

A NEW COLOR AUGMENTATION METHOD FOR DEEP LEARNING SEGMENTATION OF HISTOLOGICAL IMAGES

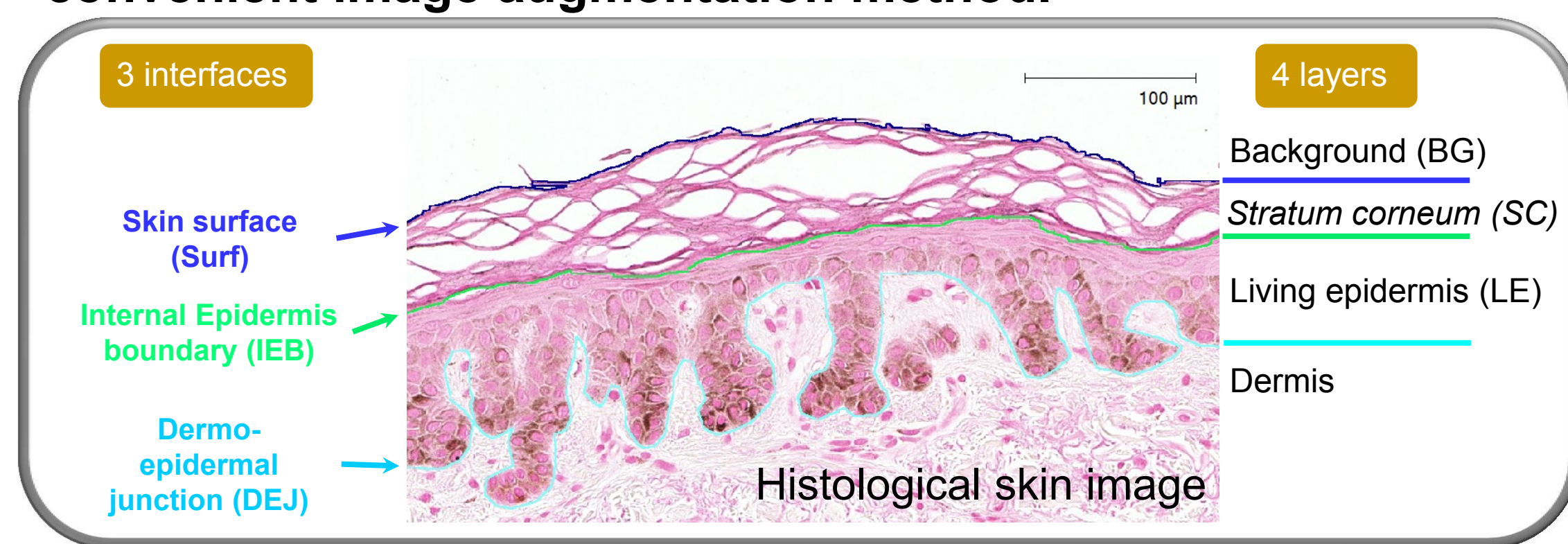
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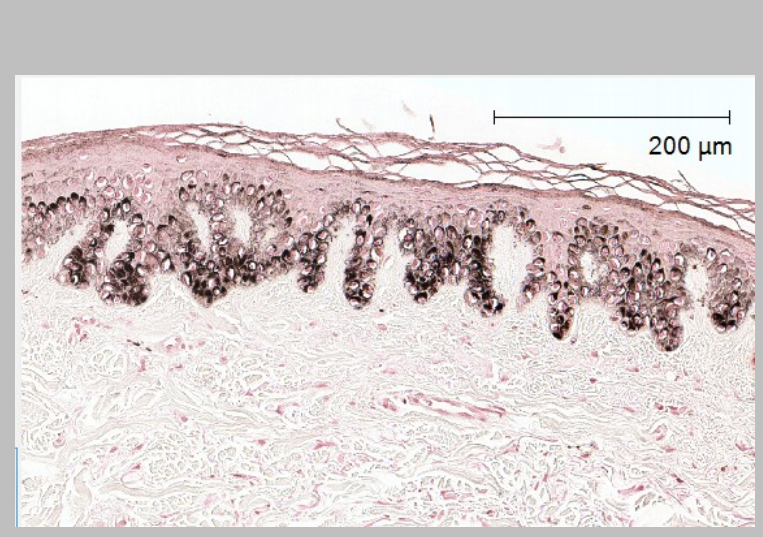


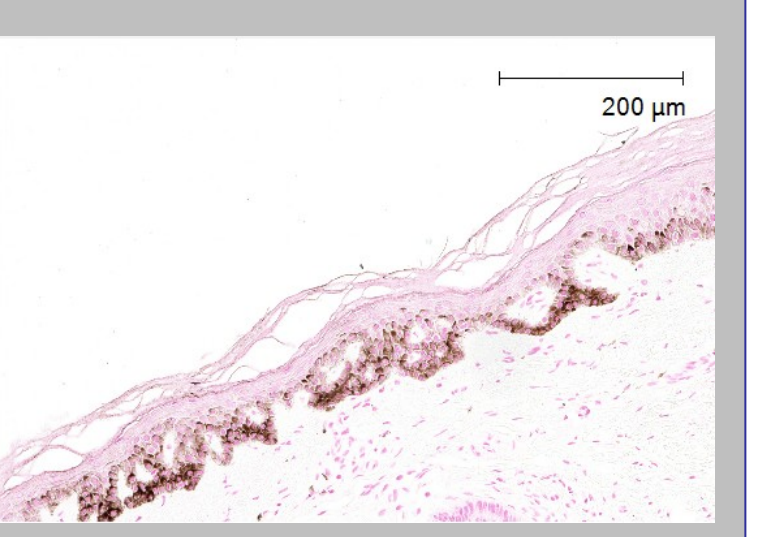


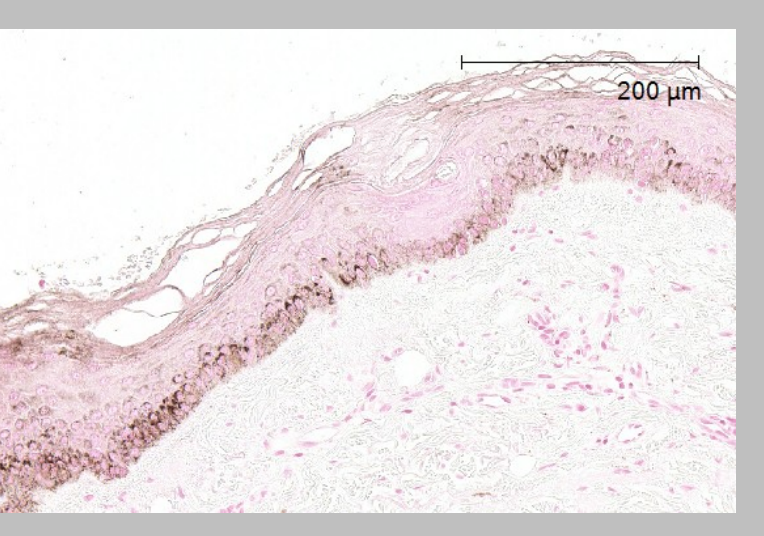
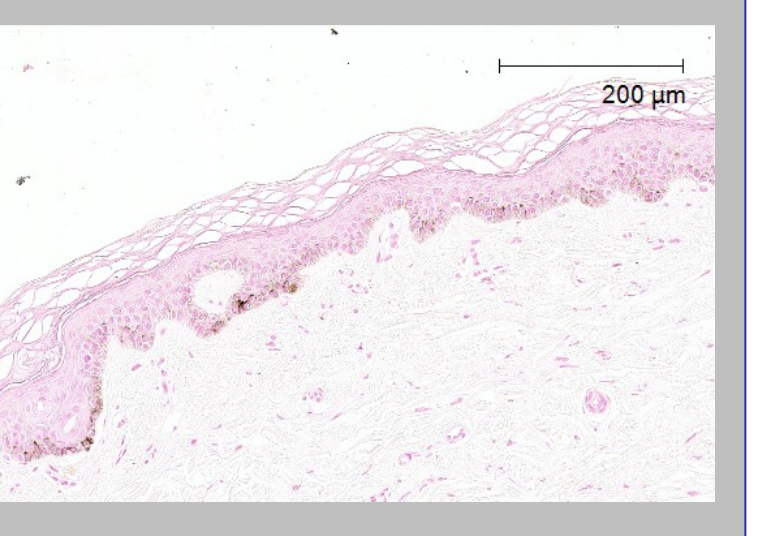
INTRODUCTION

Challenges in histological image segmentation

- With the recent advent of digital whole slide imaging, the number and the size of acquired images are growing up and there is a need of finding ways to also adapt the throughput of image quantification.
- Deep neural networks usually require large training sets to achieve an acceptable performance, while the generation of the segmentation ground-truth is very time-consuming.
- Given complex tissue structures and inconsistencies in sample preparation, **network generalization** is crucial.
- **We show that a deep neural network can learn a satisfactory segmentation model with relatively few data thanks to a convenient image augmentation method.**



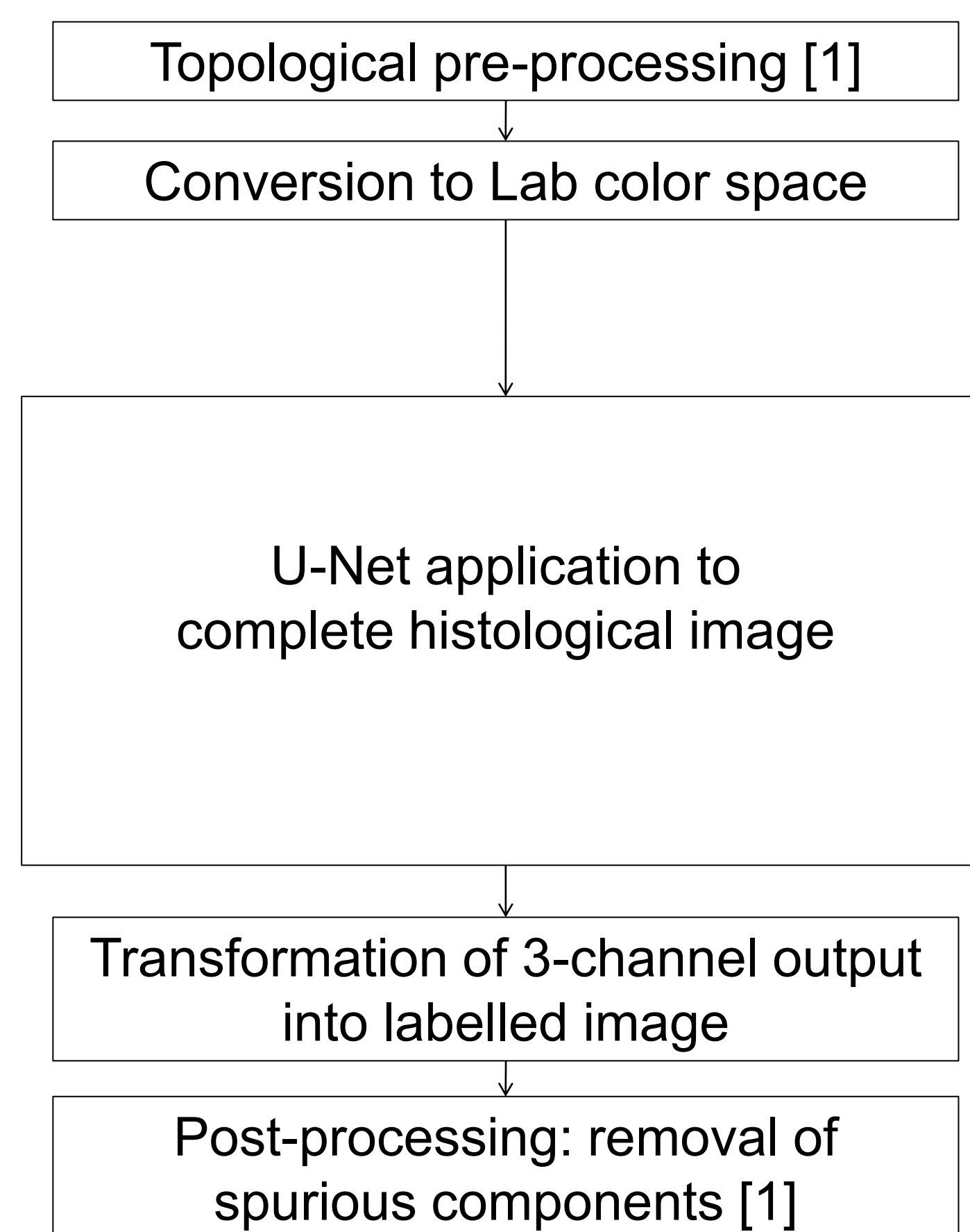
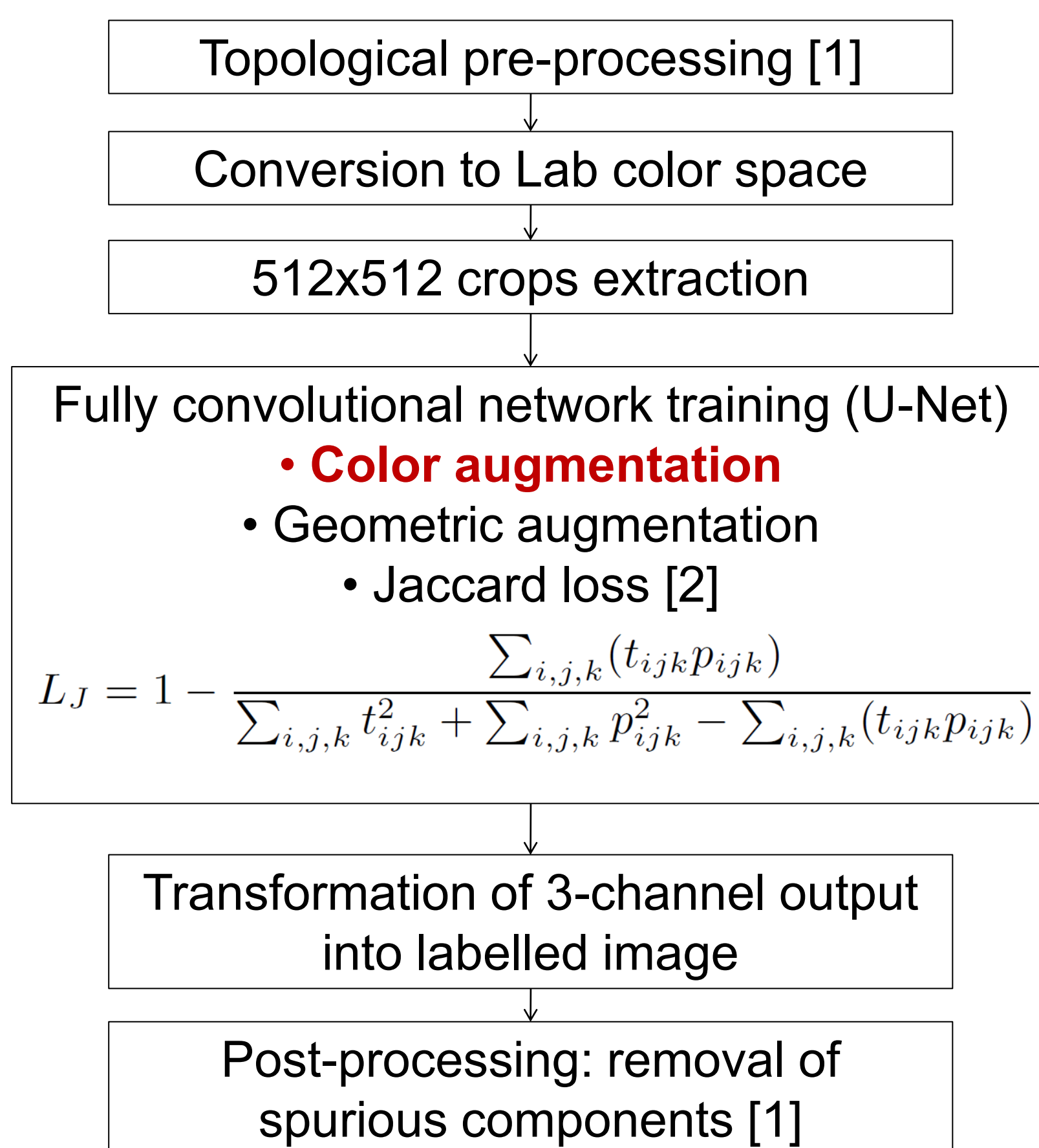
MATERIALS

Data base	Data base n°1			Data base n°2
	Training	Validation	Test	Generalization Test
N=	26 images	9 images	41 images	52 images
Study	Clinical studies n°1 & 2			Clinical study n°3
Typical image size				
				
1 million pixels (~1000 x 1000 pixels) to 10 million pixels (~3000 x 3000 pixels)				

METHODS

TRAINING

TESTING / PREDICTION



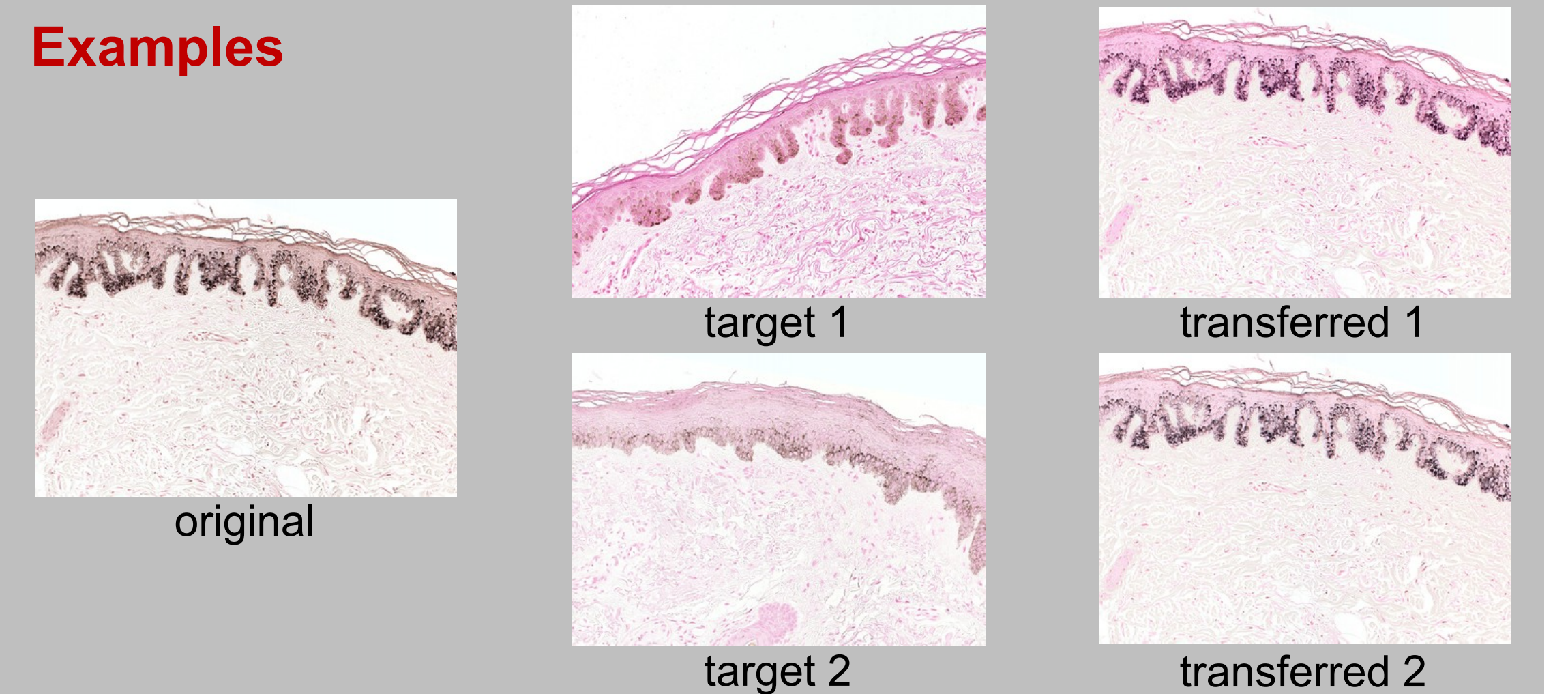
COLOR AUGMENTATION IN Lab COLOR SPACE

At training time, before feeding a crop (the *original* crop) into the network, another one (the *target* crop) is chosen and each channel of the original one is transformed:

$$C_{\text{transferred}} = C_{\text{original}} - \bar{C}_{\text{original}} + \bar{C}_{\text{target}}$$

This transformation is only applied to the pixels considered as belonging to the biological sample (threshold $0.86L_{\text{max}}$ applied to the L channel)

Examples



RESULTS

Train: the more augmentation, the less overfitting

Method	Best train loss	Best val loss
No augm	0.0060	0.0307
Geom	0.0133	0.0243
Color	0.0114	0.0272
Mixed	0.0178	0.0211

Results on Database n°1: "Test"

Color and mixed augmentation clearly enhance results

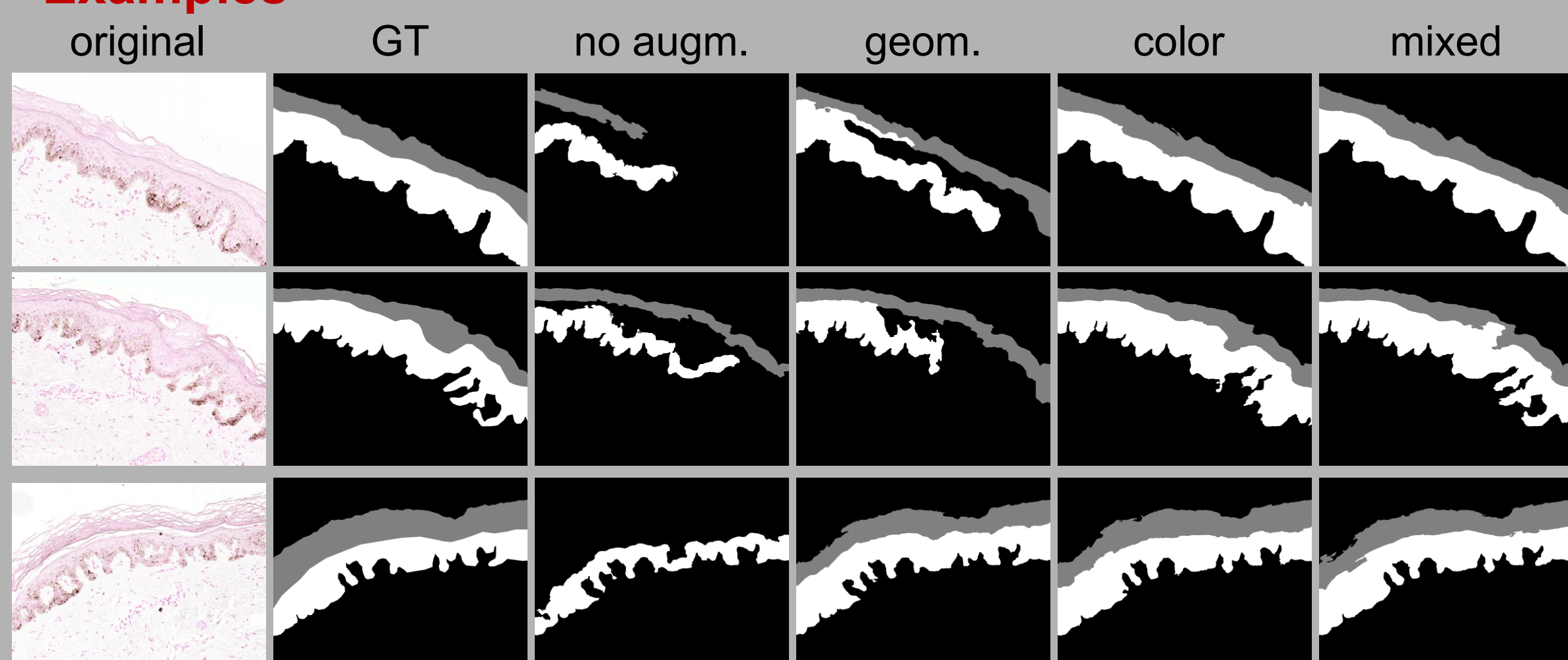
Method	Jaccard index (per class)			Mean dist. GT / prediction		
	BG	SC	LE	Surf.	IEB	DEJ
No augm	0.97	0.77	0.87	54.6	311.5	7.9
Geom	0.99	0.82	0.89	16.3	30.9	5.1
Color	0.99	0.89	0.91	2.1	9.7	4.3
Mixed	0.99	0.89	0.92	2.0	9.7	3.6

Results on Database n°2: "Generalization test"

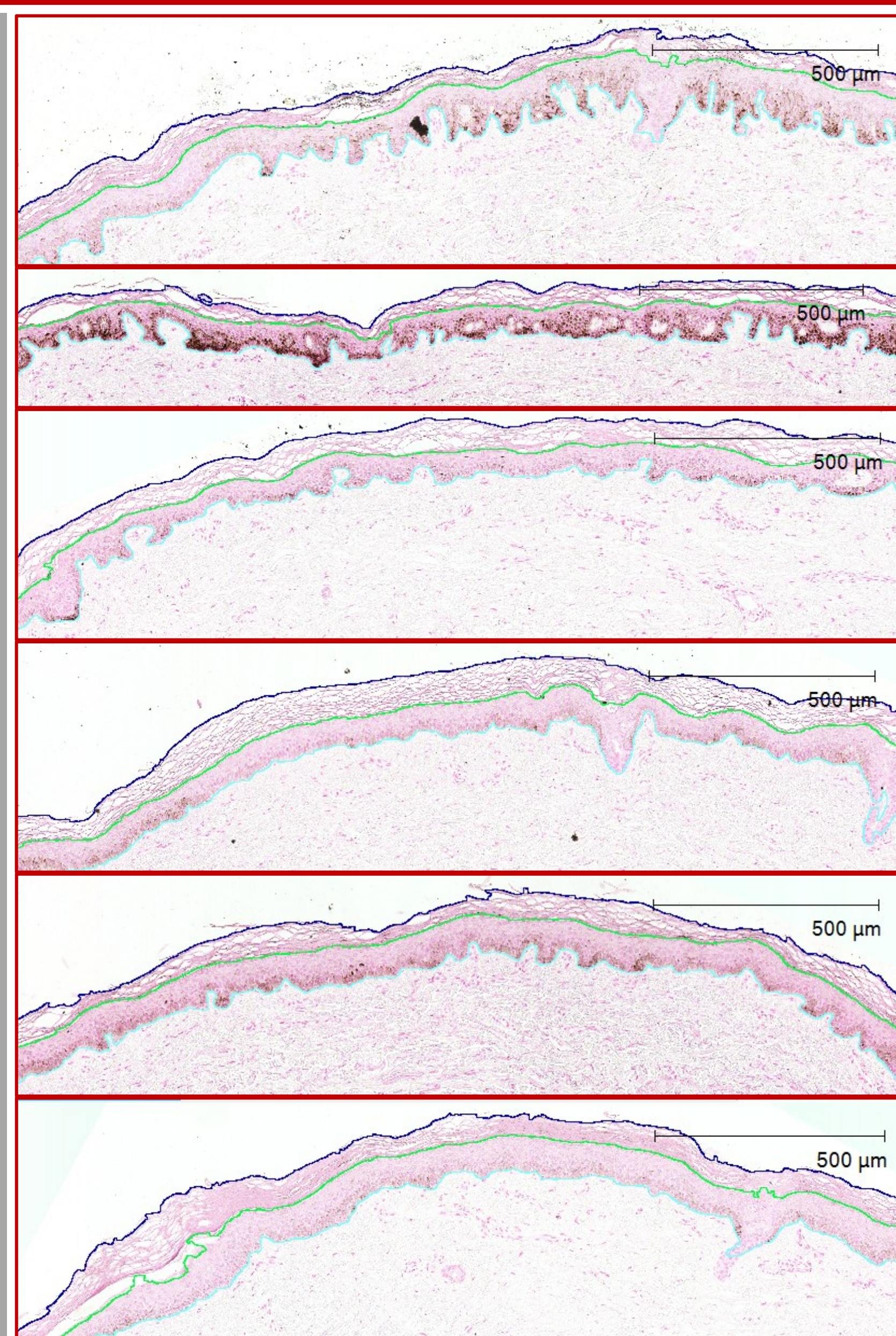
Thanks to color and mixed augmentation the model performance is the same

Method	Jaccard index (per class)			Mean dist. GT / prediction		
	BG	SC	LE	Surf.	IEB	DEJ
No augm	0.92	0.47	0.70	156.6	992.5	58.5
Geom	0.95	0.74	0.70	19.2	321.5	72.8
Color	0.99	0.91	0.91	1.8	9.0	5.1
Mixed	0.99	0.92	0.92	1.4	8.0	4.2

Examples



Segmentation results on Database n°2



CONCLUSIONS & PERSPECTIVES

- A new image augmentation method has been proposed
- We have shown that it helps improving the generalization capacity of a fully convolutional neural network trained to segment histological images
- It has been integrated in an industrial software

Perspectives:

- Generative adversarial networks might help improving the augmentation method
- Data augmentation considering elastic deformation could be combined with the proposed color augmentation method to increase the variety

REFERENCES

- [1] E. Decencière et al., "Dealing with topological information within a fully convolutional neural network," in ACIVS, 2018.
- [2] Y. Yuan et al. "Automatic skin lesion segmentation using deep fully convolutional networks with Jaccard distance," IEEE TMI, vol. 36, pp. 1876–1886, 2017.