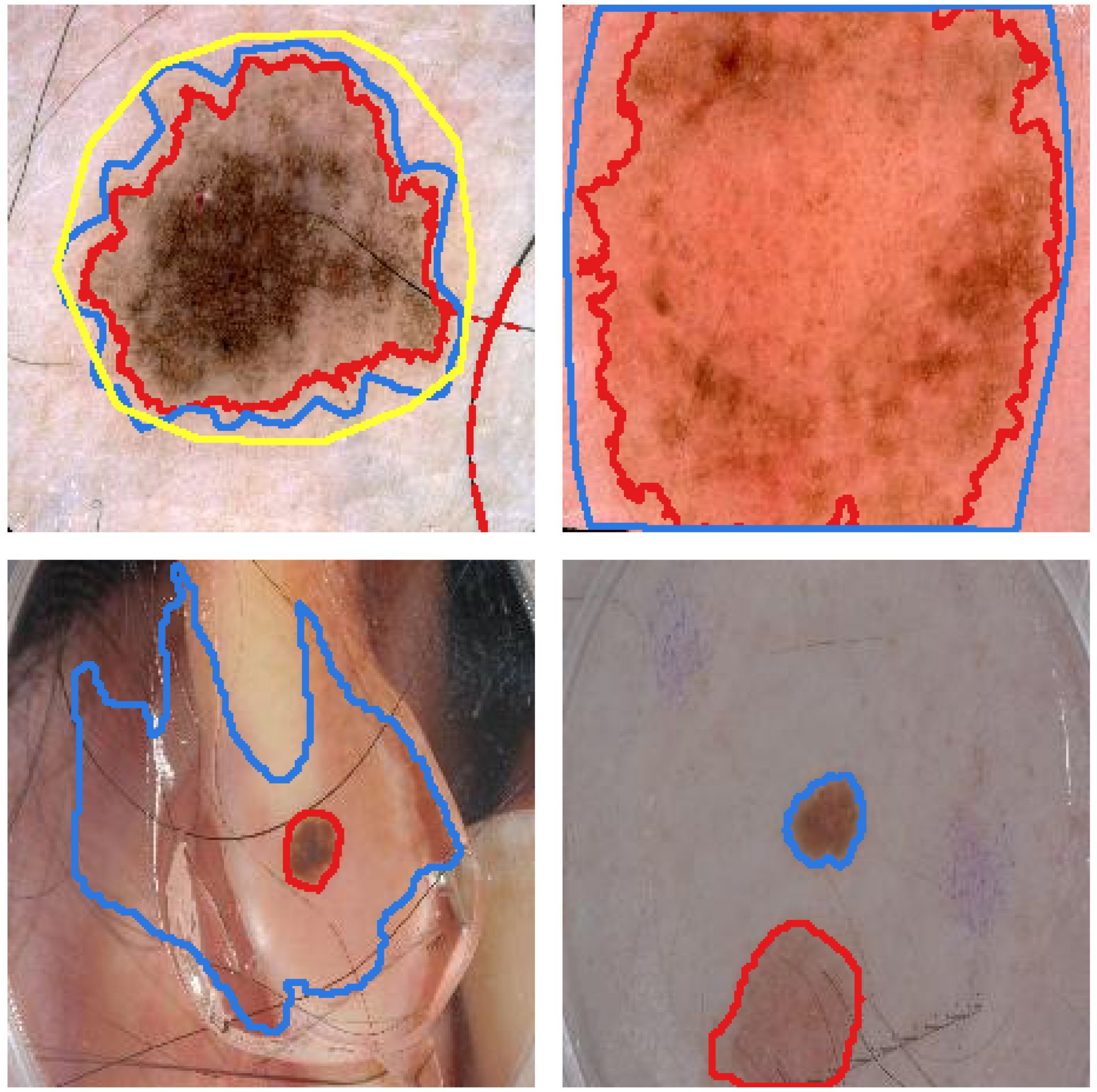
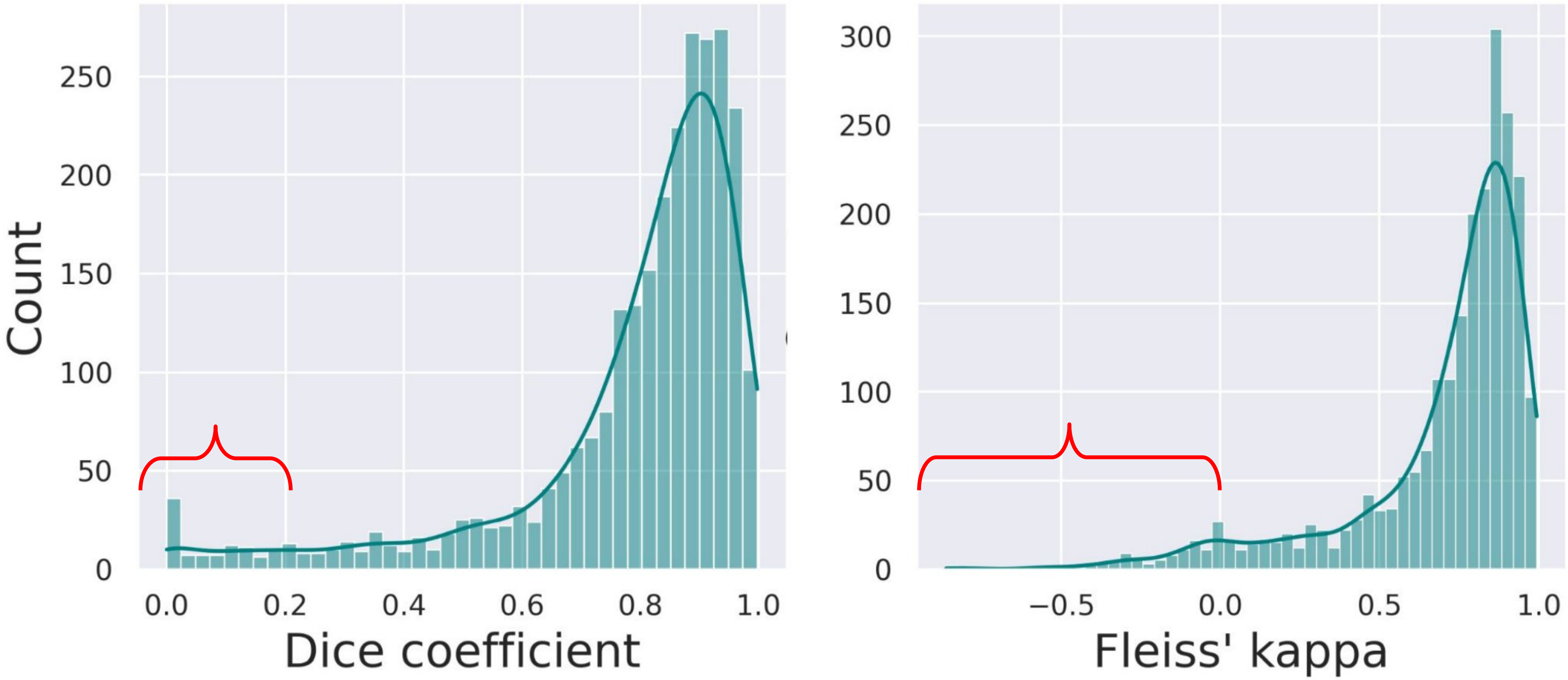
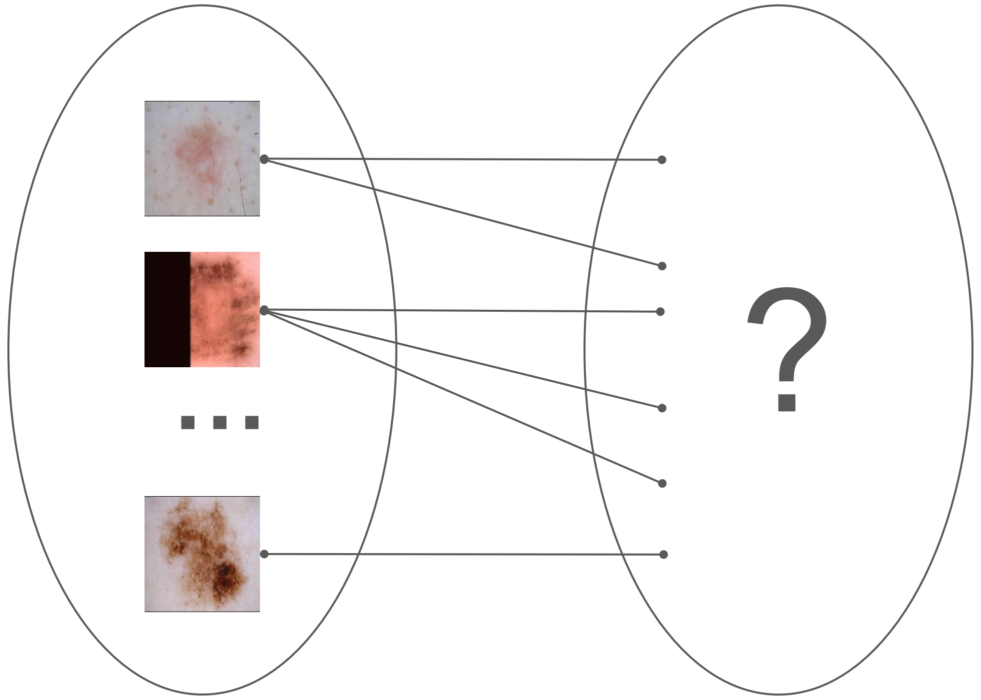




Objective

Given  , train a model that **discovers unique annotation styles** such that:

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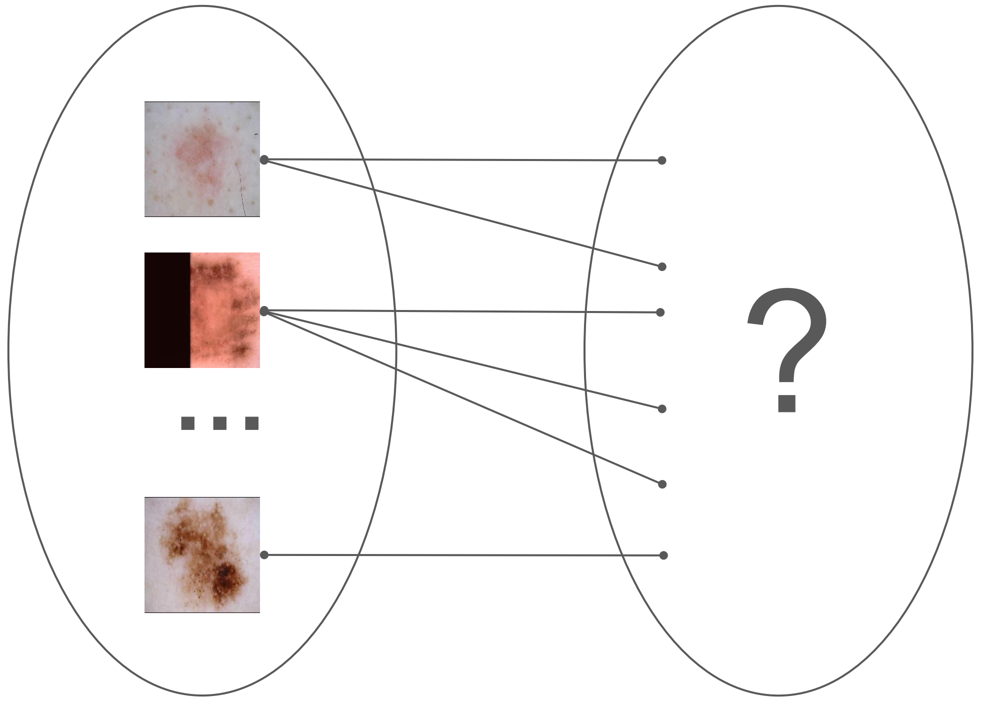

, train a model that **discovers unique annotation styles** such that:

- all the predicted segmentations are **plausible**,

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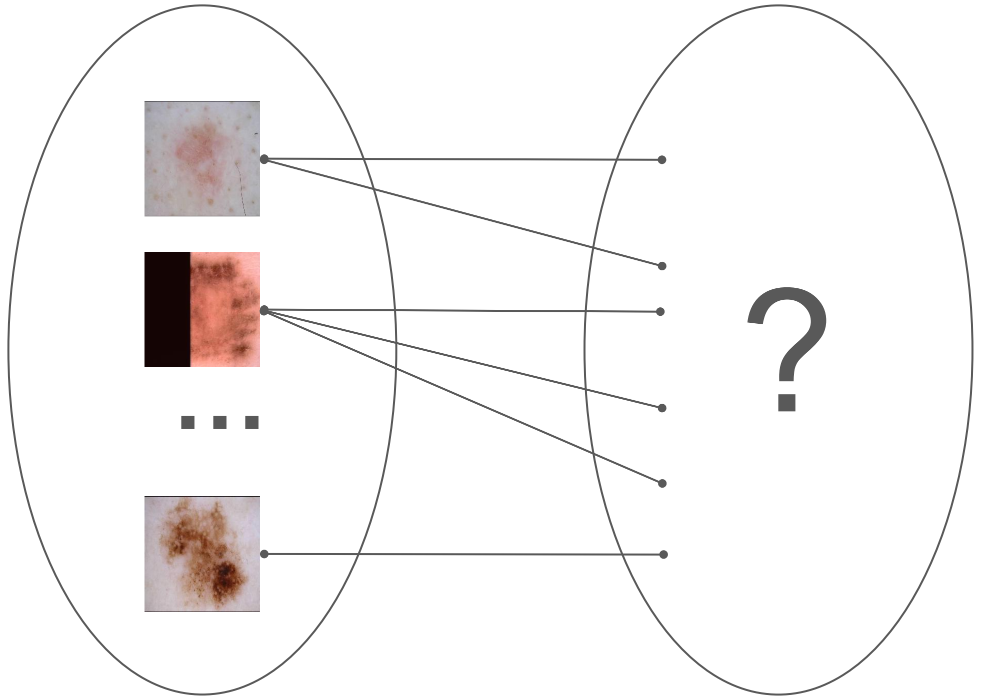
Given  , train a model that **discovers unique annotation styles** such that:

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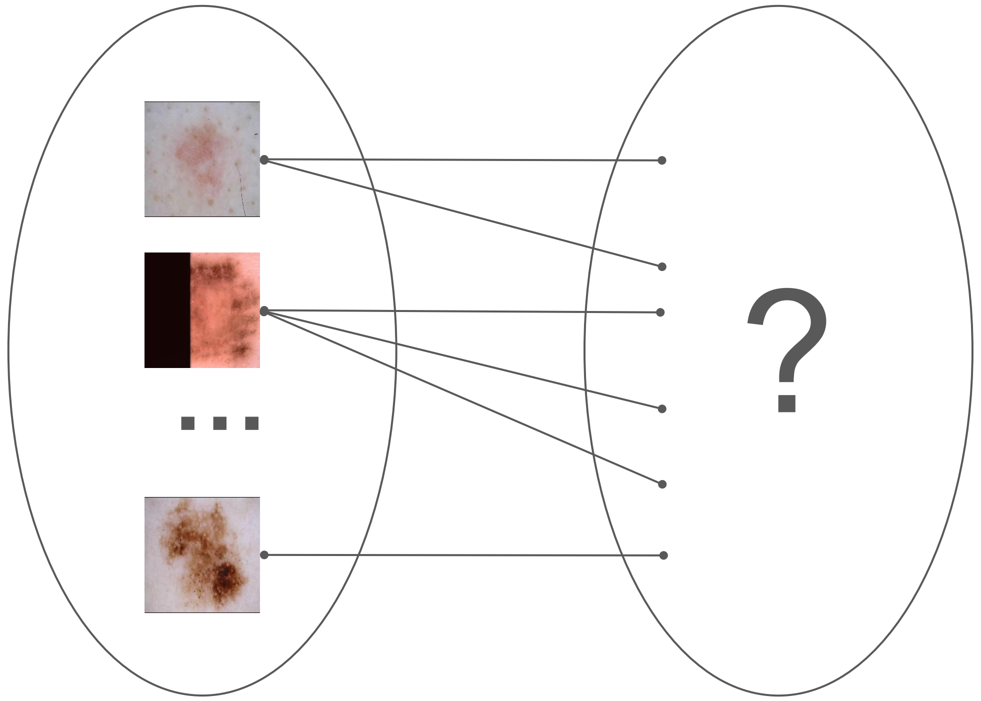
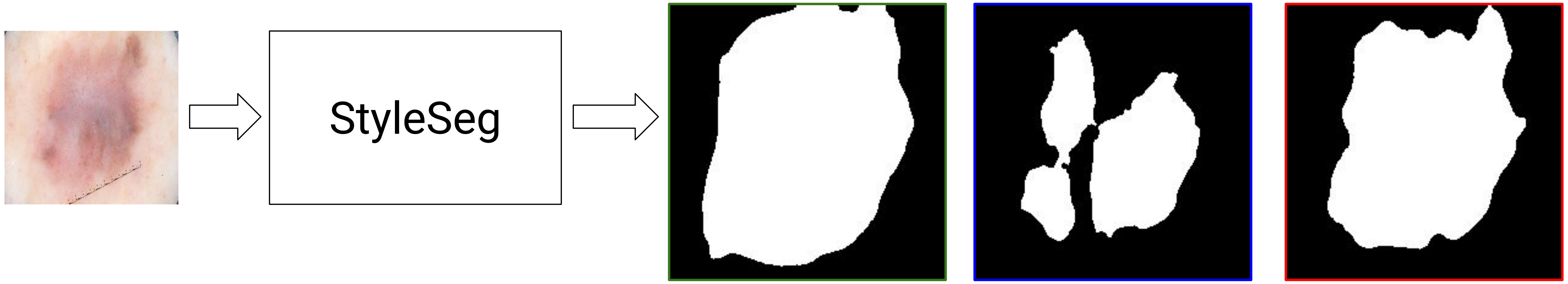
Given  , train a model that **discovers unique annotation styles** such that:

- all the predicted segmentations are **plausible**,
- the predicted segmentations are **diverse**, and
- the segmentation styles are **semantically consistent** across all images.

StyleSeg produces multiple segmentation styles



Multiple segmentation styles and their probabilities

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Style 1 Style 2 Style 3

Segmentation Model
$f_s(X_i; \Theta_s)$

M segmentation styles

Multiple segmentation styles and their probabilities

Style 1 Style 2 Style 3

Segmentation Model
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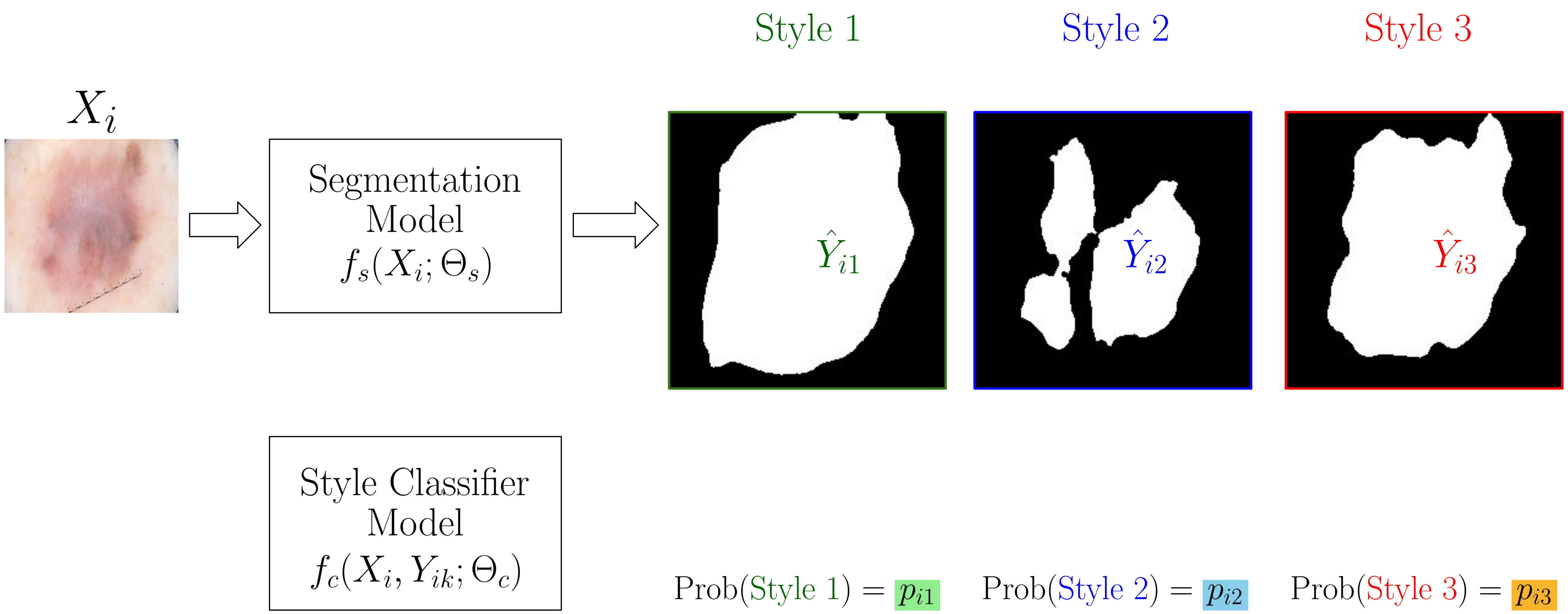
M segmentation styles

Style Classifier Model
$f_c(X_i, Y_{ik}; \Theta_c)$

$\text{Prob}(\text{Style 1}) = p_{i1}$ $\text{Prob}(\text{Style 2}) = p_{i2}$ $\text{Prob}(\text{Style 3}) = p_{i3}$

Probability of each style being the correct style.

Multiple segmentation styles and their probabilities



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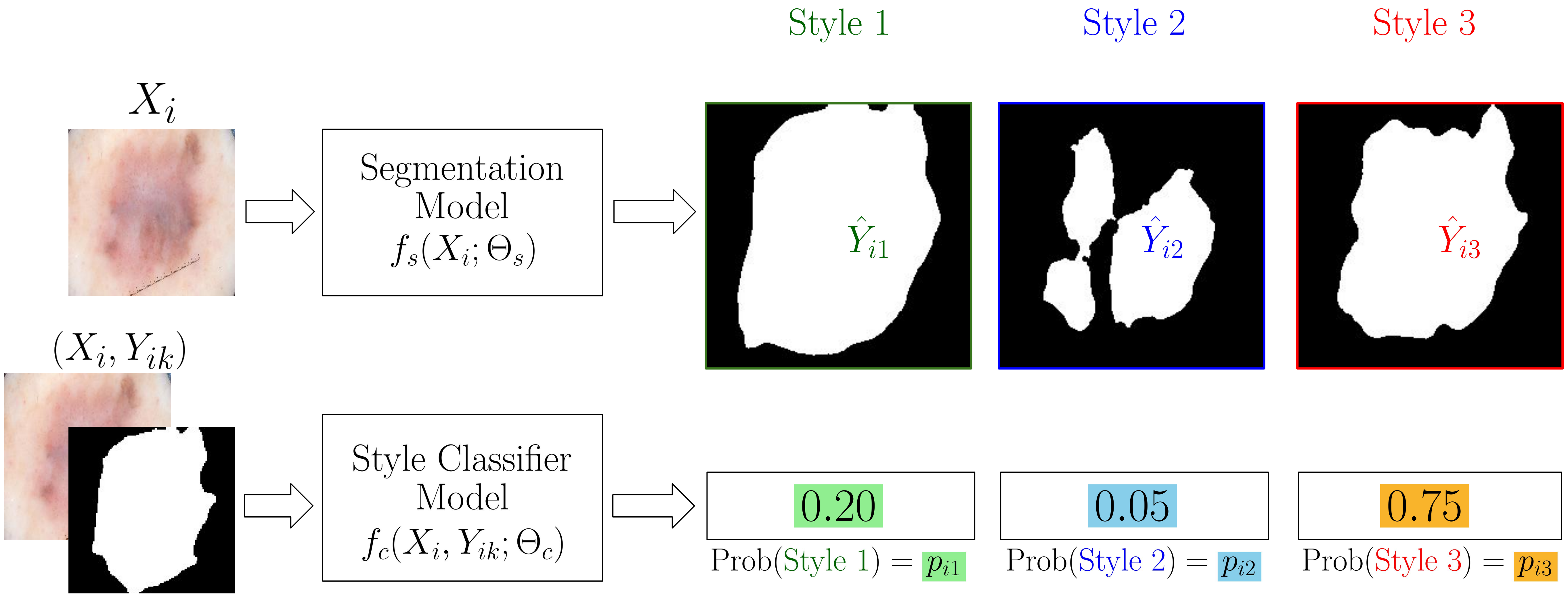

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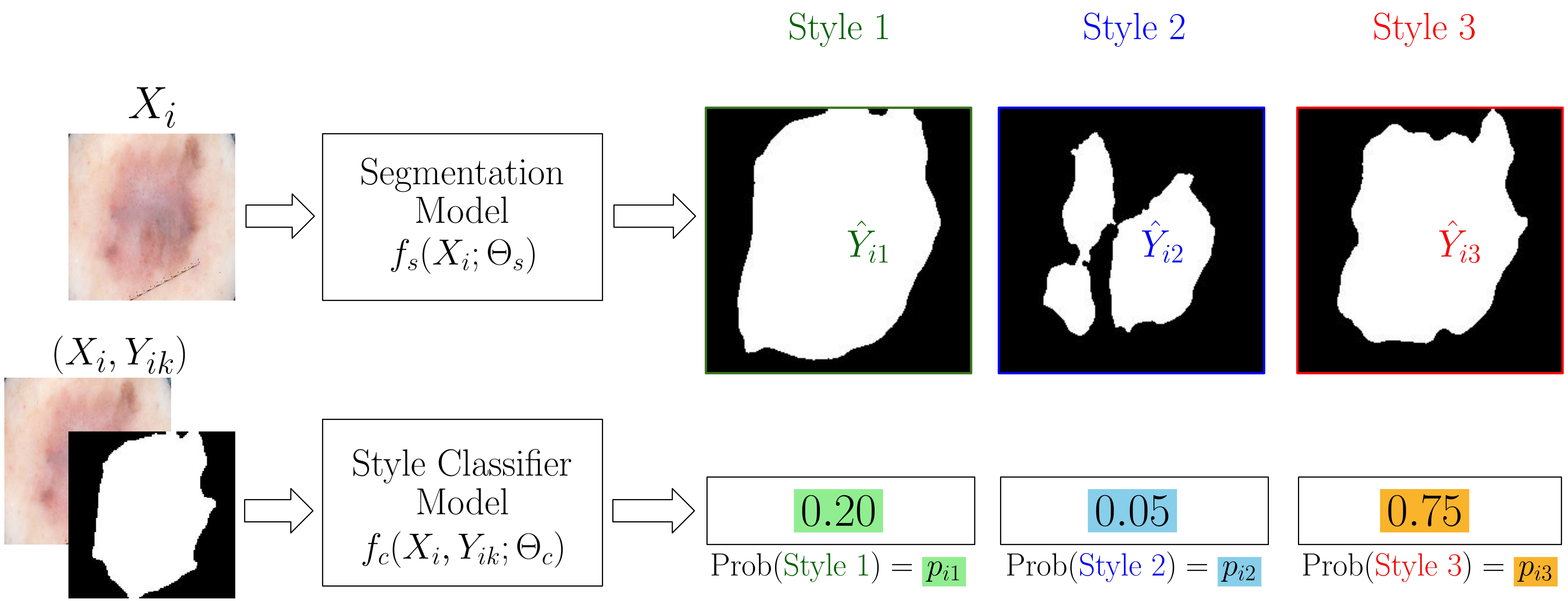
Training StyleSeg



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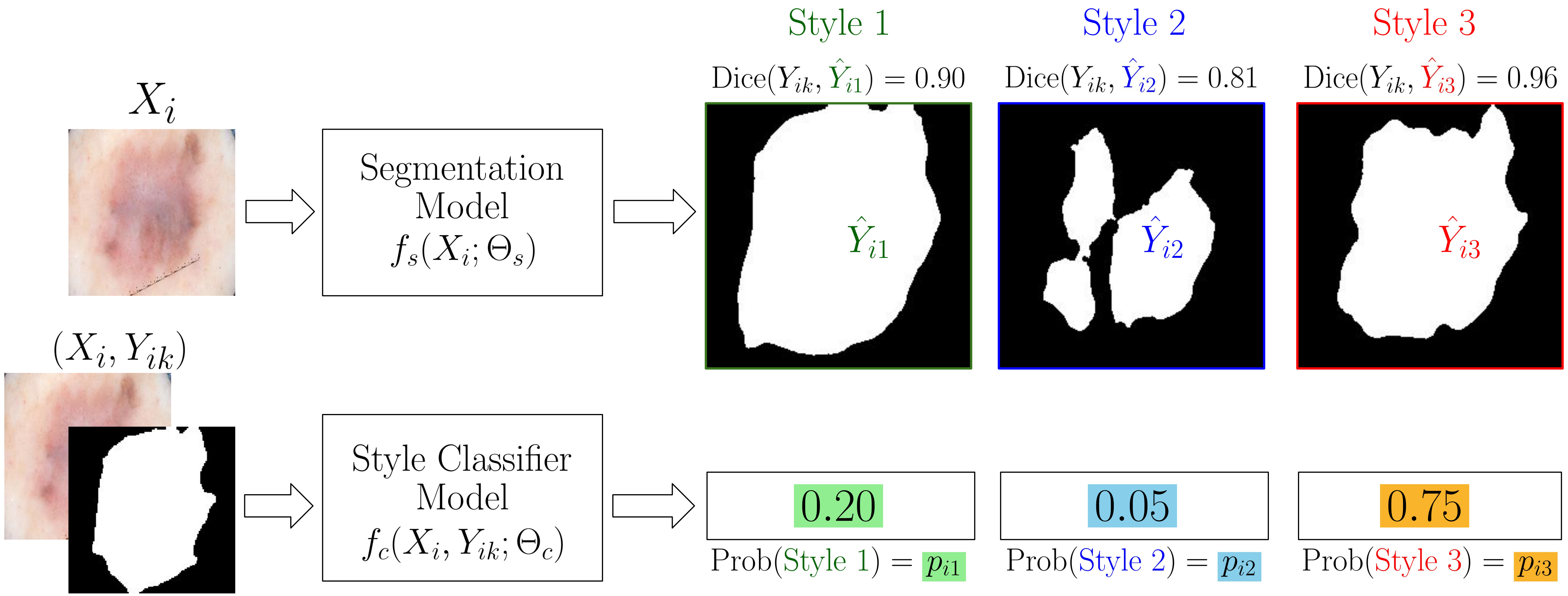

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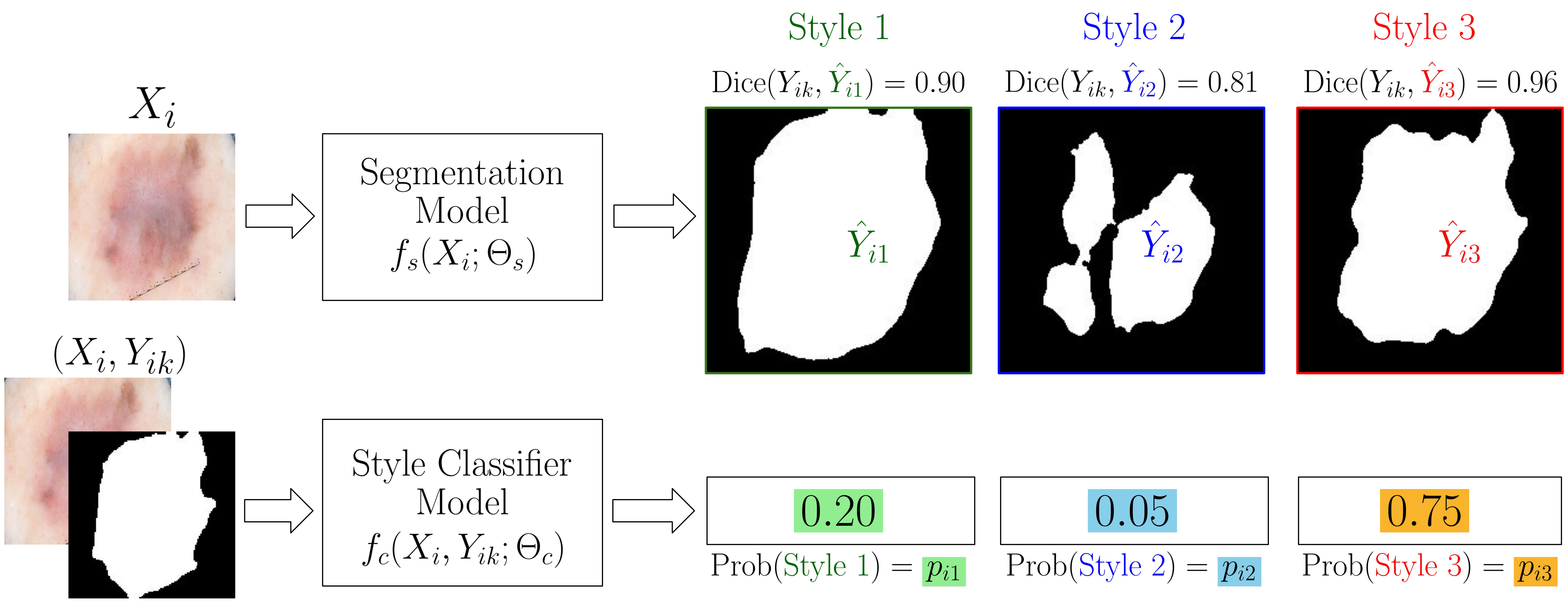
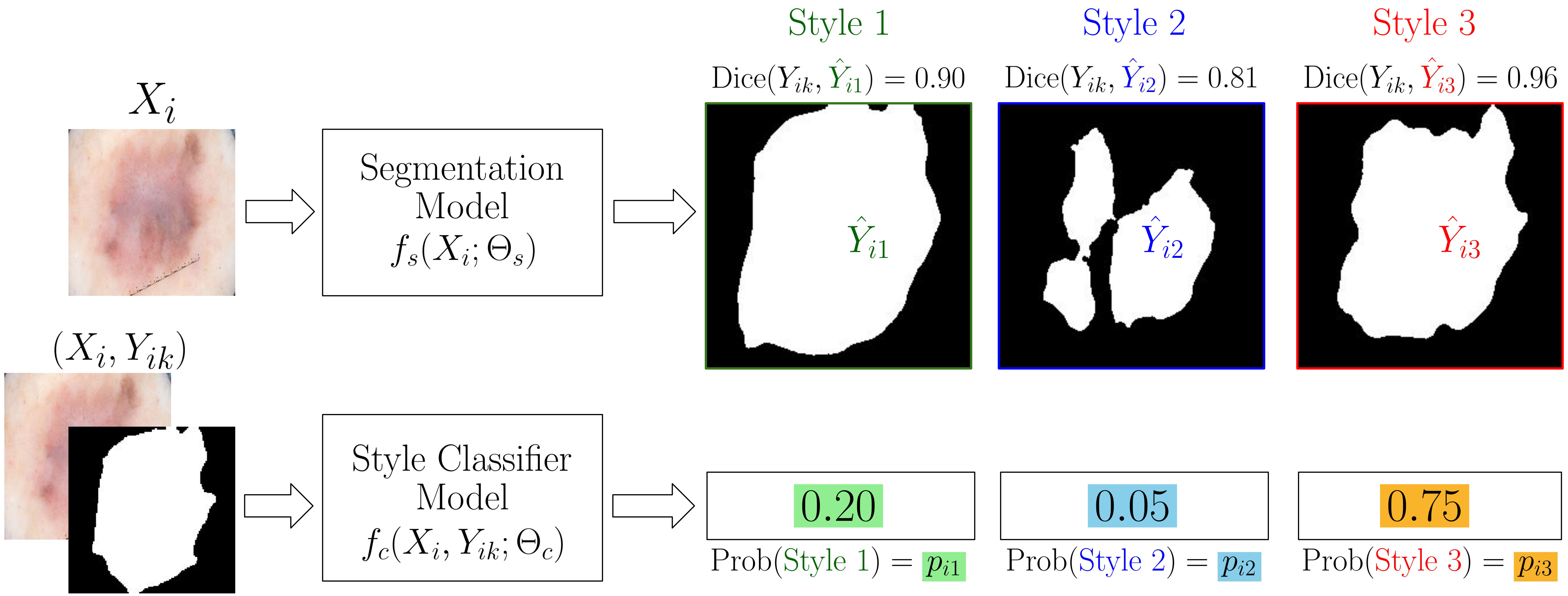


$$m^* = \arg\max_j \text{Dice}(Y_{ik}, \hat{Y}_{ij}) = 3$$

$$\mathcal{L}_1 = L_D(Y_{ik}, \hat{Y}_{i3})$$

Training StyleSeg



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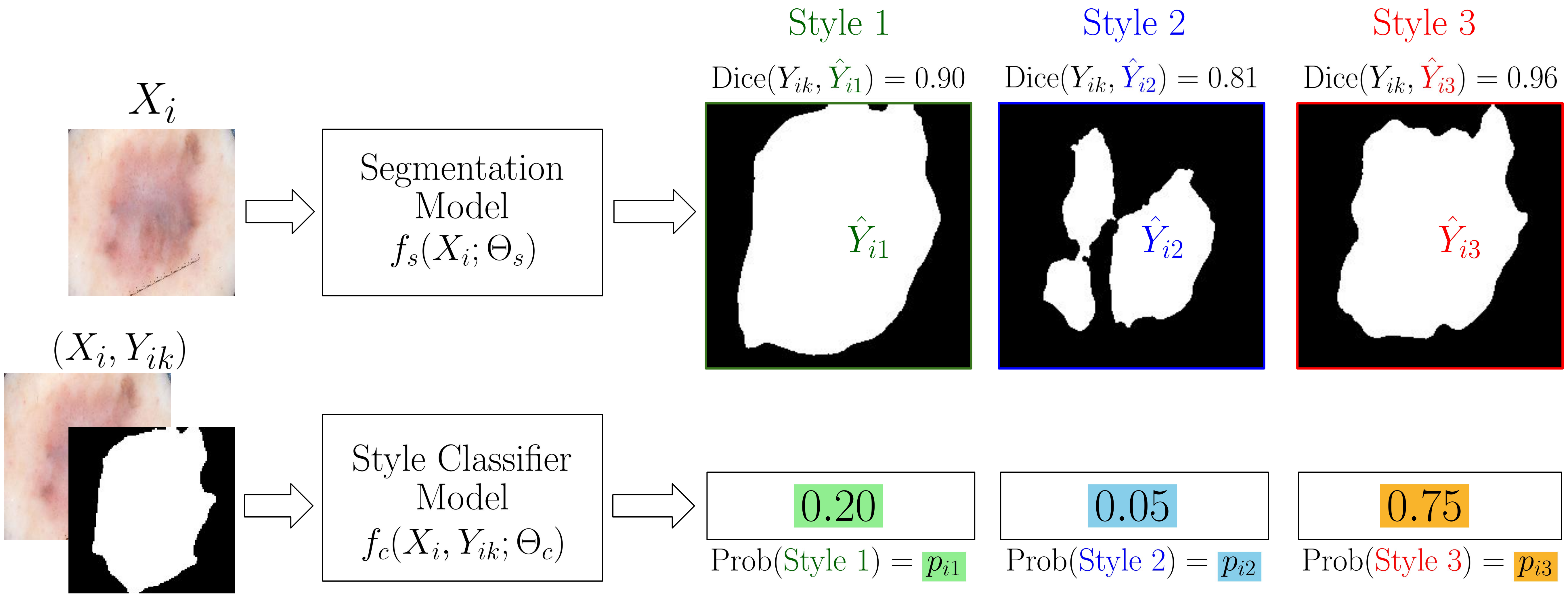
$$\mathcal{L}_2 = L_D(Y_{ik}, (0.20 * \hat{Y}_{i1}) + (0.05 * \hat{Y}_{i2}) + (0.75 * \hat{Y}_{i3}))$$

Training StyleSeg



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$$\mathcal{L}_3 = L_{CE}(\ [\ 0.20,\ 0.05,\ 0.75\ ],\ [\ 0,\ 0,\ 1\ ])$$

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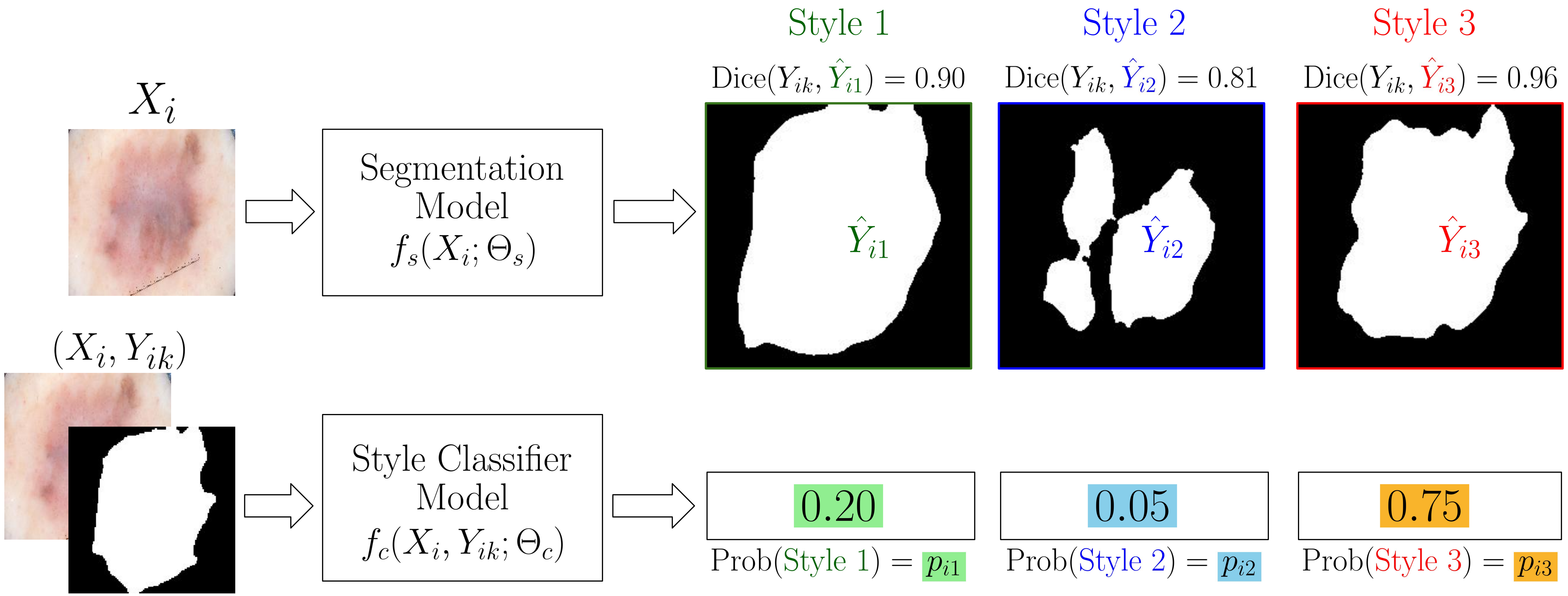

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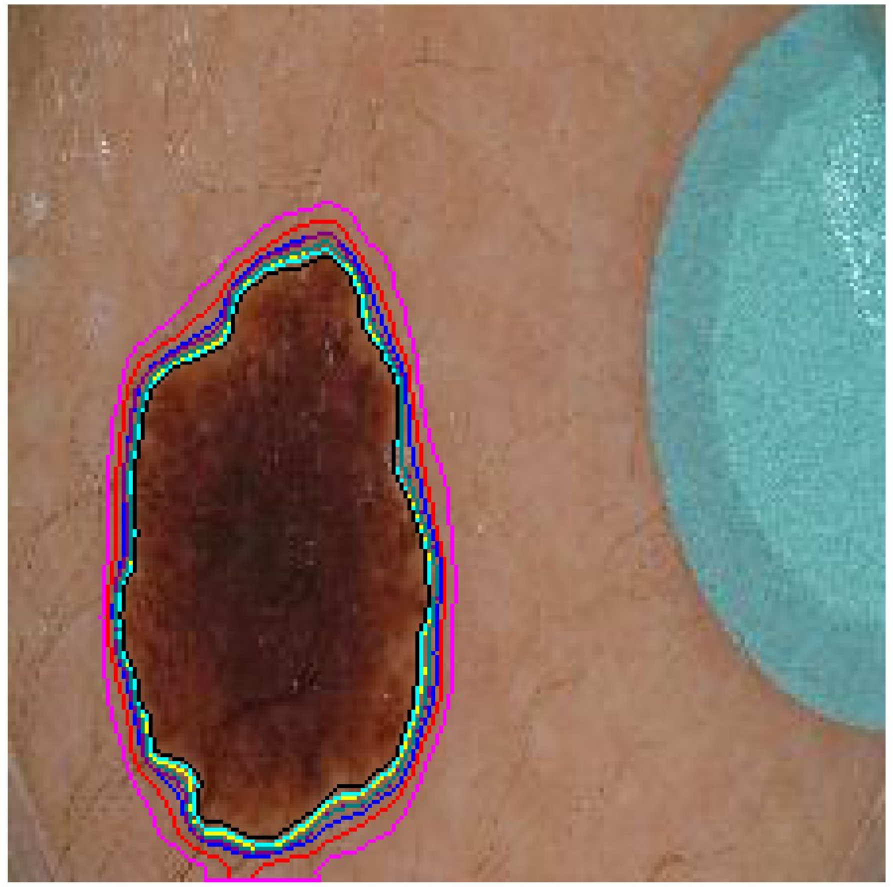
$$\mathcal{L}_{\text{total}} = \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3$$

StyleSeg Outputs Adapt to Variability in Lesion Content

ISIC_0003599



High-contrast lesion has **high agreement** across styles

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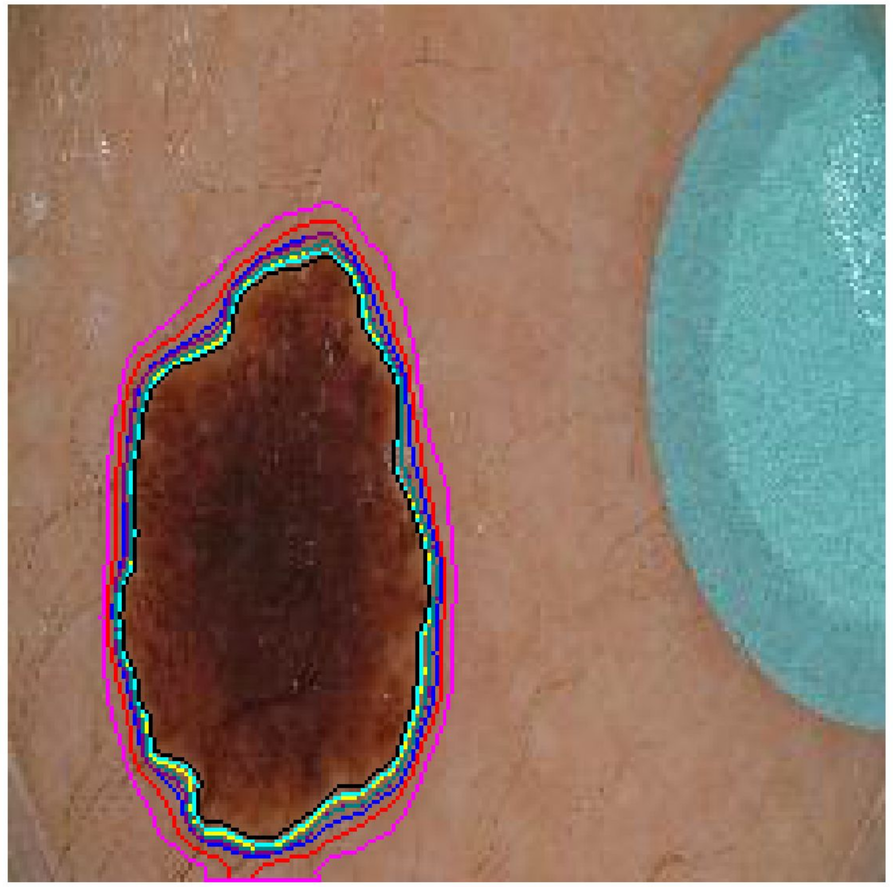

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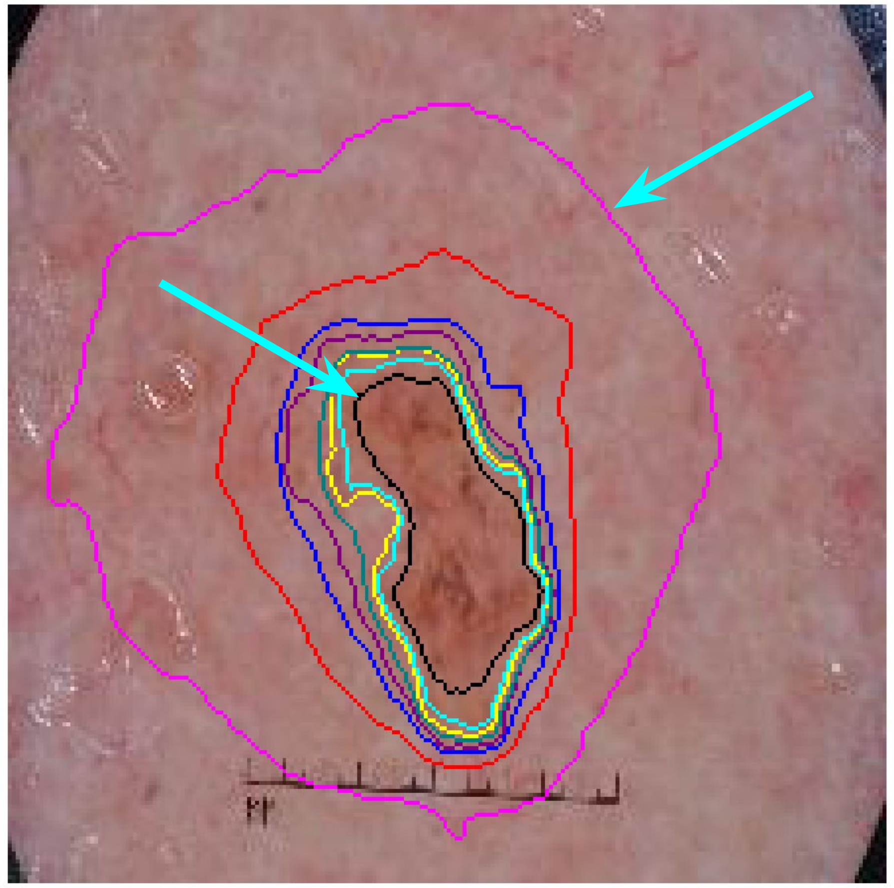
ISIC_0014337



Instances of **under-** and **over-** segmentation

StyleSeg Outputs Adapt to Variability in Lesion Content

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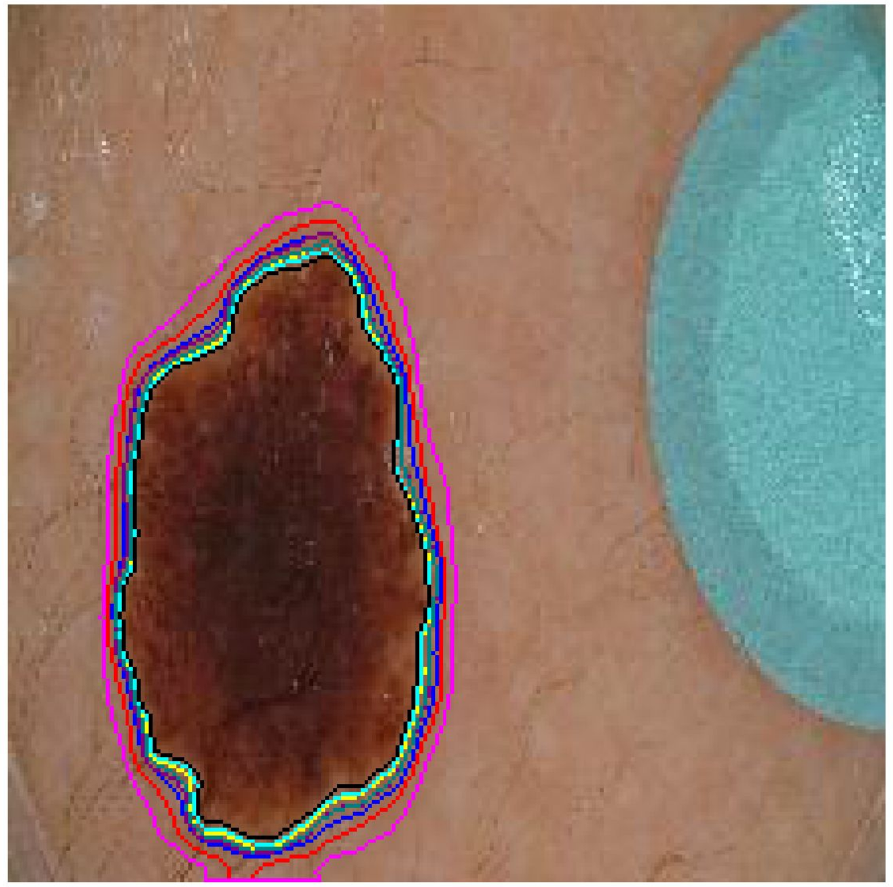
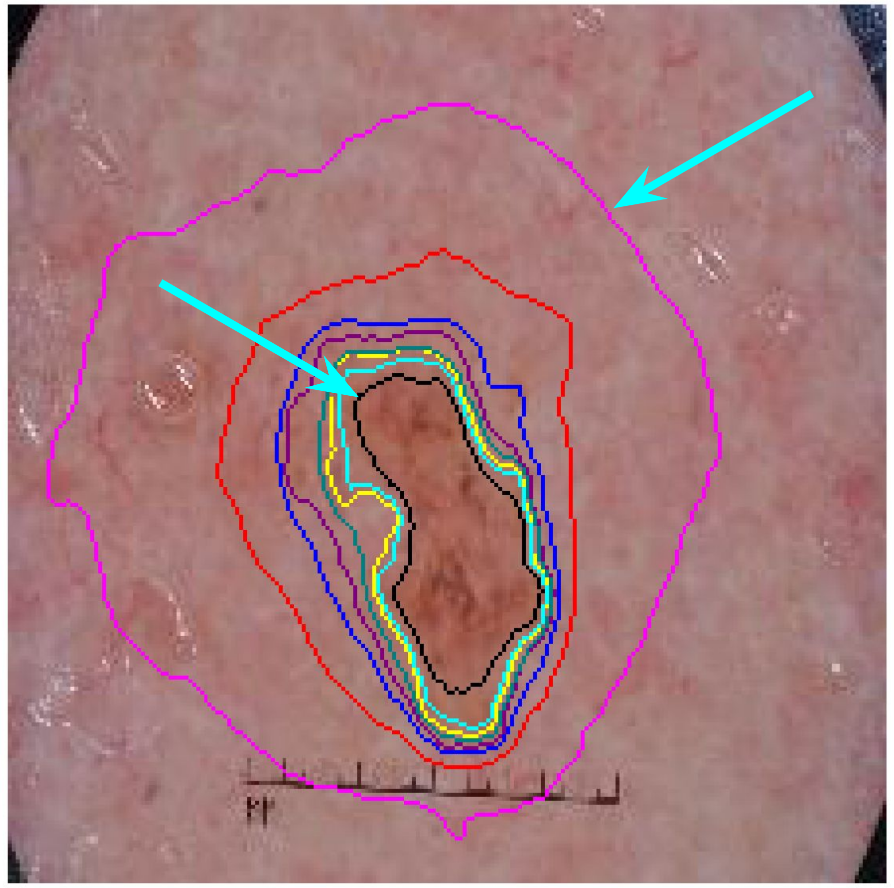


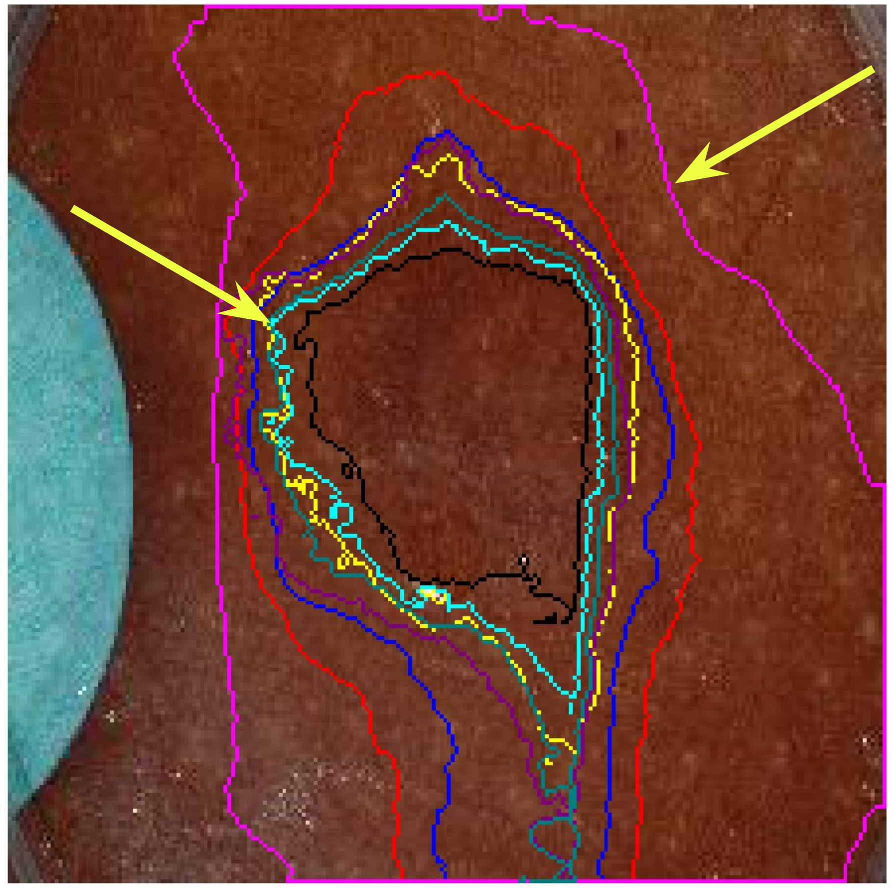
High-contrast lesion has **high agreement** across styles

ISIC_0014337



Instances of **under-** and **over-** segmentation

ISIC_0003726



Different **boundary jaggedness** across segmentations

StyleSeg Outputs Adapt to Variability in Lesion Content

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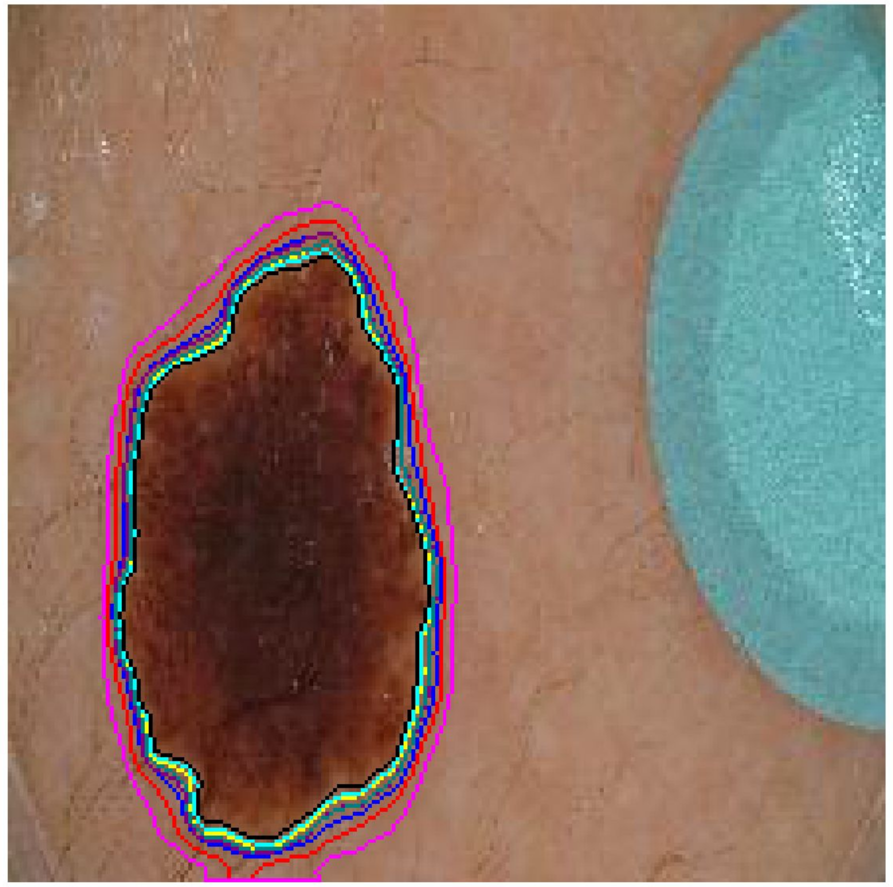

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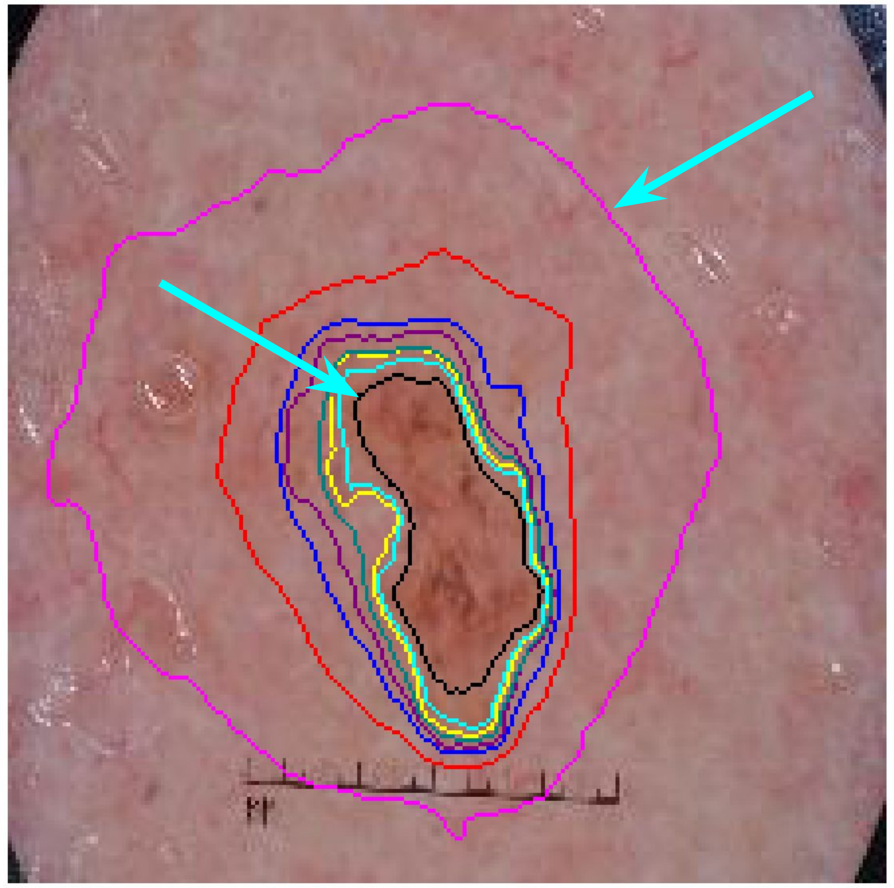

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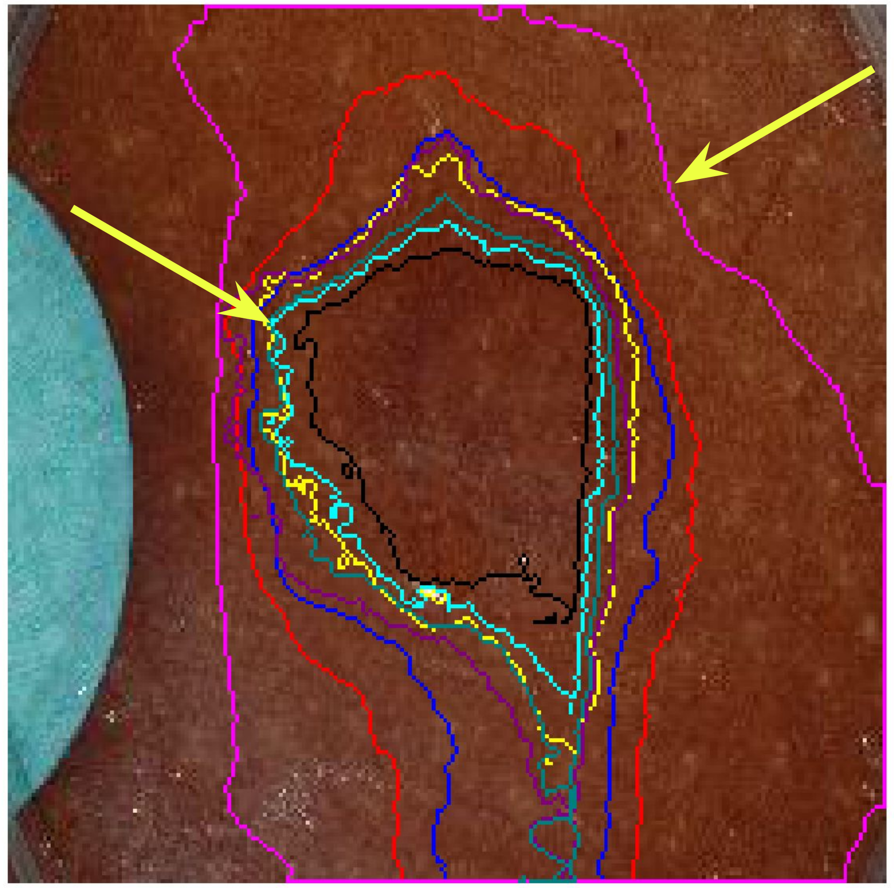

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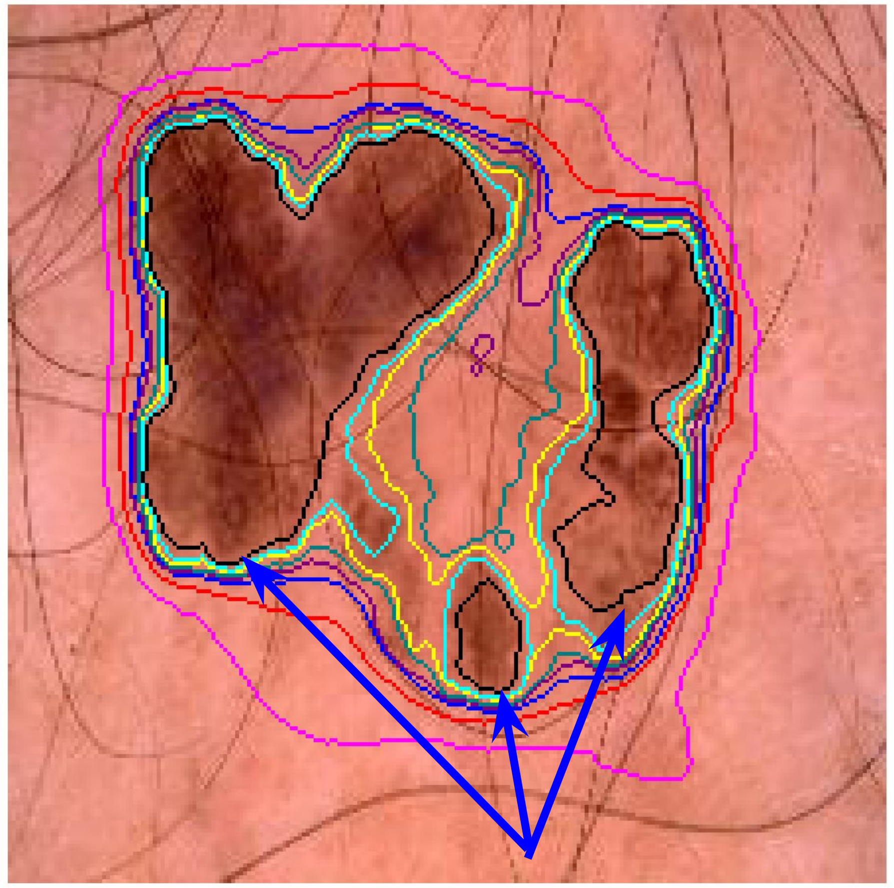
ISIC_0014831



Ambiguous boundary causes segmentation masks to **split**

Semantic Consistency of Styles

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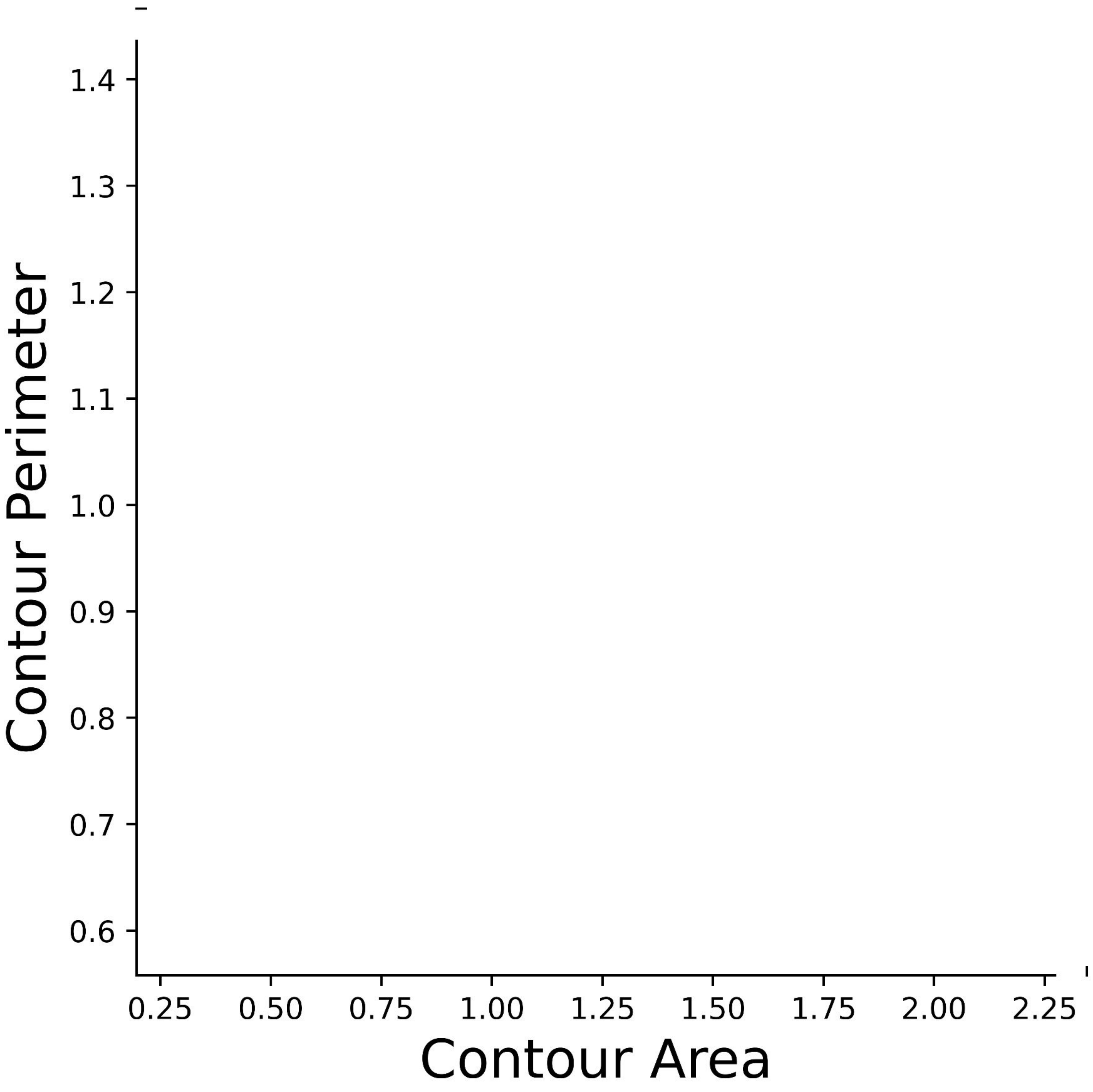

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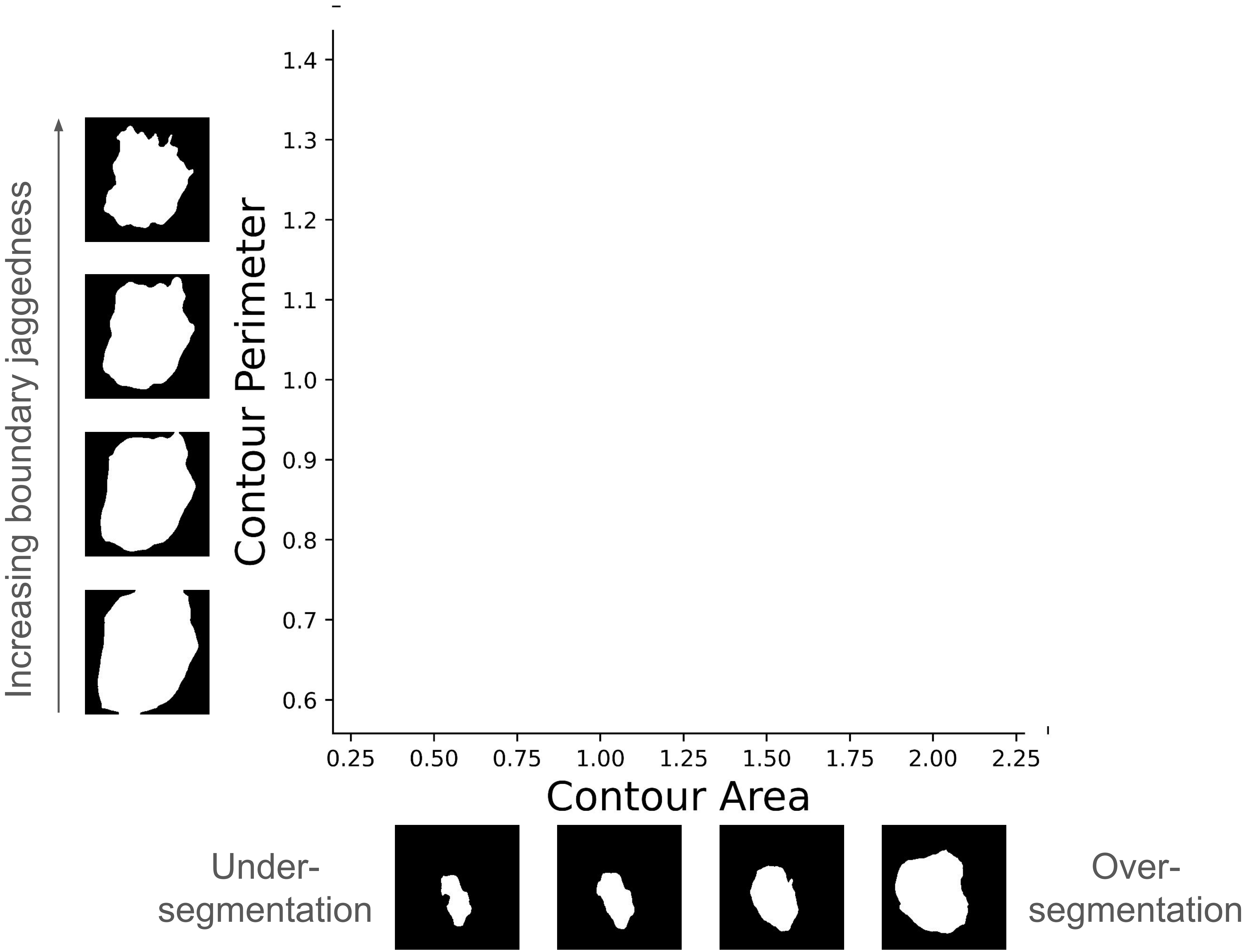
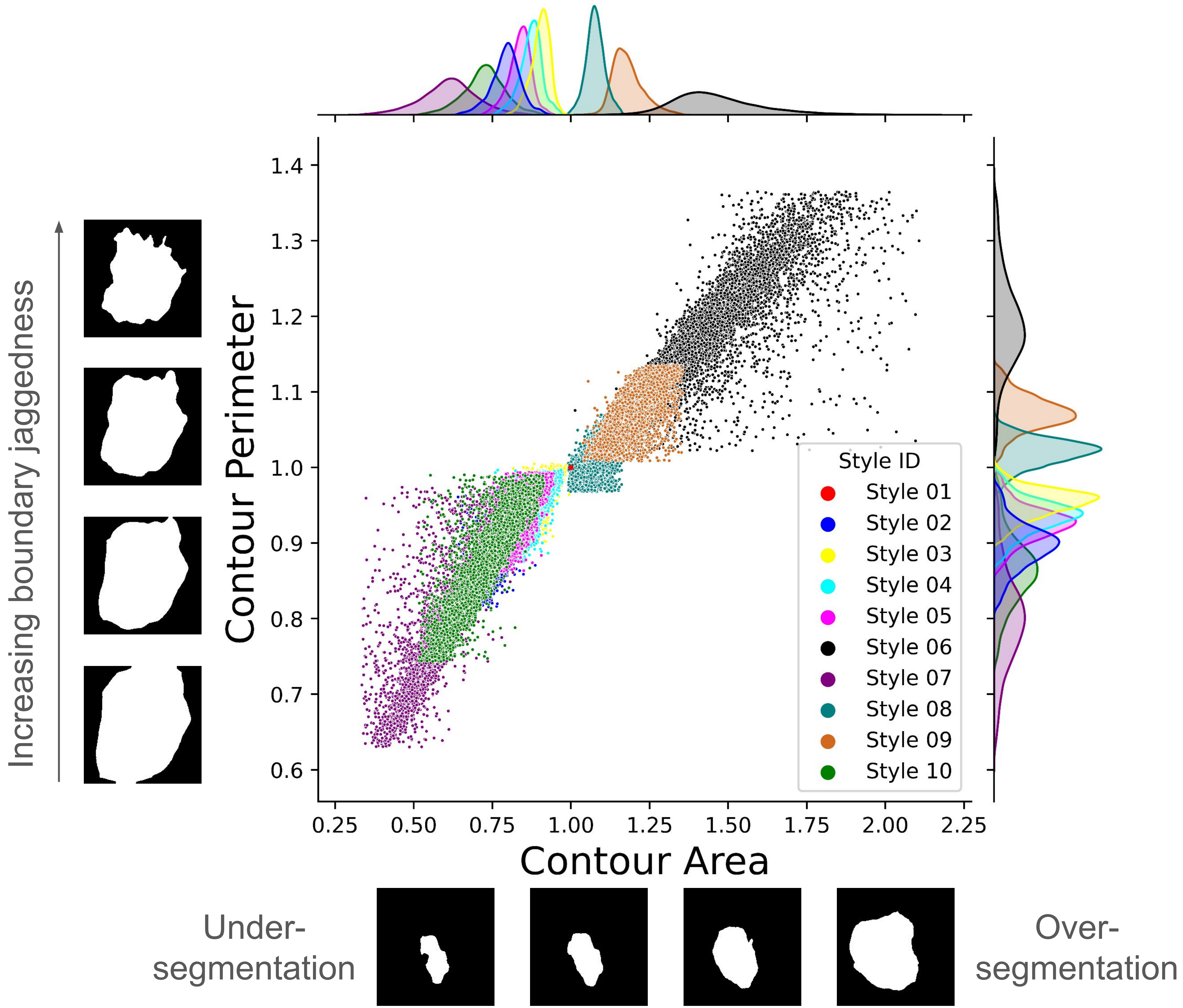


Semantic Consistency of Styles



Competing Methods

$\mathbb{SS}\mathrm{eg}$ methods	
NaiveTraining	SLS model without any annotator-specific knowledge.
RandAnnotID[2]	4 SLS models, one optimized for each annotator randomly assigned to a mask.
LessIsMore[3]	SLS model trained on a subset of the masks whose average pairwise Cohen's kappa ≥ 0.5.
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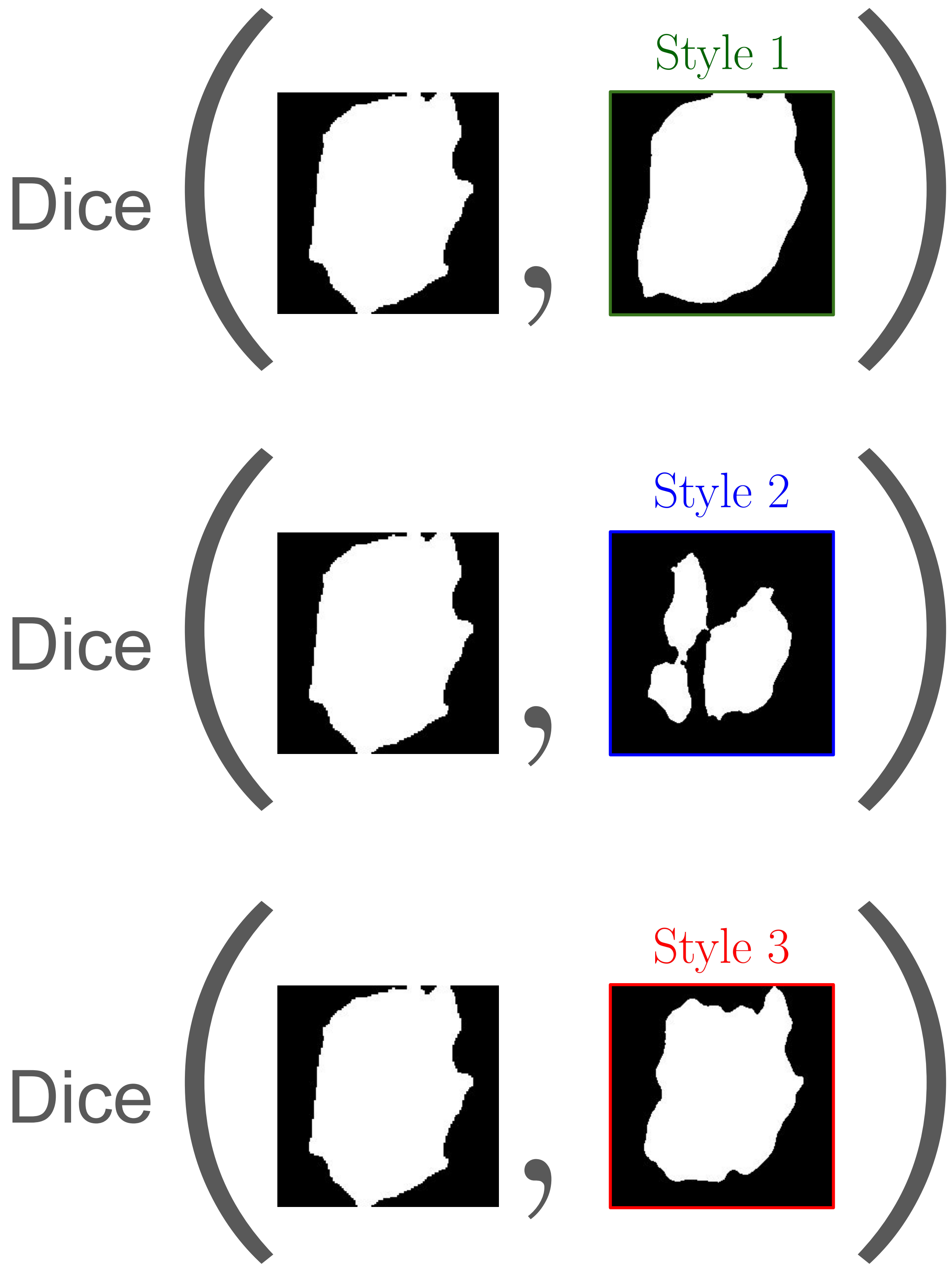
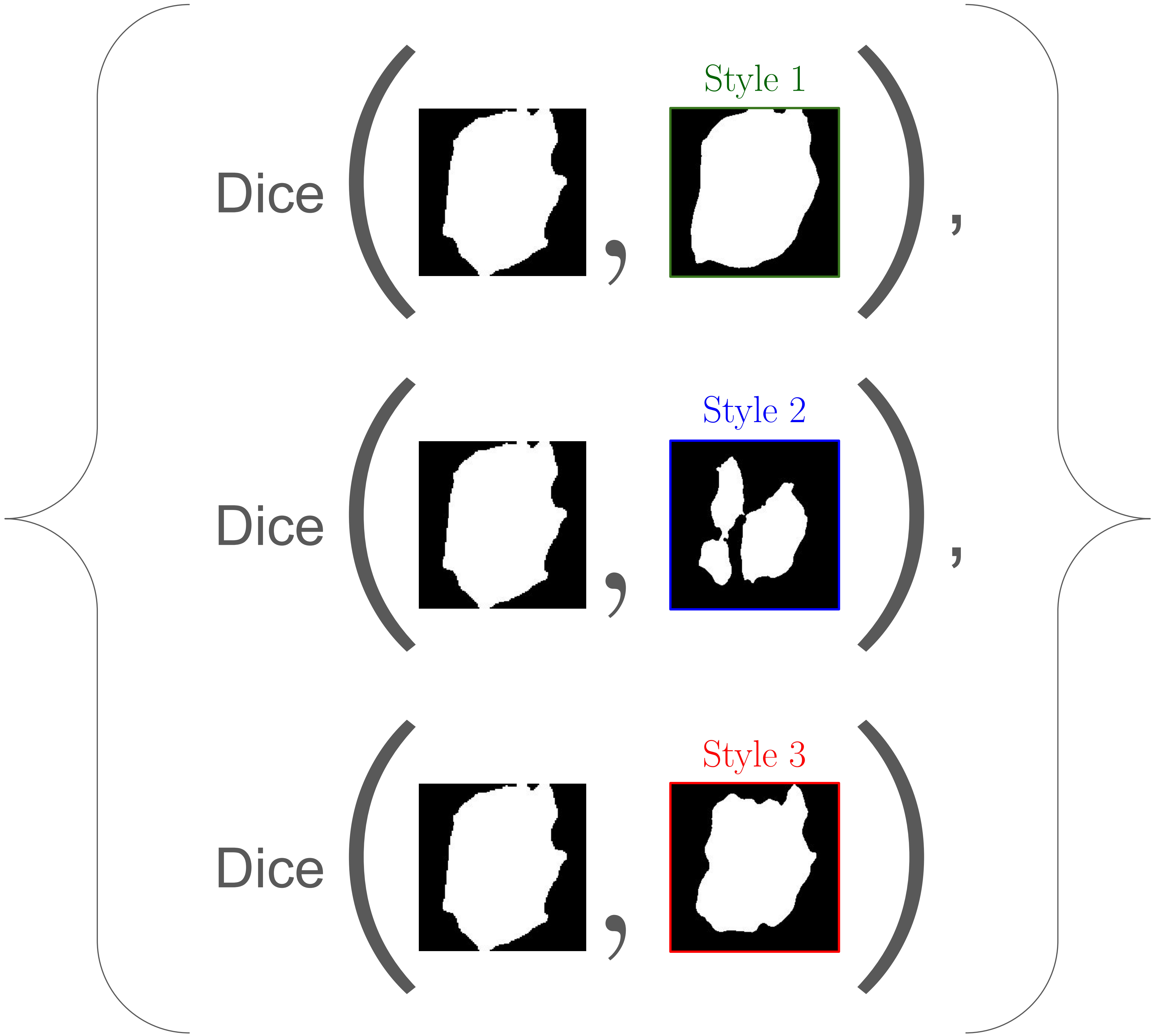
MSeg **methods**	
MHP[4]	Multi-hypothesis prediction model, repurposed for SLS.

Metrics



Metrics

- min.
- max.



Quantitative Results

Method	ISIC Archive-Test ($n = 10,000$)		DermoFit ($n = 1,300$)	
	Min. Dice	Max. Dice	Min. Dice	Max. Dice
NaiveTraining	0.800		0.842	
RandAnnotID	–		0.826	
LessIsMore	0.815		0.854	
D-LEMA	–		0.853	
2-MHP	0.727	0.864	0.707	0.882
2-StyleSeg	0.760	0.869	0.759	0.888
3-MHP	0.652	0.876	0.562	0.888
3-StyleSeg	0.713	0.881	0.720	0.897
4-MHP	0.623	0.886	0.636	0.904
4-StyleSeg	0.693	0.889	0.681	0.907
6-MHP	0.121	0.886	0.428	0.900
6-StyleSeg	0.648	0.889	0.651	0.911
8-MHP	0.099	0.896	0.309	0.908
8-StyleSeg	0.595	0.899	0.632	0.910
10-MHP	0.281	0.894	0.181	0.906
10-StyleSeg	0.603	0.899	0.579	0.918

Results on 4 datasets:

- **ISIC Archive-Test** (n = 10000)
- **DermoFit** (n = 1300)
- PH^2 (n = 200)
- SCD (n = 206)

Learning Multiple Styles Is Always Better

Method	ISIC Archive-Test ($n = 10,000$)		DermoFit ($n = 1,300$)	
	Min. Dice	Max. Dice	Min. Dice	Max. Dice
NaiveTraining	0.800		0.842	
RandAnnotID	–		0.826	
LessIsMore	0.815		0.854	
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Learning to predict more than 1 style (MSeg methods), <u>even learning to predict 2 styles</u>, consistently outperforms SSeg methods.

Diversity Increases As More Styles are Learned

Method	**ISIC Archive-Test** ($n = 10,000$)		**DermoFit** ($n = 1,300$)	
	Min. Dice	Max. Dice	Min. Dice	Max. Dice
NaiveTraining	0.800		0.842	
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As *M* increases, a larger number of diverse segmentations are generated, and the max. Dice keeps improving.

StyleSeg Outperforms MHP

Method	ISIC Archive-Test ($n = 10,000$)		DermoFit ($n = 1,300$)	
	Min. Dice	Max. Dice	Min. Dice	Max. Dice
NaiveTraining	0.800		0.842	
RandAnnotID	–		0.826	
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StyleSeg consistently outperforms MHP for all values of *M* and for all datasets.

StyleSeg Outputs Are More Plausible

Method	ISIC Archive-Test ($n = 10,000$)		DermoFit ($n = 1,300$)	
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StyleSeg consistently outperforms MHP for all values of *M* and for all datasets.

Moreover, as M increases, all StyleSeg outputs remain reasonably plausible, whereas MHP outputs exhibit diversity at the cost of plausibility.

Performance Improves Even on Single Annot. Datasets

Method	ISIC Archive-Test ($n = 10,000$)		DermoFit ($n = 1,300$)	
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NaiveTraining	0.800		0.842	
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Even for datasets without documented variability in segmentations, learning to predict multiple styles is helpful.

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A New Multi-Annotator SLS Dataset: ISIC-MultiAnnot

The **largest** multi-annotator SLS dataset curated from the ISIC Archive.

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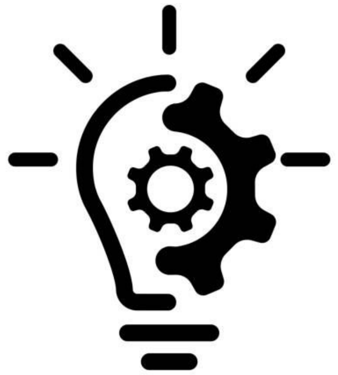
The **largest** multi-annotator SLS dataset curated from the ISIC Archive.

12,951 images

×

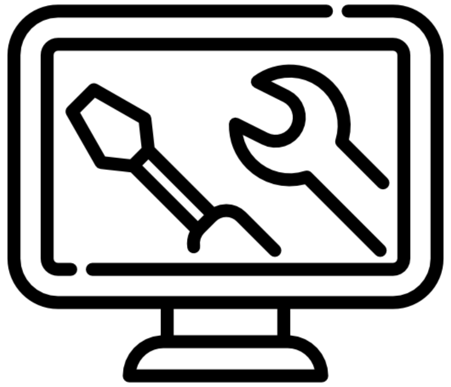
10 anonymized annotators
“A00” – “A09”

×



2 skill levels
“expert”, “novice”

×



3 tool choices
“T1” – “T3”

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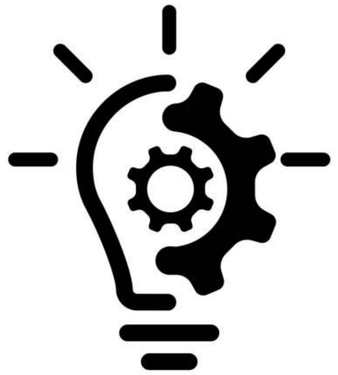

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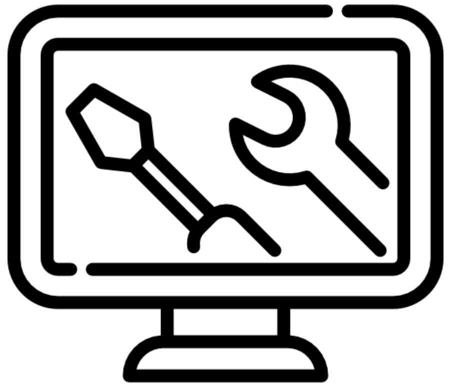
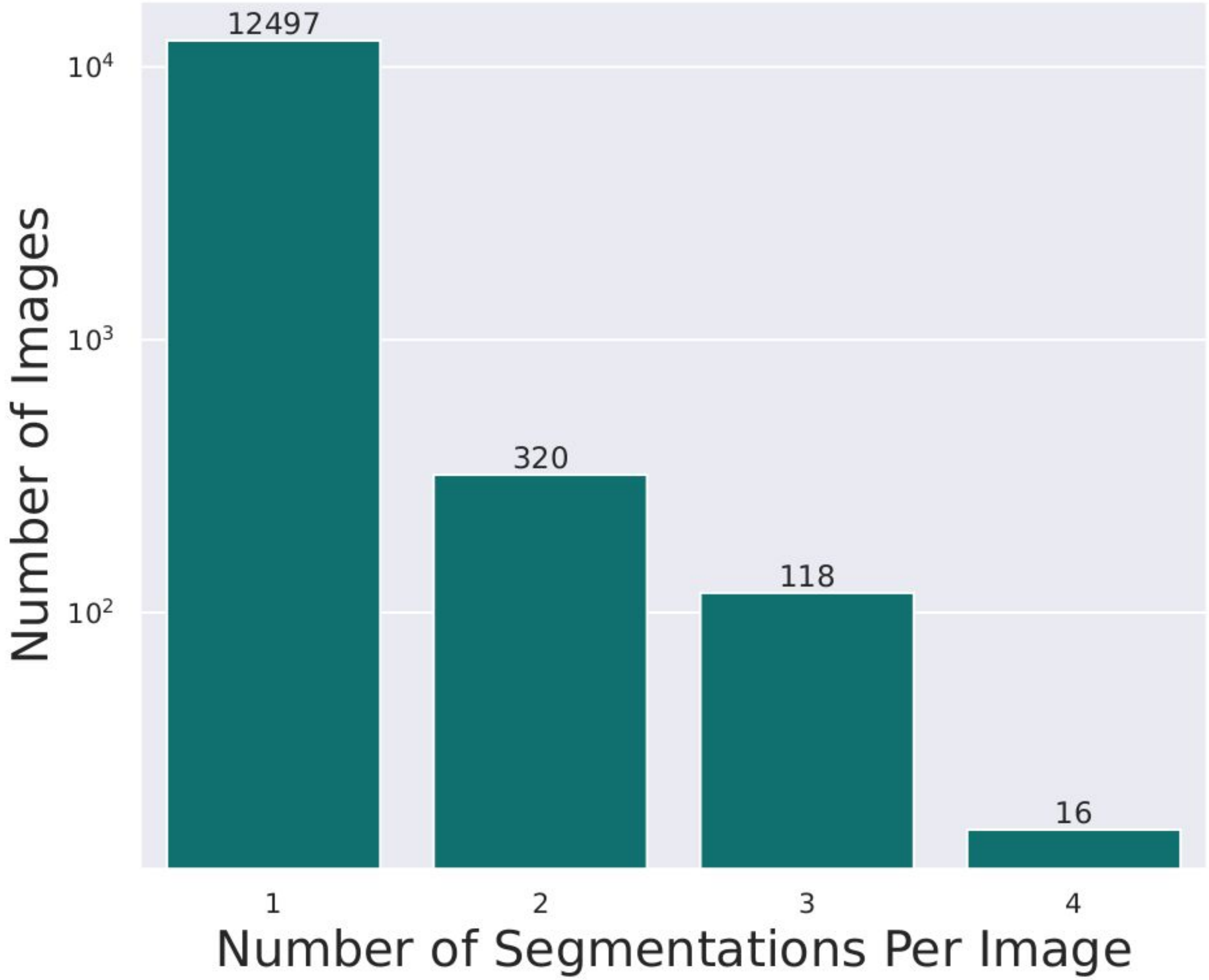
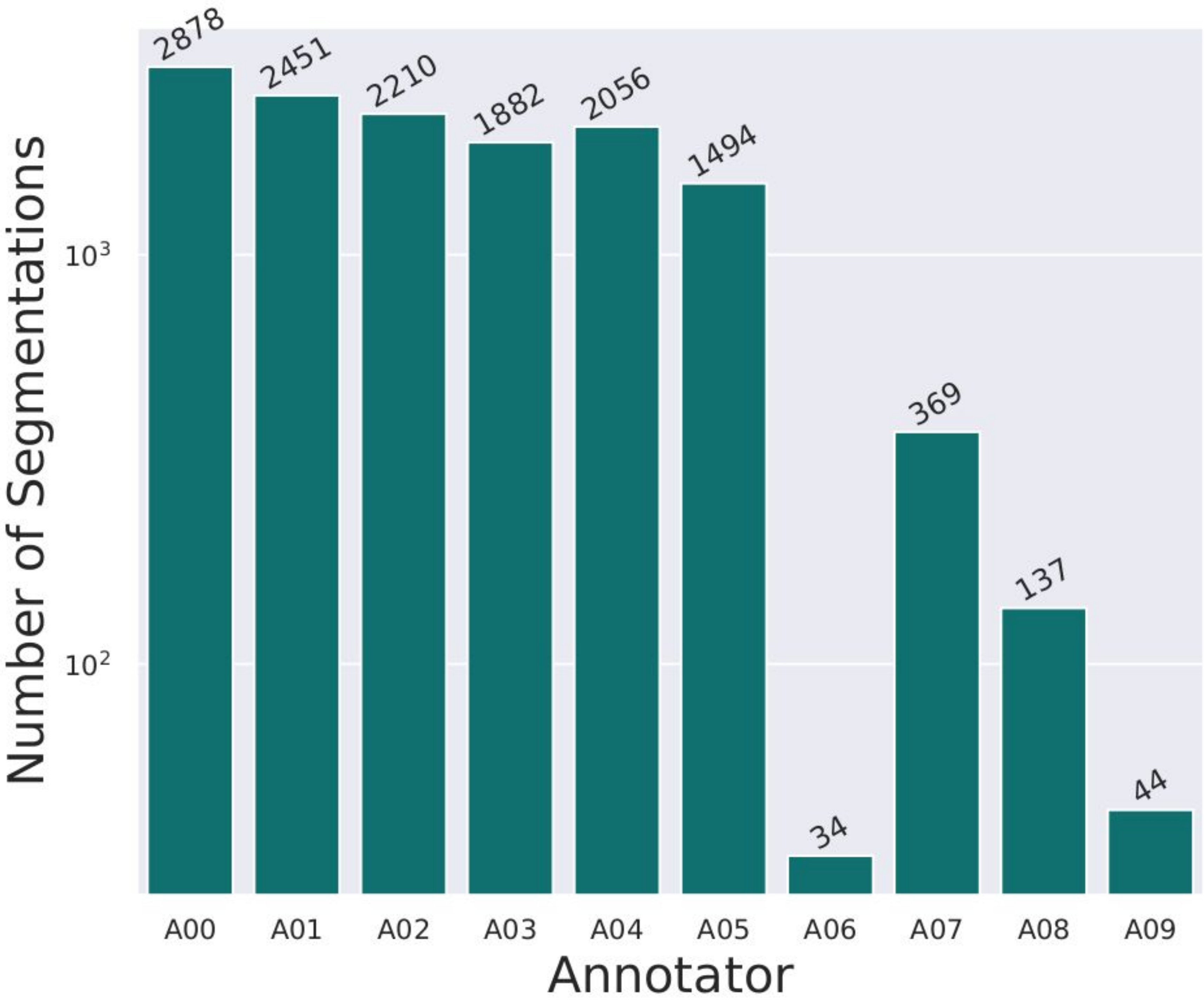


3 tool choices
“T1” – “T3”

13,555 image-mask pairs
27 unique annotator preferences

A New Multi-Annotator SLS Dataset: <u>ISIC-MultiAnnot</u>

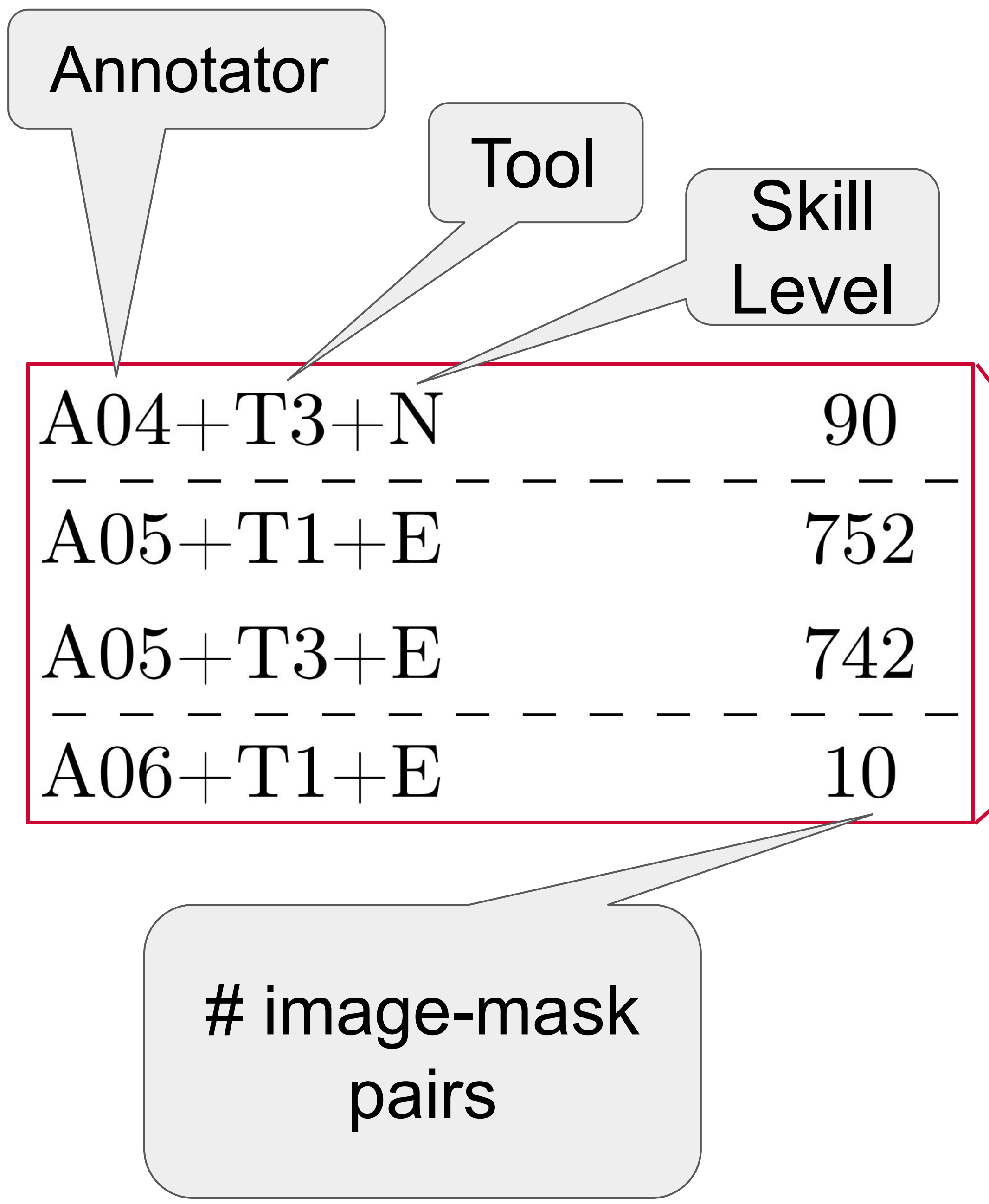




Quantitative Results on ISIC-MultiAnnot

Annotator + Tool + Experience	Seg. Count	1-StyleSeg	2-StyleSeg			3-StyleSeg			4-StyleSeg		
		$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$
A00+T2+E	1573	$0.892_{0.089}$	$0.923_{0.061}$	$0.913_{0.087}$	2	$0.944_{0.049}$	$0.913_{0.106}$	3	$0.944_{0.044}$	$0.914_{0.111}$	1
A00+T2+N	1305	$0.716_{0.302}$	$0.761_{0.293}$	$0.728_{0.308}$	2	$0.793_{0.287}$	$0.727_{0.313}$	3	$0.790_{0.290}$	$0.726_{0.304}$	3
A01+T1+N	6	$0.559_{0.362}$	$0.766_{0.152}$	$0.766_{0.152}$	1	$0.754_{0.132}$	$0.741_{0.125}$	2	$0.819_{0.106}$	$0.767_{0.113}$	2
A01+T3+E	297	$0.900_{0.104}$	$0.915_{0.093}$	$0.897_{0.107}$	2	$0.927_{0.075}$	$0.900_{0.097}$	1	$0.931_{0.067}$	$0.904_{0.090}$	3
A01+T3+N	2148	$0.829_{0.185}$	$0.857_{0.167}$	$0.817_{0.170}$	1	$0.869_{0.159}$	$0.836_{0.178}$	1	$0.876_{0.148}$	$0.836_{0.175}$	3
A02+T1+E	1742	$0.844_{0.177}$	$0.880_{0.140}$	$0.856_{0.159}$	1	$0.886_{0.132}$	$0.854_{0.159}$	1	$0.895_{0.112}$	$0.859_{0.148}$	4
A02+T3+E	468	$0.856_{0.172}$	$0.889_{0.167}$	$0.883_{0.175}$	2	$0.899_{0.161}$	$0.874_{0.188}$	3	$0.903_{0.146}$	$0.890_{0.160}$	1
A03+T1+E	1622	$0.778_{0.168}$	$0.845_{0.117}$	$0.827_{0.137}$	1	$0.854_{0.111}$	$0.824_{0.145}$	2	$0.881_{0.095}$	$0.823_{0.132}$	4
A03+T3+E	260	$0.891_{0.116}$	$0.912_{0.086}$	$0.876_{0.173}$	2	$0.923_{0.089}$	$0.868_{0.150}$	1	$0.932_{0.074}$	$0.874_{0.163}$	3
A04+T1+E	992	$0.850_{0.158}$	$0.880_{0.131}$	$0.860_{0.149}$	1	$0.888_{0.132}$	$0.866_{0.153}$	2	$0.906_{0.108}$	$0.856_{0.157}$	4
A04+T1+N	61	$0.760_{0.242}$	$0.840_{0.152}$	$0.823_{0.164}$	1	$0.837_{0.162}$	$0.786_{0.201}$	1	$0.827_{0.206}$	$0.789_{0.226}$	4
A04+T3+E	913	$0.912_{0.088}$	$0.939_{0.054}$	$0.934_{0.065}$	2	$0.948_{0.047}$	$0.926_{0.069}$	1	$0.951_{0.045}$	$0.932_{0.063}$	3
A04+T3+N	90	$0.877_{0.096}$	$0.910_{0.068}$	$0.905_{0.070}$	2	$0.928_{0.031}$	$0.908_{0.044}$	3	$0.926_{0.052}$	$0.913_{0.055}$	1
A05+T1+E	752	$0.815_{0.203}$	$0.862_{0.163}$	$0.837_{0.179}$	1	$0.873_{0.162}$	$0.827_{0.184}$	1	$0.882_{0.147}$	$0.841_{0.177}$	4
A05+T3+E	742	$0.875_{0.129}$	$0.903_{0.109}$	$0.891_{0.113}$	2	$0.916_{0.098}$	$0.878_{0.120}$	1	$0.919_{0.091}$	$0.891_{0.108}$	1
A06+T1+E	10	$0.824_{0.187}$	$0.902_{0.037}$	$0.885_{0.070}$	1	$0.909_{0.034}$	$0.889_{0.049}$	2	$0.909_{0.039}$	$0.880_{0.063}$	4
A06+T3+E	24	$0.862_{0.079}$	$0.916_{0.053}$	$0.916_{0.053}$	2	$0.934_{0.031}$	$0.923_{0.031}$	3	$0.933_{0.041}$	$0.929_{0.040}$	1
A07+T1+E	67	$0.820_{0.157}$	$0.877_{0.124}$	$0.867_{0.150}$	1	$0.890_{0.108}$	$0.862_{0.157}$	2	$0.897_{0.104}$	$0.862_{0.149}$	4
A07+T1+N	251	$0.837_{0.141}$	$0.892_{0.085}$	$0.879_{0.104}$	1	$0.903_{0.067}$	$0.875_{0.114}$	2	$0.905_{0.070}$	$0.873_{0.101}$	4
A07+T3+E	12	$0.925_{0.055}$	$0.938_{0.019}$	$0.937_{0.019}$	2	$0.939_{0.020}$	$0.916_{0.055}$	1	$0.947_{0.016}$	$0.932_{0.017}$	1
A07+T3+N	39	$0.863_{0.177}$	$0.918_{0.061}$	$0.913_{0.071}$	2	$0.933_{0.037}$	$0.899_{0.148}$	3	$0.934_{0.039}$	$0.914_{0.079}$	1
A08+T1+E	26	$0.666_{0.225}$	$0.750_{0.161}$	$0.680_{0.242}$	2	$0.747_{0.197}$	$0.653_{0.260}$	1	$0.793_{0.134}$	$0.666_{0.261}$	1
A08+T3+E	111	$0.605_{0.230}$	$0.668_{0.197}$	$0.626_{0.210}$	1	$0.677_{0.206}$	$0.628_{0.218}$	2	$0.735_{0.166}$	$0.669_{0.203}$	2
A09+T1+E	30	$0.815_{0.121}$	$0.841_{0.098}$	$0.784_{0.156}$	1	$0.873_{0.089}$	$0.833_{0.113}$	2	$0.884_{0.076}$	$0.812_{0.119}$	4
A09+T1+N	1	$0.953_{0.000}$	$0.927_{0.000}$	$0.927_{0.000}$	2	$0.955_{0.000}$	$0.955_{0.000}$	1	$0.947_{0.000}$	$0.947_{0.000}$	3
A09+T3+E	10	$0.900_{0.074}$	$0.918_{0.054}$	$0.918_{0.054}$	2	$0.933_{0.038}$	$0.909_{0.044}$	1	$0.937_{0.043}$	$0.919_{0.040}$	3
A09+T3+N	3	$0.894_{0.070}$	$0.911_{0.058}$	$0.911_{0.058}$	2	$0.957_{0.015}$	$0.957_{0.015}$	3	$0.944_{0.030}$	$0.944_{0.030}$	1

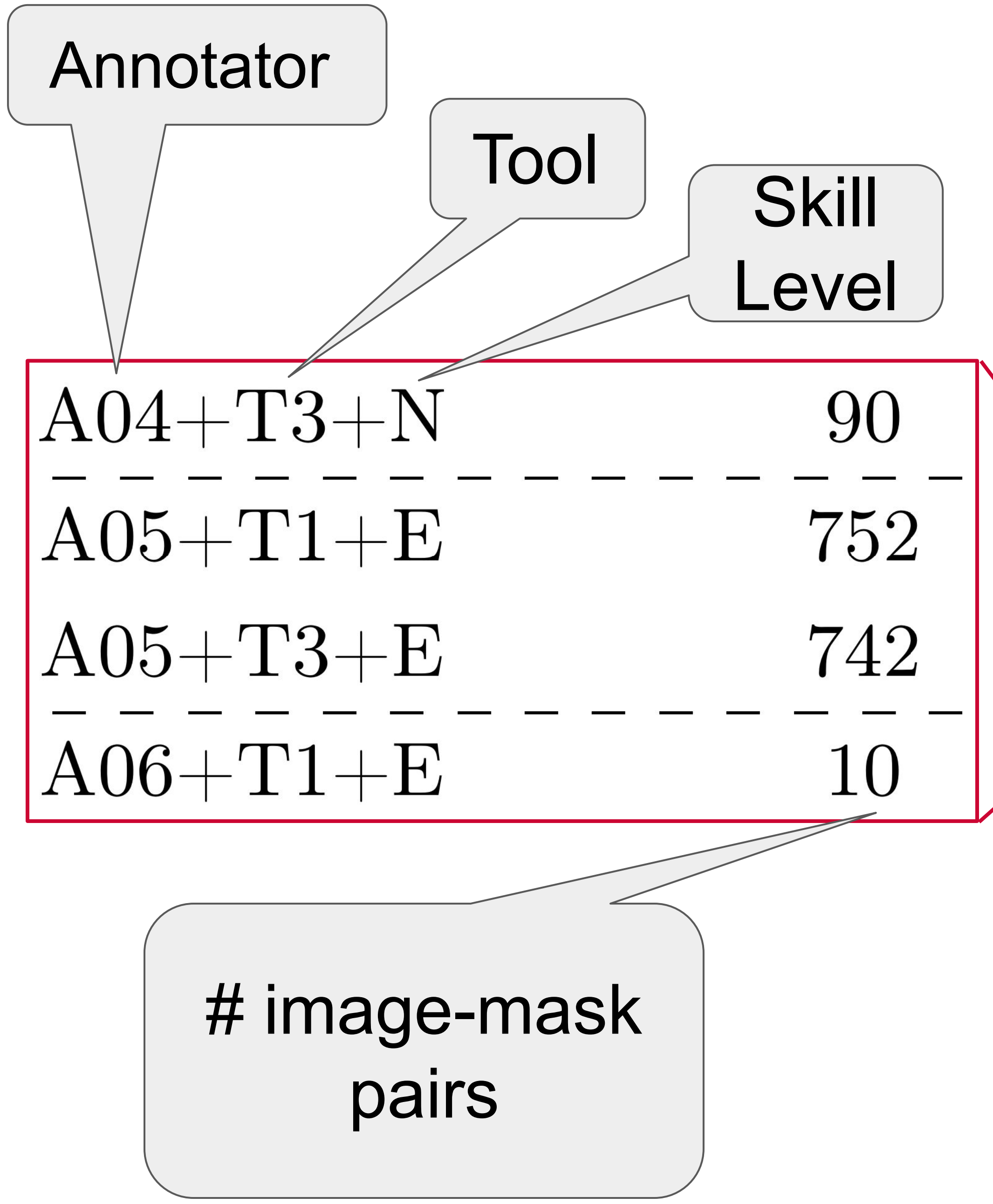
Quantitative Results on ISIC-MultiAnnot



Annotator + Tool + Experience	Seg. Count	1-StyleSeg	2-StyleSeg			3-StyleSeg			4-StyleSeg		
		$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$
A00+T2+E	1573	$0.892_{0.089}$	$0.923_{0.061}$	$0.913_{0.087}$	2	$0.944_{0.049}$	$0.913_{0.106}$	3	$0.944_{0.044}$	$0.914_{0.111}$	1
A00+T2+N	1305	$0.716_{0.302}$	$0.761_{0.293}$	$0.728_{0.308}$	2	$0.793_{0.287}$	$0.727_{0.313}$	3	$0.790_{0.290}$	$0.726_{0.304}$	3
A01+T1+N	6	$0.559_{0.362}$	$0.766_{0.152}$	$0.766_{0.152}$	1	$0.754_{0.132}$	$0.741_{0.125}$	2	$0.819_{0.106}$	$0.767_{0.113}$	2
A01+T3+E	297	$0.900_{0.104}$	$0.915_{0.093}$	$0.897_{0.107}$	2	$0.927_{0.075}$	$0.900_{0.097}$	1	$0.931_{0.067}$	$0.904_{0.090}$	3
A01+T3+N	2148	$0.829_{0.185}$	$0.857_{0.167}$	$0.817_{0.170}$	1	$0.869_{0.159}$	$0.836_{0.178}$	1	$0.876_{0.148}$	$0.836_{0.175}$	3
A02+T1+E	1742	$0.844_{0.177}$	$0.880_{0.140}$	$0.856_{0.159}$	1	$0.886_{0.132}$	$0.854_{0.159}$	1	$0.895_{0.112}$	$0.859_{0.148}$	4
A02+T3+E	468	$0.856_{0.172}$	$0.889_{0.167}$	$0.883_{0.175}$	2	$0.899_{0.161}$	$0.874_{0.188}$	3	$0.903_{0.146}$	$0.890_{0.160}$	1
A03+T1+E	1622	$0.778_{0.168}$	$0.845_{0.117}$	$0.827_{0.137}$	1	$0.854_{0.111}$	$0.824_{0.145}$	2	$0.881_{0.095}$	$0.823_{0.132}$	4
A03+T3+E	260	$0.891_{0.116}$	$0.912_{0.086}$	$0.876_{0.173}$	2	$0.923_{0.089}$	$0.868_{0.150}$	1	$0.932_{0.074}$	$0.874_{0.163}$	3
A04+T1+E	992	$0.850_{0.158}$	$0.880_{0.131}$	$0.860_{0.149}$	1	$0.888_{0.132}$	$0.866_{0.153}$	2	$0.906_{0.108}$	$0.856_{0.157}$	4
A04+T1+N	61	$0.760_{0.242}$	$0.840_{0.152}$	$0.823_{0.164}$	1	$0.837_{0.162}$	$0.786_{0.201}$	1	$0.827_{0.206}$	$0.789_{0.226}$	4
A04+T3+E	913	$0.912_{0.088}$	$0.939_{0.054}$	$0.934_{0.065}$	2	$0.948_{0.047}$	$0.926_{0.069}$	1	$0.951_{0.045}$	$0.932_{0.063}$	3
A04+T3+N	90	$0.877_{0.096}$	$0.910_{0.068}$	$0.905_{0.070}$	2	$0.928_{0.031}$	$0.908_{0.044}$	3	$0.926_{0.052}$	$0.913_{0.055}$	1
A05+T1+E	752	$0.815_{0.203}$	$0.862_{0.163}$	$0.837_{0.179}$	1	$0.873_{0.162}$	$0.827_{0.184}$	1	$0.882_{0.147}$	$0.841_{0.177}$	4
A05+T3+E	742	$0.875_{0.129}$	$0.903_{0.109}$	$0.891_{0.113}$	2	$0.916_{0.098}$	$0.878_{0.120}$	1	$0.919_{0.091}$	$0.891_{0.108}$	1
A06+T1+E	10	$0.824_{0.187}$	$0.902_{0.037}$	$0.885_{0.070}$	1	$0.909_{0.034}$	$0.889_{0.049}$	2	$0.909_{0.039}$	$0.880_{0.063}$	4
A06+T3+E	24	$0.862_{0.079}$	$0.916_{0.053}$	$0.916_{0.053}$	2	$0.934_{0.031}$	$0.923_{0.031}$	3	$0.933_{0.041}$	$0.929_{0.040}$	1
A07+T1+E	67	$0.820_{0.157}$	$0.877_{0.124}$	$0.867_{0.150}$	1	$0.890_{0.108}$	$0.862_{0.157}$	2	$0.897_{0.104}$	$0.862_{0.149}$	4
A07+T1+N	251	$0.837_{0.141}$	$0.892_{0.085}$	$0.879_{0.104}$	1	$0.903_{0.067}$	$0.875_{0.114}$	2	$0.905_{0.070}$	$0.873_{0.101}$	4
A07+T3+E	12	$0.925_{0.055}$	$0.938_{0.019}$	$0.937_{0.019}$	2	$0.939_{0.020}$	$0.916_{0.055}$	1	$0.947_{0.016}$	$0.932_{0.017}$	1
A07+T3+N	39	$0.863_{0.177}$	$0.918_{0.061}$	$0.913_{0.071}$	2	$0.933_{0.037}$	$0.899_{0.148}$	3	$0.934_{0.039}$	$0.914_{0.079}$	1
A08+T1+E	26	$0.666_{0.225}$	$0.750_{0.161}$	$0.680_{0.242}$	2	$0.747_{0.197}$	$0.653_{0.260}$	1	$0.793_{0.134}$	$0.666_{0.261}$	1
A08+T3+E	111	$0.605_{0.230}$	$0.668_{0.197}$	$0.626_{0.210}$	1	$0.677_{0.206}$	$0.628_{0.218}$	2	$0.735_{0.166}$	$0.669_{0.203}$	2
A09+T1+E	30	$0.815_{0.121}$	$0.841_{0.098}$	$0.784_{0.156}$	1	$0.873_{0.089}$	$0.833_{0.113}$	2	$0.884_{0.076}$	$0.812_{0.119}$	4
A09+T1+N	1	$0.953_{0.000}$	$0.927_{0.000}$	$0.927_{0.000}$	2	$0.955_{0.000}$	$0.955_{0.000}$	1	$0.947_{0.000}$	$0.947_{0.000}$	3
A09+T3+E	10	$0.900_{0.074}$	$0.918_{0.054}$	$0.918_{0.054}$	2	$0.933_{0.038}$	$0.909_{0.044}$	1	$0.937_{0.043}$	$0.919_{0.040}$	3
A09+T3+N	3	$0.894_{0.070}$	$0.911_{0.058}$	$0.911_{0.058}$	2	$0.957_{0.015}$	$0.957_{0.015}$	3	$0.944_{0.030}$	$0.944_{0.030}$	1

Quantitative Results on ISIC-MultiAnnot

4-StyleSeg



Annotator + Tool + Experience	Seg. Count	1-StyleSeg	2-StyleSeg			3-StyleSeg			4-StyleSeg		
		$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$
A00+T2+E	1573	$0.892_{0.089}$	$0.923_{0.061}$	$0.913_{0.087}$	2	$0.944_{0.049}$	$0.913_{0.106}$	3	$0.944_{0.044}$	$0.914_{0.111}$	1
A00+T2+N	1305	$0.716_{0.302}$	$0.761_{0.293}$	$0.728_{0.308}$	2	$0.793_{0.287}$	$0.727_{0.313}$	3	$0.790_{0.290}$	$0.726_{0.304}$	3
A01+T1+N	6	$0.559_{0.362}$	$0.766_{0.152}$	$0.766_{0.152}$	1	$0.754_{0.132}$	$0.741_{0.125}$	2	$0.819_{0.106}$	$0.767_{0.113}$	2
A01+T3+E	297	$0.900_{0.104}$	$0.915_{0.093}$	$0.897_{0.107}$	2	$0.927_{0.075}$	$0.900_{0.097}$	1	$0.931_{0.067}$	$0.904_{0.090}$	3
A01+T3+N	2148	$0.829_{0.185}$	$0.857_{0.167}$	$0.817_{0.170}$	1	$0.869_{0.159}$	$0.836_{0.178}$	1	$0.876_{0.148}$	$0.836_{0.175}$	3
A02+T1+E	1742	$0.844_{0.177}$	$0.880_{0.140}$	$0.856_{0.159}$	1	$0.886_{0.132}$	$0.854_{0.159}$	1	$0.895_{0.112}$	$0.859_{0.148}$	4
A02+T3+E	468	$0.856_{0.172}$	$0.889_{0.167}$	$0.883_{0.175}$	2	$0.899_{0.161}$	$0.874_{0.188}$	3	$0.903_{0.146}$	$0.890_{0.160}$	1
A03+T1+E	1622	$0.778_{0.168}$	$0.845_{0.117}$	$0.827_{0.137}$	1	$0.854_{0.111}$	$0.824_{0.145}$	2	$0.881_{0.095}$	$0.823_{0.132}$	4
A03+T3+E	260	$0.891_{0.116}$	$0.912_{0.086}$	$0.876_{0.173}$	2	$0.923_{0.089}$	$0.868_{0.150}$	1	$0.932_{0.074}$	$0.874_{0.163}$	3
A04+T1+E	992	$0.850_{0.158}$	$0.880_{0.131}$	$0.860_{0.149}$	1	$0.888_{0.132}$	$0.866_{0.153}$	2	$0.906_{0.108}$	$0.856_{0.157}$	4
A04+T1+N	61	$0.760_{0.242}$	$0.840_{0.152}$	$0.823_{0.164}$	1	$0.837_{0.162}$	$0.786_{0.201}$	1	$0.827_{0.206}$	$0.789_{0.226}$	4
A04+T3+E	913	$0.912_{0.088}$	$0.939_{0.054}$	$0.934_{0.065}$	2	$0.948_{0.047}$	$0.926_{0.069}$	1	$0.951_{0.045}$	$0.932_{0.063}$	3
A04+T3+N	90	$0.877_{0.096}$	$0.910_{0.068}$	$0.905_{0.070}$	2	$0.928_{0.031}$	$0.908_{0.044}$	3	$0.926_{0.052}$	$0.913_{0.055}$	1
A05+T1+E	752	$0.815_{0.203}$	$0.862_{0.163}$	$0.837_{0.179}$	1	$0.873_{0.162}$	$0.827_{0.184}$	1	$0.882_{0.147}$	$0.841_{0.177}$	4
A05+T3+E	742	$0.875_{0.129}$	$0.903_{0.109}$	$0.891_{0.113}$	2	$0.916_{0.098}$	$0.878_{0.120}$	1	$0.919_{0.091}$	$0.891_{0.108}$	1
A06+T1+E	10	$0.824_{0.187}$	$0.902_{0.037}$	$0.885_{0.070}$	1	$0.909_{0.034}$	$0.889_{0.049}$	2	$0.909_{0.039}$	$0.880_{0.063}$	4
A06+T3+E	24	$0.862_{0.079}$	$0.916_{0.053}$	$0.916_{0.053}$	2	$0.934_{0.031}$	$0.923_{0.031}$	3	$0.933_{0.041}$	$0.929_{0.040}$	1
A07+T1+E	67	$0.820_{0.157}$	$0.877_{0.124}$	$0.867_{0.150}$	1	$0.890_{0.108}$	$0.862_{0.157}$	2	$0.897_{0.104}$	$0.862_{0.149}$	4
A07+T1+N	251	$0.837_{0.141}$	$0.892_{0.085}$	$0.879_{0.104}$	1	$0.903_{0.067}$	$0.875_{0.114}$	2	$0.905_{0.070}$	$0.873_{0.101}$	4
A07+T3+E	12	$0.925_{0.055}$	$0.938_{0.019}$	$0.937_{0.019}$	2	$0.939_{0.020}$	$0.916_{0.055}$	1	$0.947_{0.016}$	$0.932_{0.017}$	1
A07+T3+N	39	$0.863_{0.177}$	$0.918_{0.061}$	$0.913_{0.071}$	2	$0.933_{0.037}$	$0.899_{0.148}$	3	$0.934_{0.039}$	$0.914_{0.079}$	1
A08+T1+E	26	$0.666_{0.225}$	$0.750_{0.161}$	$0.680_{0.242}$	2	$0.747_{0.197}$	$0.653_{0.260}$	1	$0.793_{0.134}$	$0.666_{0.261}$	1
A08+T3+E	111	$0.605_{0.230}$	$0.668_{0.197}$	$0.626_{0.210}$	1	$0.677_{0.206}$	$0.628_{0.218}$	2	$0.735_{0.166}$	$0.669_{0.203}$	2
A09+T1+E	30	$0.815_{0.121}$	$0.841_{0.098}$	$0.784_{0.156}$	1	$0.873_{0.089}$	$0.833_{0.113}$	2	$0.884_{0.076}$	$0.812_{0.119}$	4
A09+T1+N	1	$0.953_{0.000}$	$0.927_{0.000}$	$0.927_{0.000}$	2	$0.955_{0.000}$	$0.955_{0.000}$	1	$0.947_{0.000}$	$0.947_{0.000}$	3
A09+T3+E	10	$0.900_{0.074}$	$0.918_{0.054}$	$0.918_{0.054}$	2	$0.933_{0.038}$	$0.909_{0.044}$	1	$0.937_{0.043}$	$0.919_{0.040}$	3
A09+T3+N	3	$0.894_{0.070}$	$0.911_{0.058}$	$0.911_{0.058}$	2	$0.957_{0.015}$	$0.957_{0.015}$	3	$0.944_{0.030}$	$0.944_{0.030}$	1

Annotator + Tool + Experience	Seg. Count	1-StyleSeg	2-StyleSeg			3-StyleSeg			4-StyleSeg		
		$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$
A00+T2+E	1573	$0.892_{0.089}$	$0.923_{0.061}$	$0.913_{0.087}$	2	$0.944_{0.049}$	$0.913_{0.106}$	3	$0.944_{0.044}$	$0.914_{0.111}$	1
A00+T2+N	1305	$0.716_{0.302}$	$0.761_{0.293}$	$0.728_{0.308}$	2	$0.793_{0.287}$	$0.727_{0.313}$	3	$0.790_{0.290}$	$0.726_{0.304}$	3
A01+T1+N	6	$0.559_{0.362}$	$0.766_{0.152}$	$0.766_{0.152}$	1	$0.754_{0.132}$	$0.741_{0.125}$	2	$0.819_{0.106}$	$0.767_{0.113}$	2
A01+T3+E	297	$0.900_{0.104}$	$0.915_{0.093}$	$0.897_{0.107}$	2	$0.927_{0.075}$	$0.900_{0.097}$	1	$0.931_{0.067}$	$0.904_{0.090}$	3
A01+T3+N	2148	$0.829_{0.185}$	$0.857_{0.167}$	$0.817_{0.170}$	1	$0.869_{0.159}$	$0.836_{0.178}$	1	$0.876_{0.148}$	$0.836_{0.175}$	3
A02+T1+E	1742	$0.844_{0.177}$	$0.880_{0.140}$	$0.856_{0.159}$	1	$0.886_{0.132}$	$0.854_{0.159}$	1	$0.895_{0.112}$	$0.859_{0.148}$	4
A02+T3+E	468	$0.856_{0.172}$	$0.889_{0.167}$	$0.883_{0.175}$	2	$0.899_{0.161}$	$0.874_{0.188}$	3	$0.903_{0.146}$	$0.890_{0.160}$	1
A03+T1+E	1622	$0.778_{0.168}$	$0.845_{0.117}$	$0.827_{0.137}$	1	$0.854_{0.111}$	$0.824_{0.145}$	2	$0.881_{0.095}$	$0.823_{0.132}$	4
A03+T3+E	260	$0.891_{0.116}$	$0.912_{0.086}$	$0.876_{0.173}$	2	$0.923_{0.089}$	$0.868_{0.150}$	1	$0.932_{0.074}$	$0.874_{0.163}$	3
A04+T1+E	992	$0.850_{0.158}$	$0.880_{0.131}$	$0.860_{0.149}$	1	$0.888_{0.132}$	$0.866_{0.153}$	2	$0.906_{0.108}$	$0.856_{0.157}$	4
A04+T1+N	61	$0.760_{0.242}$	$0.840_{0.152}$	$0.823_{0.164}$	1	$0.837_{0.162}$	$0.786_{0.201}$	1	$0.827_{0.206}$	$0.789_{0.226}$	4
A04+T3+E	913	$0.912_{0.088}$	$0.939_{0.054}$	$0.934_{0.065}$	2	$0.948_{0.047}$	$0.926_{0.069}$	1	$0.951_{0.045}$	$0.932_{0.063}$	3
A04+T3+N	90	$0.877_{0.096}$	$0.910_{0.068}$	$0.905_{0.070}$	2	$0.928_{0.031}$	$0.908_{0.044}$	3	$0.926_{0.052}$	$0.913_{0.055}$	1
A05+T1+E	752	$0.815_{0.203}$	$0.862_{0.163}$	$0.837_{0.179}$	1	$0.873_{0.162}$	$0.827_{0.184}$	1	$0.882_{0.147}$	$0.841_{0.177}$	4
A05+T3+E	742	$0.875_{0.129}$	$0.903_{0.109}$	$0.891_{0.113}$	2	$0.916_{0.098}$	$0.878_{0.120}$	1	$0.919_{0.091}$	$0.891_{0.108}$	1
A06+T1+E	10	$0.824_{0.187}$	$0.902_{0.037}$	$0.885_{0.070}$	1	$0.909_{0.034}$	$0.889_{0.049}$	2	$0.909_{0.039}$	$0.880_{0.063}$	4
A06+T3+E	24	$0.862_{0.079}$	$0.916_{0.053}$	$0.916_{0.053}$	2	$0.934_{0.031}$	$0.923_{0.031}$	3	$0.933_{0.041}$	$0.929_{0.040}$	1
A07+T1+E	67	$0.820_{0.157}$	$0.877_{0.124}$	$0.867_{0.150}$	1	$0.890_{0.108}$	$0.862_{0.157}$	2	$0.897_{0.104}$	$0.862_{0.149}$	4
A07+T1+N	251	$0.837_{0.141}$	$0.892_{0.085}$	$0.879_{0.104}$	1	$0.903_{0.067}$	$0.875_{0.114}$	2	$0.905_{0.070}$	$0.873_{0.101}$	4
A07+T3+E	12	$0.925_{0.055}$	$0.938_{0.019}$	$0.937_{0.019}$	2	$0.939_{0.020}$	$0.916_{0.055}$	1	$0.947_{0.016}$	$0.932_{0.017}$	1
A07+T3+N	39	$0.863_{0.177}$	$0.918_{0.061}$	$0.913_{0.071}$	2	$0.933_{0.037}$	$0.899_{0.148}$	3	$0.934_{0.039}$	$0.914_{0.079}$	1
A08+T1+E	26	$0.666_{0.225}$	$0.750_{0.161}$	$0.680_{0.242}$	2	$0.747_{0.197}$	$0.653_{0.260}$	1	$0.793_{0.134}$	$0.666_{0.261}$	1
A08+T3+E	111	$0.605_{0.230}$	$0.668_{0.197}$	$0.626_{0.210}$	1	$0.677_{0.206}$	$0.628_{0.218}$	2	$0.735_{0.166}$	$0.669_{0.203}$	2
A09+T1+E	30	$0.815_{0.121}$	$0.841_{0.098}$	$0.784_{0.156}$	1	$0.873_{0.089}$	$0.833_{0.113}$	2	$0.884_{0.076}$	$0.812_{0.119}$	4
A09+T1+N	1	$0.953_{0.000}$	$0.927_{0.000}$	$0.927_{0.000}$	2	$0.955_{0.000}$	$0.955_{0.000}$	1	$0.947_{0.000}$	$0.947_{0.000}$	3
A09+T3+E	10	$0.900_{0.074}$	$0.918_{0.054}$	$0.918_{0.054}$	2	$0.933_{0.038}$	$0.909_{0.044}$	1	$0.937_{0.043}$	$0.919_{0.040}$	3
A09+T3+N	3	$0.894_{0.070}$	$0.911_{0.058}$	$0.911_{0.058}$	2	$0.957_{0.015}$	$0.957_{0.015}$	3	$0.944_{0.030}$	$0.944_{0.030}$	1

ISIC-MultiAnnot Results: Key Takeaways

1. **Improved diversity without compromising quality**: for all *M* ≥ 2, choosing a single style that, for each annotator preference, maximizes agreement with the "ground truth" still outperforms 1-StyleSeg.

ISIC-MultiAnnot Results: Key Takeaways

Annotator + Tool + Experience	Seg. Count	1-StyleSeg	2-StyleSeg			3-StyleSeg			4-StyleSeg		
		$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$
A00+T2+E	1573	$0.892_{0.089}$	$0.923_{0.061}$	$0.913_{0.087}$	2	$0.944_{0.049}$	$0.913_{0.106}$	3	$0.944_{0.044}$	$0.914_{0.111}$	1
A00+T2+N	1305	$0.716_{0.302}$	$0.761_{0.293}$	$0.728_{0.308}$	2	$0.793_{0.287}$	$0.727_{0.313}$	3	$0.790_{0.290}$	$0.726_{0.304}$	3
A01+T1+N	6	$0.559_{0.362}$	$0.766_{0.152}$	$0.766_{0.152}$	1	$0.754_{0.132}$	$0.741_{0.125}$	2	$0.819_{0.106}$	$0.767_{0.113}$	2
A01+T3+E	297	$0.900_{0.104}$	$0.915_{0.093}$	$0.897_{0.107}$	2	$0.927_{0.075}$	$0.900_{0.097}$	1	$0.931_{0.067}$	$0.904_{0.090}$	3
A01+T3+N	2148	$0.829_{0.185}$	$0.857_{0.167}$	$0.817_{0.170}$	1	$0.869_{0.159}$	$0.836_{0.178}$	1	$0.876_{0.148}$	$0.836_{0.175}$	3
A02+T1+E	1742	$0.844_{0.177}$	$0.880_{0.140}$	$0.856_{0.159}$	1	$0.886_{0.132}$	$0.854_{0.159}$	1	$0.895_{0.112}$	$0.859_{0.148}$	4
A02+T3+E	468	$0.856_{0.172}$	$0.889_{0.167}$	$0.883_{0.175}$	2	$0.899_{0.161}$	$0.874_{0.188}$	3	$0.903_{0.146}$	$0.890_{0.160}$	1
A03+T1+E	1622	$0.778_{0.168}$	$0.845_{0.117}$	$0.827_{0.137}$	1	$0.854_{0.111}$	$0.824_{0.145}$	2	$0.881_{0.095}$	$0.823_{0.132}$	4
A03+T3+E	260	$0.891_{0.116}$	$0.912_{0.086}$	$0.876_{0.173}$	2	$0.923_{0.089}$	$0.868_{0.150}$	1	$0.932_{0.074}$	$0.874_{0.163}$	3
A04+T1+E	992	$0.850_{0.158}$	$0.880_{0.131}$	$0.860_{0.149}$	1	$0.888_{0.132}$	$0.866_{0.153}$	2	$0.906_{0.108}$	$0.856_{0.157}$	4
A04+T1+N	61	$0.760_{0.242}$	$0.840_{0.152}$	$0.823_{0.164}$	1	$0.837_{0.162}$	$0.786_{0.201}$	1	$0.827_{0.206}$	$0.789_{0.226}$	4
A04+T3+E	913	$0.912_{0.088}$	$0.939_{0.054}$	$0.934_{0.065}$	2	$0.948_{0.047}$	$0.926_{0.069}$	1	$0.951_{0.045}$	$0.932_{0.063}$	3
A04+T3+N	90	$0.877_{0.096}$	$0.910_{0.068}$	$0.905_{0.070}$	2	$0.928_{0.031}$	$0.908_{0.044}$	3	$0.926_{0.052}$	$0.913_{0.055}$	1
A05+T1+E	752	$0.815_{0.203}$	$0.862_{0.163}$	$0.837_{0.179}$	1	$0.873_{0.162}$	$0.827_{0.184}$	1	$0.882_{0.147}$	$0.841_{0.177}$	4
A05+T3+E	742	$0.875_{0.129}$	$0.903_{0.109}$	$0.891_{0.113}$	2	$0.916_{0.098}$	$0.878_{0.120}$	1	$0.919_{0.091}$	$0.891_{0.108}$	1
A06+T1+E	10	$0.824_{0.187}$	$0.902_{0.037}$	$0.885_{0.070}$	1	$0.909_{0.034}$	$0.889_{0.049}$	2	$0.909_{0.039}$	$0.880_{0.063}$	4
A06+T3+E	24	$0.862_{0.079}$	$0.916_{0.053}$	$0.916_{0.053}$	2	$0.934_{0.031}$	$0.923_{0.031}$	3	$0.933_{0.041}$	$0.929_{0.040}$	1
A07+T1+E	67	$0.820_{0.157}$	$0.877_{0.124}$	$0.867_{0.150}$	1	$0.890_{0.108}$	$0.862_{0.157}$	2	$0.897_{0.104}$	$0.862_{0.149}$	4
A07+T1+N	251	$0.837_{0.141}$	$0.892_{0.085}$	$0.879_{0.104}$	1	$0.903_{0.067}$	$0.875_{0.114}$	2	$0.905_{0.070}$	$0.873_{0.101}$	4
A07+T3+E	12	$0.925_{0.055}$	$0.938_{0.019}$	$0.937_{0.019}$	2	$0.939_{0.020}$	$0.916_{0.055}$	1	$0.947_{0.016}$	$0.932_{0.017}$	1
A07+T3+N	39	$0.863_{0.177}$	$0.918_{0.061}$	$0.913_{0.071}$	2	$0.933_{0.037}$	$0.899_{0.148}$	3	$0.934_{0.039}$	$0.914_{0.079}$	1
A08+T1+E	26	$0.666_{0.225}$	$0.750_{0.161}$	$0.680_{0.242}$	2	$0.747_{0.197}$	$0.653_{0.260}$	1	$0.793_{0.134}$	$0.666_{0.261}$	1
A08+T3+E	111	$0.605_{0.230}$	$0.668_{0.197}$	$0.626_{0.210}$	1	$0.677_{0.206}$	$0.628_{0.218}$	2	$0.735_{0.166}$	$0.669_{0.203}$	2
A09+T1+E	30	$0.815_{0.121}$	$0.841_{0.098}$	$0.784_{0.156}$	1	$0.873_{0.089}$	$0.833_{0.113}$	2	$0.884_{0.076}$	$0.812_{0.119}$	4
A09+T1+N	1	$0.953_{0.000}$	$0.927_{0.000}$	$0.927_{0.000}$	2	$0.955_{0.000}$	$0.955_{0.000}$	1	$0.947_{0.000}$	$0.947_{0.000}$	3
A09+T3+E	10	$0.900_{0.074}$	$0.918_{0.054}$	$0.918_{0.054}$	2	$0.933_{0.038}$	$0.909_{0.044}$	1	$0.937_{0.043}$	$0.919_{0.040}$	3
A09+T3+N	3	$0.894_{0.070}$	$0.911_{0.058}$	$0.911_{0.058}$	2	$0.957_{0.015}$	$0.957_{0.015}$	3	$0.944_{0.030}$	$0.944_{0.030}$	1

1. **Improved diversity without compromising quality**: for all $M \geq 2$, choosing a single style that, for each annotator preference, maximizes agreement with the “ground truth” still outperforms 1-StyleSeg.

Personalization in segmentation: each user can choose their own style.

ISIC-MultiAnnot Results: Key Takeaways

Annotator + Tool + Experience	Seg. Count	1-StyleSeg	2-StyleSeg			3-StyleSeg			4-StyleSeg		
		$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$
A00+T2+E	1573	$0.892_{0.089}$	$0.923_{0.061}$	$0.913_{0.087}$	2	$0.944_{0.049}$	$0.913_{0.106}$	3	$0.944_{0.044}$	$0.914_{0.111}$	1
A00+T2+N	1305	$0.716_{0.302}$	$0.761_{0.293}$	$0.728_{0.308}$	2	$0.793_{0.287}$	$0.727_{0.313}$	3	$0.790_{0.290}$	$0.726_{0.304}$	3
A01+T1+N	6	$0.559_{0.362}$	$0.766_{0.152}$	$0.766_{0.152}$	1	$0.754_{0.132}$	$0.741_{0.125}$	2	$0.819_{0.106}$	$0.767_{0.113}$	2
A01+T3+E	297	$0.900_{0.104}$	$0.915_{0.093}$	$0.897_{0.107}$	2	$0.927_{0.075}$	$0.900_{0.097}$	1	$0.931_{0.067}$	$0.904_{0.090}$	3
A01+T3+N	2148	$0.829_{0.185}$	$0.857_{0.167}$	$0.817_{0.170}$	1	$0.869_{0.159}$	$0.836_{0.178}$	1	$0.876_{0.148}$	$0.836_{0.175}$	3
A02+T1+E	1742	$0.844_{0.177}$	$0.880_{0.140}$	$0.856_{0.159}$	1	$0.886_{0.132}$	$0.854_{0.159}$	1	$0.895_{0.112}$	$0.859_{0.148}$	4
A02+T3+E	468	$0.856_{0.172}$	$0.889_{0.167}$	$0.883_{0.175}$	2	$0.899_{0.161}$	$0.874_{0.188}$	3	$0.903_{0.146}$	$0.890_{0.160}$	1
A03+T1+E	1622	$0.778_{0.168}$	$0.845_{0.117}$	$0.827_{0.137}$	1	$0.854_{0.111}$	$0.824_{0.145}$	2	$0.881_{0.095}$	$0.823_{0.132}$	4
A03+T3+E	260	$0.891_{0.116}$	$0.912_{0.086}$	$0.876_{0.173}$	2	$0.923_{0.089}$	$0.868_{0.150}$	1	$0.932_{0.074}$	$0.874_{0.163}$	3
A04+T1+E	992	$0.850_{0.158}$	$0.880_{0.131}$	$0.860_{0.149}$	1	$0.888_{0.132}$	$0.866_{0.153}$	2	$0.906_{0.108}$	$0.856_{0.157}$	4
A04+T1+N	61	$0.760_{0.242}$	$0.840_{0.152}$	$0.823_{0.164}$	1	$0.837_{0.162}$	$0.786_{0.201}$	1	$0.827_{0.206}$	$0.789_{0.226}$	4
A04+T3+E	913	$0.912_{0.088}$	$0.939_{0.054}$	$0.934_{0.065}$	2	$0.948_{0.047}$	$0.926_{0.069}$	1	$0.951_{0.045}$	$0.932_{0.063}$	3
A04+T3+N	90	$0.877_{0.096}$	$0.910_{0.068}$	$0.905_{0.070}$	2	$0.928_{0.031}$	$0.908_{0.044}$	3	$0.926_{0.052}$	$0.913_{0.055}$	1
A05+T1+E	752	$0.815_{0.203}$	$0.862_{0.163}$	$0.837_{0.179}$	1	$0.873_{0.162}$	$0.827_{0.184}$	1	$0.882_{0.147}$	$0.841_{0.177}$	4
A05+T3+E	742	$0.875_{0.129}$	$0.903_{0.109}$	$0.891_{0.113}$	2	$0.916_{0.098}$	$0.878_{0.120}$	1	$0.919_{0.091}$	$0.891_{0.108}$	1
A06+T1+E	10	$0.824_{0.187}$	$0.902_{0.037}$	$0.885_{0.070}$	1	$0.909_{0.034}$	$0.889_{0.049}$	2	$0.909_{0.039}$	$0.880_{0.063}$	4
A06+T3+E	24	$0.862_{0.079}$	$0.916_{0.053}$	$0.916_{0.053}$	2	$0.934_{0.031}$	$0.923_{0.031}$	3	$0.933_{0.041}$	$0.929_{0.040}$	1
A07+T1+E	67	$0.820_{0.157}$	$0.877_{0.124}$	$0.867_{0.150}$	1	$0.890_{0.108}$	$0.862_{0.157}$	2	$0.897_{0.104}$	$0.862_{0.149}$	4
A07+T1+N	251	$0.837_{0.141}$	$0.892_{0.085}$	$0.879_{0.104}$	1	$0.903_{0.067}$	$0.875_{0.114}$	2	$0.905_{0.070}$	$0.873_{0.101}$	4
A07+T3+E	12	$0.925_{0.055}$	$0.938_{0.019}$	$0.937_{0.019}$	2	$0.939_{0.020}$	$0.916_{0.055}$	1	$0.947_{0.016}$	$0.932_{0.017}$	1
A07+T3+N	39	$0.863_{0.177}$	$0.918_{0.061}$	$0.913_{0.071}$	2	$0.933_{0.037}$	$0.899_{0.148}$	3	$0.934_{0.039}$	$0.914_{0.079}$	1
A08+T1+E	26	$0.666_{0.225}$	$0.750_{0.161}$	$0.680_{0.242}$	2	$0.747_{0.197}$	$0.653_{0.260}$	1	$0.793_{0.134}$	$0.666_{0.261}$	1
A08+T3+E	111	$0.605_{0.230}$	$0.668_{0.197}$	$0.626_{0.210}$	1	$0.677_{0.206}$	$0.628_{0.218}$	2	$0.735_{0.166}$	$0.669_{0.203}$	2
A09+T1+E	30	$0.815_{0.121}$	$0.841_{0.098}$	$0.784_{0.156}$	1	$0.873_{0.089}$	$0.833_{0.113}$	2	$0.884_{0.076}$	$0.812_{0.119}$	4
A09+T1+N	1	$0.953_{0.000}$	$0.927_{0.000}$	$0.927_{0.000}$	2	$0.955_{0.000}$	$0.955_{0.000}$	1	$0.947_{0.000}$	$0.947_{0.000}$	3
A09+T3+E	10	$0.900_{0.074}$	$0.918_{0.054}$	$0.918_{0.054}$	2	$0.933_{0.038}$	$0.909_{0.044}$	1	$0.937_{0.043}$	$0.919_{0.040}$	3
A09+T3+N	3	$0.894_{0.070}$	$0.911_{0.058}$	$0.911_{0.058}$	2	$0.957_{0.015}$	$0.957_{0.015}$	3	$0.944_{0.030}$	$0.944_{0.030}$	1

1. **Improved diversity without compromising quality**: for all *M* ≥ 2, choosing a single style that, for each annotator preference, maximizes agreement with the “ground truth” still outperforms 1-StyleSeg.

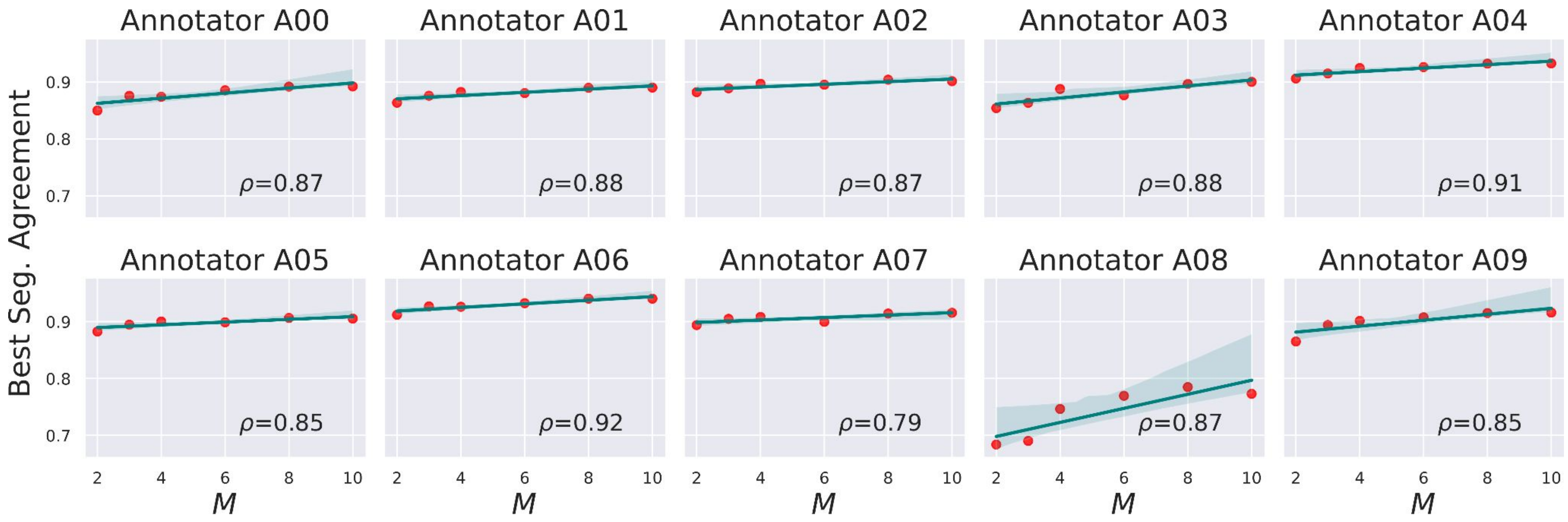
2. **Performance improves as *M* increases.**

Annotator + Tool + Experience	Seg. Count	1-StyleSeg	2-StyleSeg			3-StyleSeg			4-StyleSeg		
		$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$
A00+T2+E	1573	$0.892_{0.089}$	$0.923_{0.061}$	$0.913_{0.087}$	2	$0.944_{0.049}$	$0.913_{0.106}$	3	$0.944_{0.044}$	$0.914_{0.111}$	1
A00+T2+N	1305	$0.716_{0.302}$	$0.761_{0.293}$	$0.728_{0.308}$	2	$0.793_{0.287}$	$0.727_{0.313}$	3	$0.790_{0.290}$	$0.726_{0.304}$	3
A01+T1+N	6	$0.559_{0.362}$	$0.766_{0.152}$	$0.766_{0.152}$	1	$0.754_{0.132}$	$0.741_{0.125}$	2	$0.819_{0.106}$	$0.767_{0.113}$	2
A01+T3+E	297	$0.900_{0.104}$	$0.915_{0.093}$	$0.897_{0.107}$	2	$0.927_{0.075}$	$0.900_{0.097}$	1	$0.931_{0.067}$	$0.904_{0.090}$	3
A01+T3+N	2148	$0.829_{0.185}$	$0.857_{0.167}$	$0.817_{0.170}$	1	$0.869_{0.159}$	$0.836_{0.178}$	1	$0.876_{0.148}$	$0.836_{0.175}$	3
A02+T1+E	1742	$0.844_{0.177}$	$0.880_{0.140}$	$0.856_{0.159}$	1	$0.886_{0.132}$	$0.854_{0.159}$	1	$0.895_{0.112}$	$0.859_{0.148}$	4
A02+T3+E	468	$0.856_{0.172}$	$0.889_{0.167}$	$0.883_{0.175}$	2	$0.899_{0.161}$	$0.874_{0.188}$	3	$0.903_{0.146}$	$0.890_{0.160}$	1
A03+T1+E	1622	$0.778_{0.168}$	$0.845_{0.117}$	$0.827_{0.137}$	1	$0.854_{0.111}$	$0.824_{0.145}$	2	$0.881_{0.095}$	$0.823_{0.132}$	4
A03+T3+E	260	$0.891_{0.116}$	$0.912_{0.086}$	$0.876_{0.173}$	2	$0.923_{0.089}$	$0.868_{0.150}$	1	$0.932_{0.074}$	$0.874_{0.163}$	3
A04+T1+E	992	$0.850_{0.158}$	$0.880_{0.131}$	$0.860_{0.149}$	1	$0.888_{0.132}$	$0.866_{0.153}$	2	$0.906_{0.108}$	$0.856_{0.157}$	4
A04+T1+N	61	$0.760_{0.242}$	$0.840_{0.152}$	$0.823_{0.164}$	1	$0.837_{0.162}$	$0.786_{0.201}$	1	$0.827_{0.206}$	$0.789_{0.226}$	4
A04+T3+E	913	$0.912_{0.088}$	$0.939_{0.054}$	$0.934_{0.065}$	2	$0.948_{0.047}$	$0.926_{0.069}$	1	$0.951_{0.045}$	$0.932_{0.063}$	3
A04+T3+N	90	$0.877_{0.096}$	$0.910_{0.068}$	$0.905_{0.070}$	2	$0.928_{0.031}$	$0.908_{0.044}$	3	$0.926_{0.052}$	$0.913_{0.055}$	1
A05+T1+E	752	$0.815_{0.203}$	$0.862_{0.163}$	$0.837_{0.179}$	1	$0.873_{0.162}$	$0.827_{0.184}$	1	$0.882_{0.147}$	$0.841_{0.177}$	4
A05+T3+E	742	$0.875_{0.129}$	$0.903_{0.109}$	$0.891_{0.113}$	2	$0.916_{0.098}$	$0.878_{0.120}$	1	$0.919_{0.091}$	$0.891_{0.108}$	1
A06+T1+E	10	$0.824_{0.187}$	$0.902_{0.037}$	$0.885_{0.070}$	1	$0.909_{0.034}$	$0.889_{0.049}$	2	$0.909_{0.039}$	$0.880_{0.063}$	4
A06+T3+E	24	$0.862_{0.079}$	$0.916_{0.053}$	$0.916_{0.053}$	2	$0.934_{0.031}$	$0.923_{0.031}$	3	$0.933_{0.041}$	$0.929_{0.040}$	1
A07+T1+E	67	$0.820_{0.157}$	$0.877_{0.124}$	$0.867_{0.150}$	1	$0.890_{0.108}$	$0.862_{0.157}$	2	$0.897_{0.104}$	$0.862_{0.149}$	4
A07+T1+N	251	$0.837_{0.141}$	$0.892_{0.085}$	$0.879_{0.104}$	1	$0.903_{0.067}$	$0.875_{0.114}$	2	$0.905_{0.070}$	$0.873_{0.101}$	4
A07+T3+E	12	$0.925_{0.055}$	$0.938_{0.019}$	$0.937_{0.019}$	2	$0.939_{0.020}$	$0.916_{0.055}$	1	$0.947_{0.016}$	$0.932_{0.017}$	1
A07+T3+N	39	$0.863_{0.177}$	$0.918_{0.061}$	$0.913_{0.071}$	2	$0.933_{0.037}$	$0.899_{0.148}$	3	$0.934_{0.039}$	$0.914_{0.079}$	1
A08+T1+E	26	$0.666_{0.225}$	$0.750_{0.161}$	$0.680_{0.242}$	2	$0.747_{0.197}$	$0.653_{0.260}$	1	$0.793_{0.134}$	$0.666_{0.261}$	1
A08+T3+E	111	$0.605_{0.230}$	$0.668_{0.197}$	$0.626_{0.210}$	1	$0.677_{0.206}$	$0.628_{0.218}$	2	$0.735_{0.166}$	$0.669_{0.203}$	2
A09+T1+E	30	$0.815_{0.121}$	$0.841_{0.098}$	$0.784_{0.156}$	1	$0.873_{0.089}$	$0.833_{0.113}$	2	$0.884_{0.076}$	$0.812_{0.119}$	4
A09+T1+N	1	$0.953_{0.000}$	$0.927_{0.000}$	$0.927_{0.000}$	2	$0.955_{0.000}$	$0.955_{0.000}$	1	$0.947_{0.000}$	$0.947_{0.000}$	3
A09+T3+E	10	$0.900_{0.074}$	$0.918_{0.054}$	$0.918_{0.054}$	2	$0.933_{0.038}$	$0.909_{0.044}$	1	$0.937_{0.043}$	$0.919_{0.040}$	3
A09+T3+N	3	$0.894_{0.070}$	$0.911_{0.058}$	$0.911_{0.058}$	2	$0.957_{0.015}$	$0.957_{0.015}$	3	$0.944_{0.030}$	$0.944_{0.030}$	1

ISIC-MultiAnnot Results: Key Takeaways

1. **Improved diversity without compromising quality**: for all $M \geq 2$, choosing a single style that, for each annotator preference, maximizes agreement with the “ground truth” still outperforms 1-StyleSeg.

2. **Performance improves as *M* increases.**



ISIC-MultiAnnot Results: Key Takeaways

Annotator + Tool + Experience	Seg. Count	1-StyleSeg	2-StyleSeg			3-StyleSeg			4-StyleSeg		
		$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$	$\text{Dice}_{\text{ISSS}}$	$\text{Dice}_{\text{ASSS}}$	$\mathcal{J}$
A00+T2+E	1573	$0.892_{0.089}$	$0.923_{0.061}$	$0.913_{0.087}$	2	$0.944_{0.049}$	$0.913_{0.106}$	3	$0.944_{0.044}$	$0.914_{0.111}$	1
A00+T2+N	1305	$0.716_{0.302}$	$0.761_{0.293}$	$0.728_{0.308}$	2	$0.793_{0.287}$	$0.727_{0.313}$	3	$0.790_{0.290}$	$0.726_{0.304}$	3
A01+T1+N	6	$0.559_{0.362}$	$0.766_{0.152}$	$0.766_{0.152}$	1	$0.754_{0.132}$	$0.741_{0.125}$	2	$0.819_{0.106}$	$0.767_{0.113}$	2
A01+T3+E	297	$0.900_{0.104}$	$0.915_{0.093}$	$0.897_{0.107}$	2	$0.927_{0.075}$	$0.900_{0.097}$	1	$0.931_{0.067}$	$0.904_{0.090}$	3
A01+T3+N	2148	$0.829_{0.185}$	$0.857_{0.167}$	$0.817_{0.170}$	1	$0.869_{0.159}$	$0.836_{0.178}$	1	$0.876_{0.148}$	$0.836_{0.175}$	3
A02+T1+E	1742	$0.844_{0.177}$	$0.880_{0.140}$	$0.856_{0.159}$	1	$0.886_{0.132}$	$0.854_{0.159}$	1	$0.895_{0.112}$	$0.859_{0.148}$	4
A02+T3+E	468	$0.856_{0.172}$	$0.889_{0.167}$	$0.883_{0.175}$	2	$0.899_{0.161}$	$0.874_{0.188}$	3	$0.903_{0.146}$	$0.890_{0.160}$	1
A03+T1+E	1622	$0.778_{0.168}$	$0.845_{0.117}$	$0.827_{0.137}$	1	$0.854_{0.111}$	$0.824_{0.145}$	2	$0.881_{0.095}$	$0.823_{0.132}$	4
A03+T3+E	260	$0.891_{0.116}$	$0.912_{0.086}$	$0.876_{0.173}$	2	$0.923_{0.089}$	$0.868_{0.150}$	1	$0.932_{0.074}$	$0.874_{0.163}$	3
A04+T1+E	992	$0.850_{0.158}$	$0.880_{0.131}$	$0.860_{0.149}$	1	$0.888_{0.132}$	$0.866_{0.153}$	2	$0.906_{0.108}$	$0.856_{0.157}$	4
A04+T1+N	61	$0.760_{0.242}$	$0.840_{0.152}$	$0.823_{0.164}$	1	$0.837_{0.162}$	$0.786_{0.201}$	1	$0.827_{0.206}$	$0.789_{0.226}$	4
A04+T3+E	913	$0.912_{0.088}$	$0.939_{0.054}$	$0.934_{0.065}$	2	$0.948_{0.047}$	$0.926_{0.069}$	1	$0.951_{0.045}$	$0.932_{0.063}$	3
A04+T3+N	90	$0.877_{0.096}$	$0.910_{0.068}$	$0.905_{0.070}$	2	$0.928_{0.031}$	$0.908_{0.044}$	3	$0.926_{0.052}$	$0.913_{0.055}$	1
A05+T1+E	752	$0.815_{0.203}$	$0.862_{0.163}$	$0.837_{0.179}$	1	$0.873_{0.162}$	$0.827_{0.184}$	1	$0.882_{0.147}$	$0.841_{0.177}$	4
A05+T3+E	742	$0.875_{0.129}$	$0.903_{0.109}$	$0.891_{0.113}$	2	$0.916_{0.098}$	$0.878_{0.120}$	1	$0.919_{0.091}$	$0.891_{0.108}$	1
A06+T1+E	10	$0.824_{0.187}$	$0.902_{0.037}$	$0.885_{0.070}$	1	$0.909_{0.034}$	$0.889_{0.049}$	2	$0.909_{0.039}$	$0.880_{0.063}$	4
A06+T3+E	24	$0.862_{0.079}$	$0.916_{0.053}$	$0.916_{0.053}$	2	$0.934_{0.031}$	$0.923_{0.031}$	3	$0.933_{0.041}$	$0.929_{0.040}$	1
A07+T1+E	67	$0.820_{0.157}$	$0.877_{0.124}$	$0.867_{0.150}$	1	$0.890_{0.108}$	$0.862_{0.157}$	2	$0.897_{0.104}$	$0.862_{0.149}$	4
A07+T1+N	251	$0.837_{0.141}$	$0.892_{0.085}$	$0.879_{0.104}$	1	$0.903_{0.067}$	$0.875_{0.114}$	2	$0.905_{0.070}$	$0.873_{0.101}$	4
A07+T3+E	12	$0.925_{0.055}$	$0.938_{0.019}$	$0.937_{0.019}$	2	$0.939_{0.020}$	$0.916_{0.055}$	1	$0.947_{0.016}$	$0.932_{0.017}$	1
A07+T3+N	39	$0.863_{0.177}$	$0.918_{0.061}$	$0.913_{0.071}$	2	$0.933_{0.037}$	$0.899_{0.148}$	3	$0.934_{0.039}$	$0.914_{0.079}$	1
A08+T1+E	26	$0.666_{0.225}$	$0.750_{0.161}$	$0.680_{0.242}$	2	$0.747_{0.197}$	$0.653_{0.260}$	1	$0.793_{0.134}$	$0.666_{0.261}$	1
A08+T3+E	111	$0.605_{0.230}$	$0.668_{0.197}$	$0.626_{0.210}$	1	$0.677_{0.206}$	$0.628_{0.218}$	2	$0.735_{0.166}$	$0.669_{0.203}$	2
A09+T1+E	30	$0.815_{0.121}$	$0.841_{0.098}$	$0.784_{0.156}$	1	$0.873_{0.089}$	$0.833_{0.113}$	2	$0.884_{0.076}$	$0.812_{0.119}$	4
A09+T1+N	1	$0.953_{0.000}$	$0.927_{0.000}$	$0.927_{0.000}$	2	$0.955_{0.000}$	$0.955_{0.000}$	1	$0.947_{0.000}$	$0.947_{0.000}$	3
A09+T3+E	10	$0.900_{0.074}$	$0.918_{0.054}$	$0.918_{0.054}$	2	$0.933_{0.038}$	$0.909_{0.044}$	1	$0.937_{0.043}$	$0.919_{0.040}$	3
A09+T3+N	3	$0.894_{0.070}$	$0.911_{0.058}$	$0.911_{0.058}$	2	$0.957_{0.015}$	$0.957_{0.015}$	3	$0.944_{0.030}$	$0.944_{0.030}$	1

1. **Improved diversity without compromising quality**: for all *M* ≥ 2, choosing a single style that, for each annotator preference, maximizes agreement with the "ground truth" still outperforms 1-StyleSeg.

2. **Performance improves as *M* increases.**

3. **Ability to learn tool-specific latent factors:** Without specifically training for it, a 3-StyleSeg model is able to choose a unique style for each of the three tools ("T1", "T2", "T3").

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If we model 3 styles, the best style can be the one that

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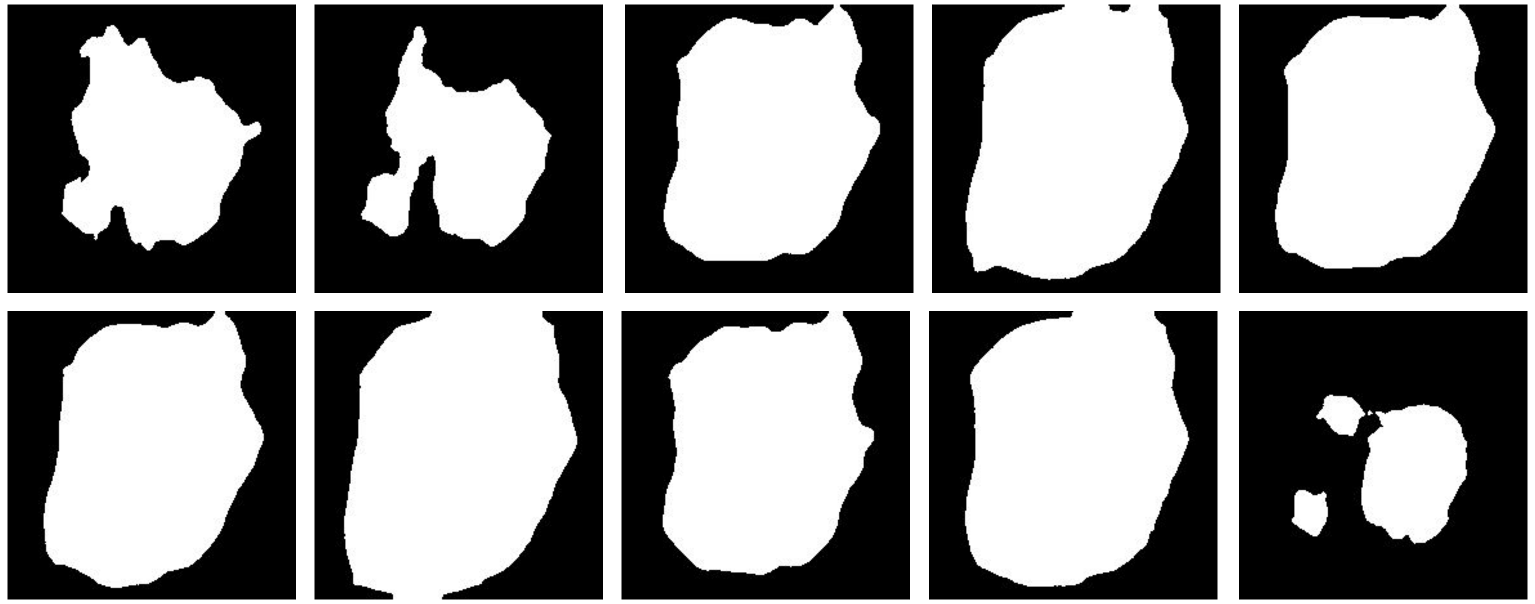

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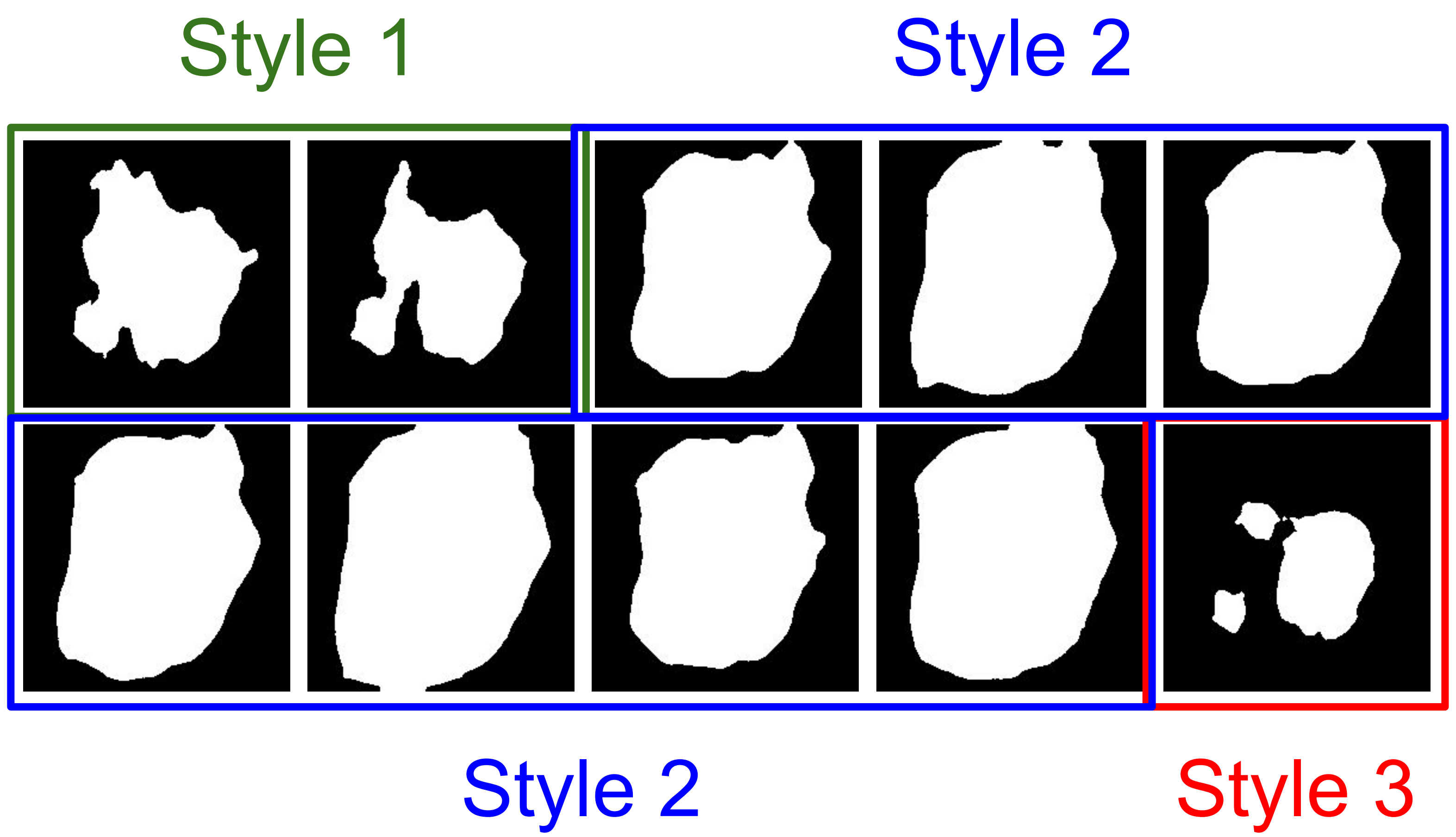

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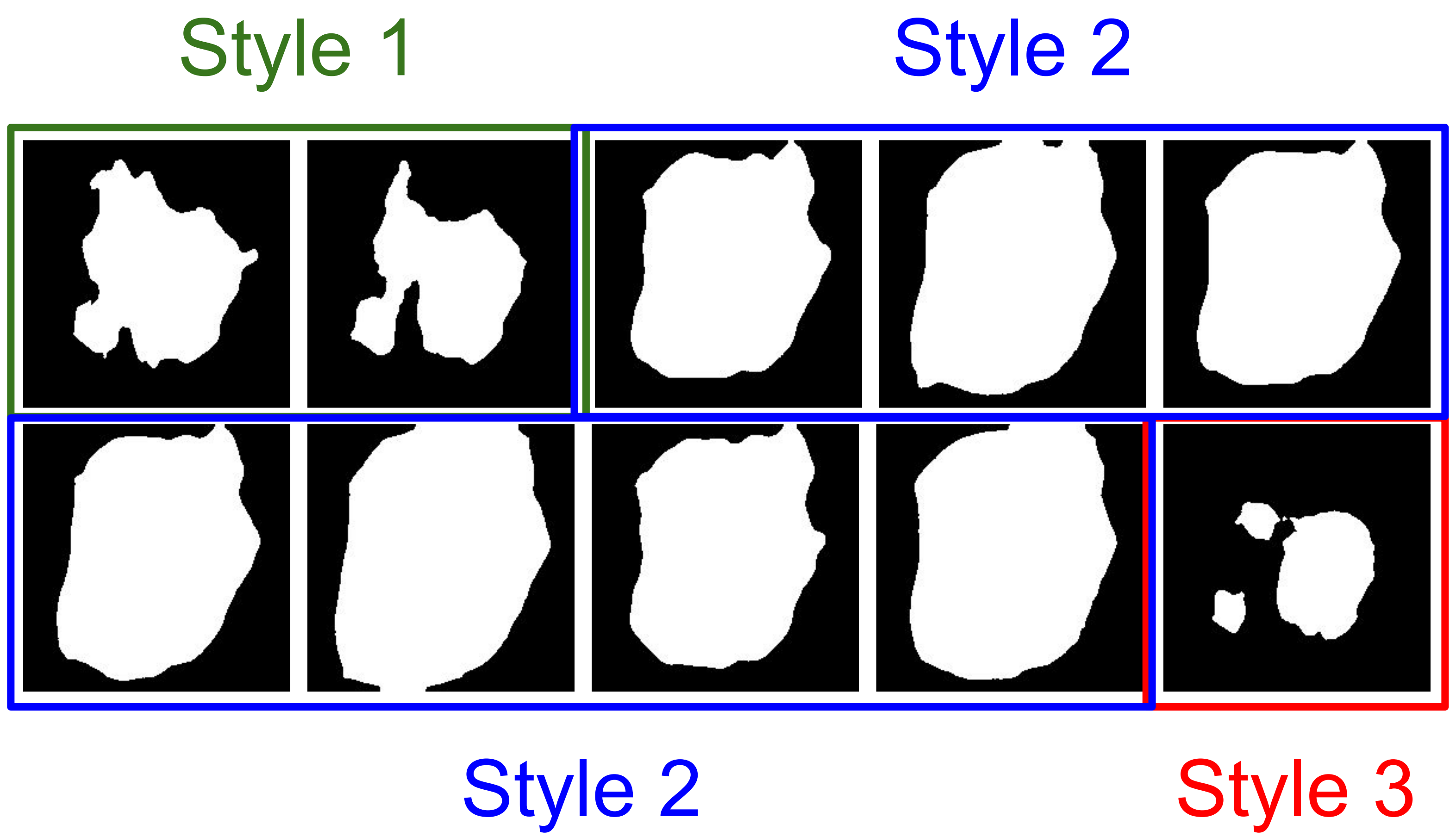
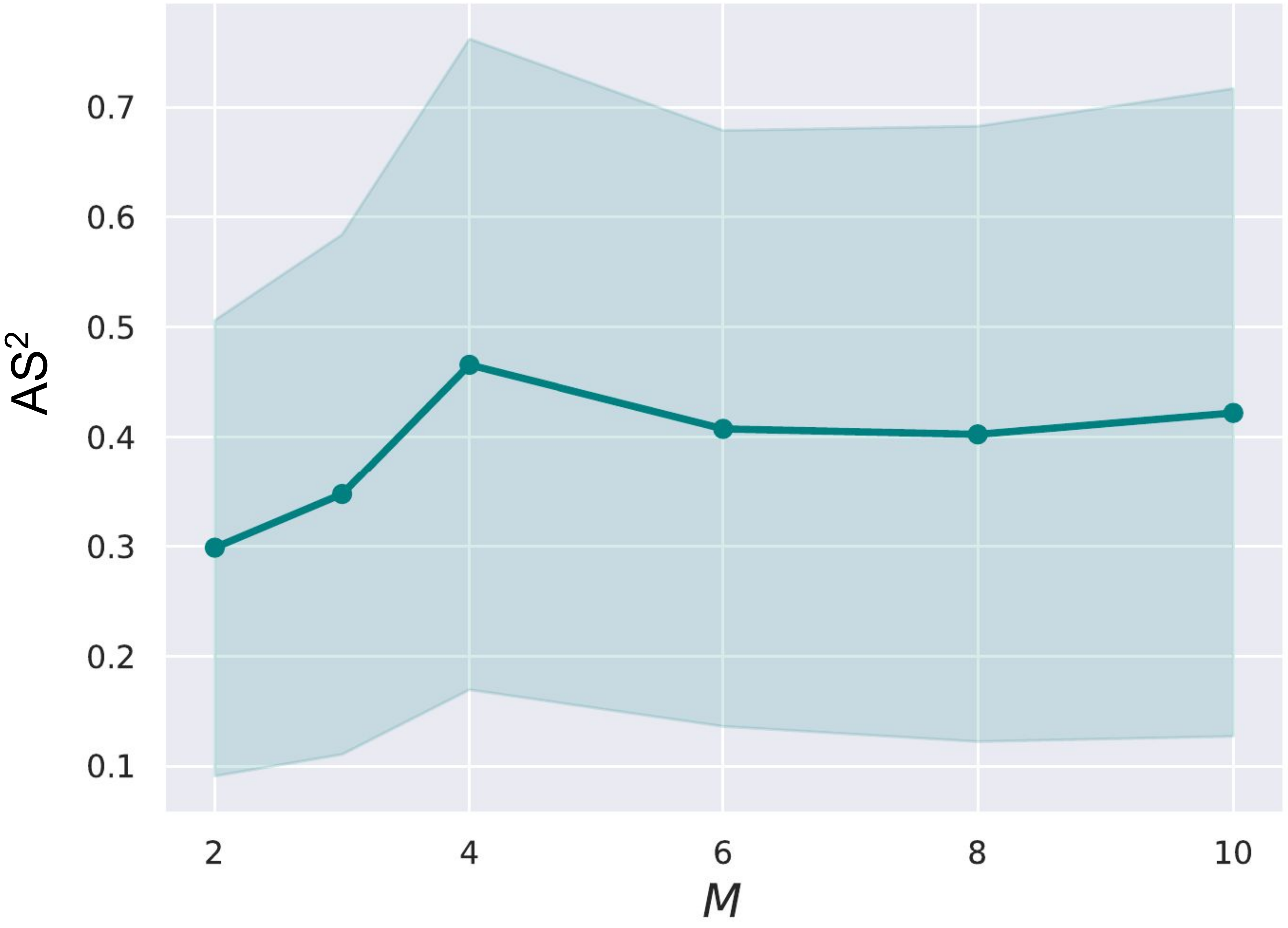


$q_1 = 0.2$, $q_2 = 0.7$, $q_3 = 0.1$

$q = [0.2, 0.7, 0.1] \Rightarrow \mathrm{AS}^2 = 0.27.$

Quantifying Annotator-Style Alignment



Modeling **more styles** captures **more diversity** and is not detrimental to segmentation quality.

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- **Future work** may look at approaches to **finding the optimal number of styles** in a segmentation dataset.

References

[1] Silletti et al., “Variability in human and automatic segmentation of melanocytic lesions”, *EMBC*, 2009.

[2] Mirikharaji et al., “D-LEMA: Deep learning ensembles from multiple annotations-application to skin lesion segmentation”, *CVPR ISIC* 2021.

[3] Ribeiro et al., “Less is more: Sample selection and label conditioning improve skin lesion segmentation”, *CVPR ISIC* 2020.

[4] Rupprecht et al., “Learning in an uncertain world: Representing ambiguity through multiple hypotheses”, *ICCV* 2017.

Thank you.

Questions?

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Acknowledgements

NSERC CRSNG

Digital Research Alliance of Canada | Alliance de recherche numérique du Canada

NVIDIA