DTU

Insights into the behaviour of multi-task deep neural networks for medical image segmentation

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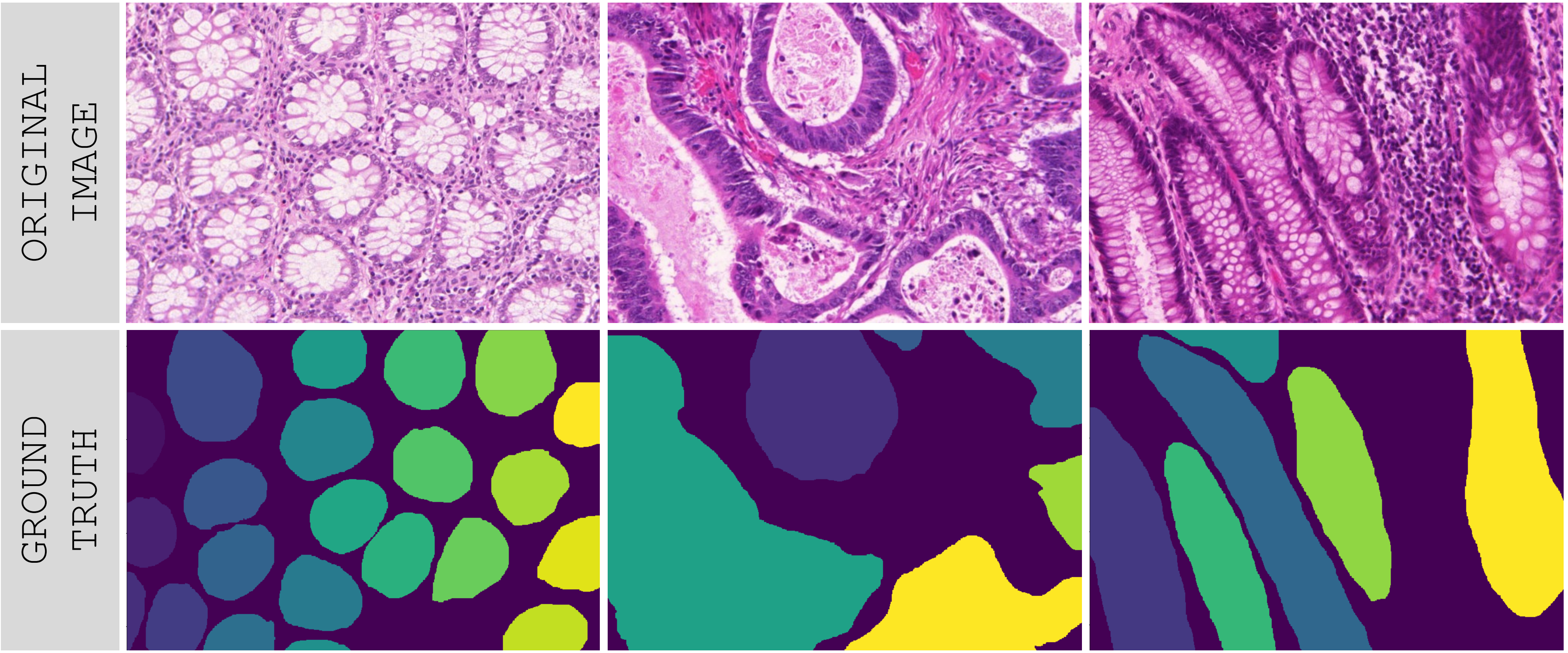
Agenda

Introduction | Prior art | Methods | Results | Conclusions

Gland segmentation



Cancer diagnosis → Glandular morphology → Gland segmentation

Why gland image is different than natural image?

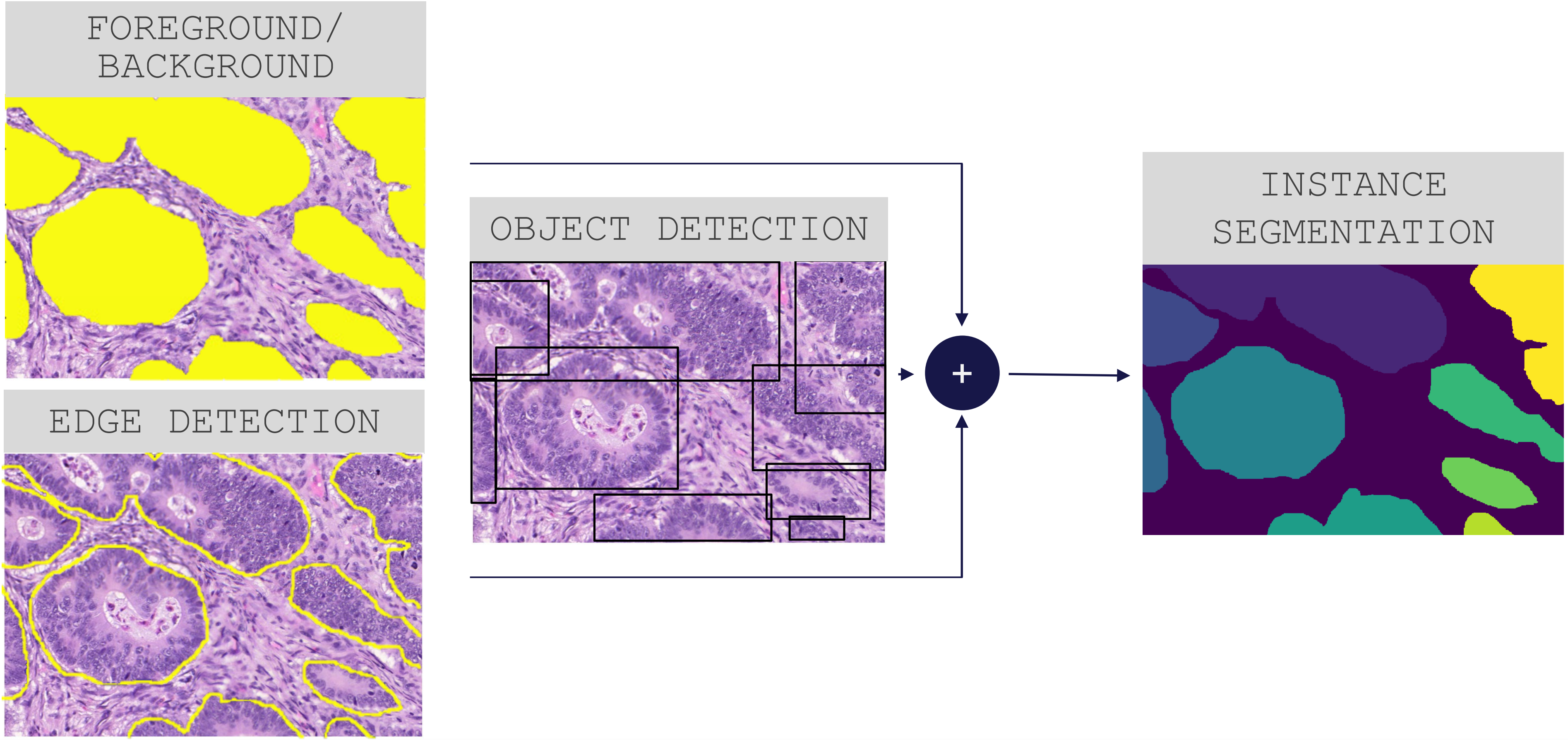
1. Heterogeneous shape

2. Anisochromasia causes background noise

3. Coalescence problem

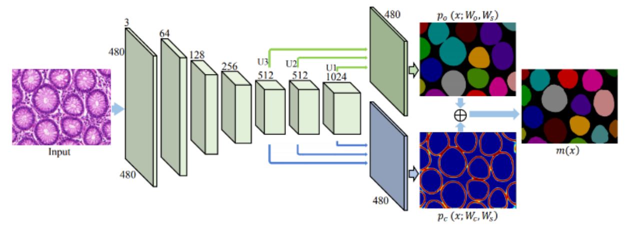
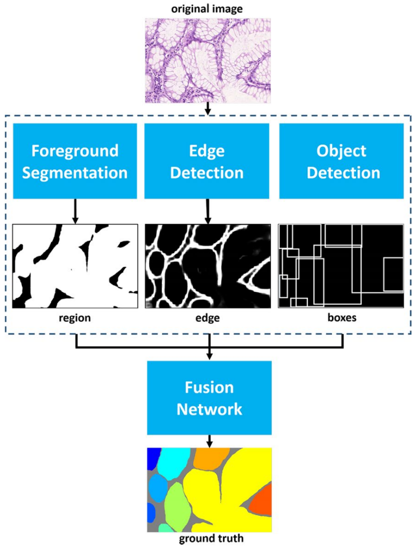
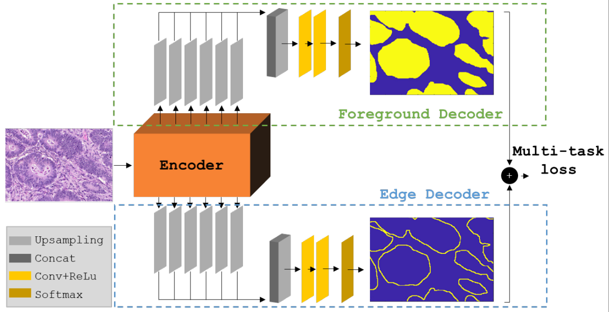
GLAND IMAGES	NATURAL IMGES

Prior art

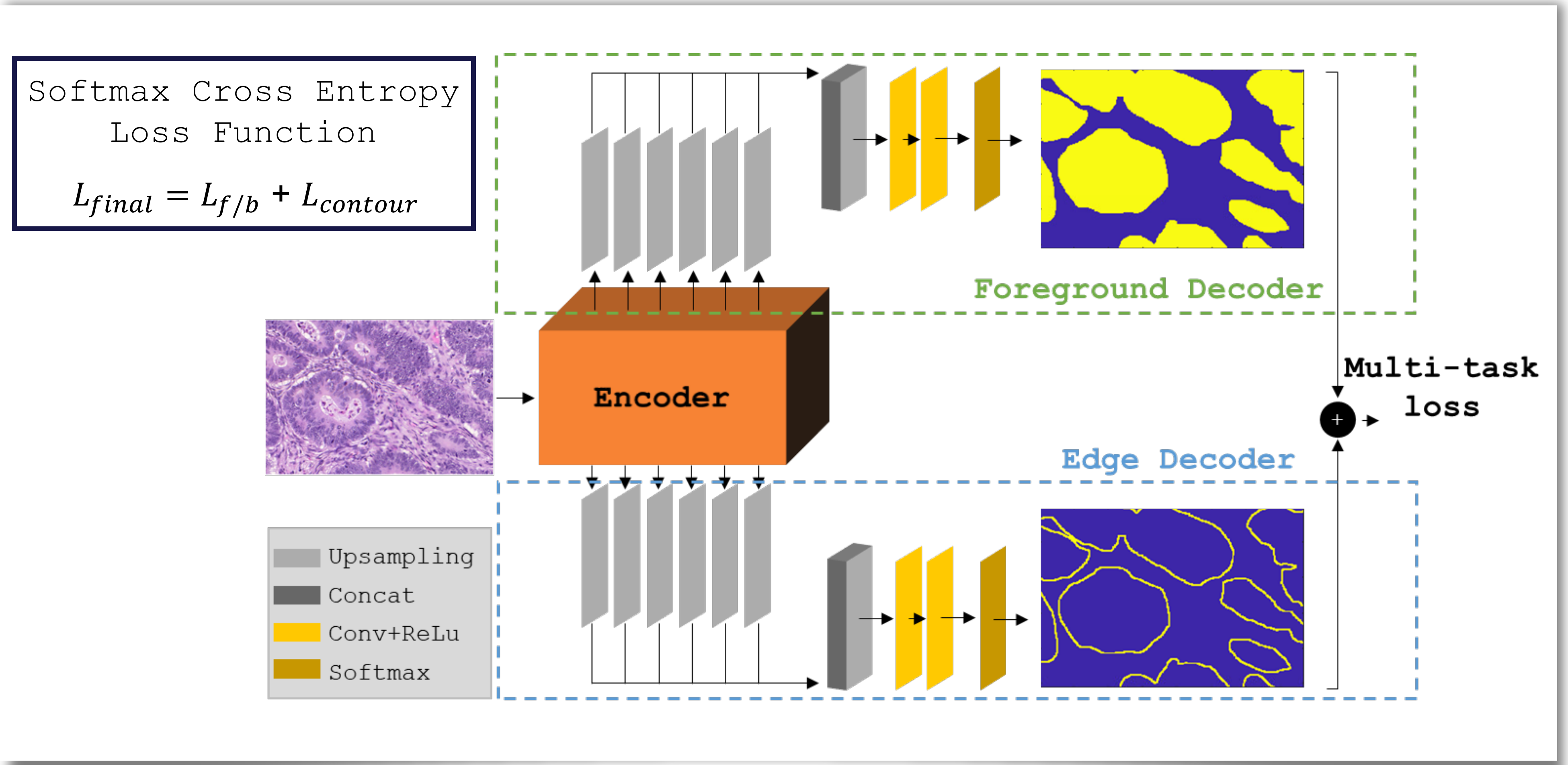


Multi-task learning for medical image segmentation

Gland Segmentation

DCAN	→	Multichannel	→	SA-FCN
				
2015	→	2016	→	2017

SA-FCN



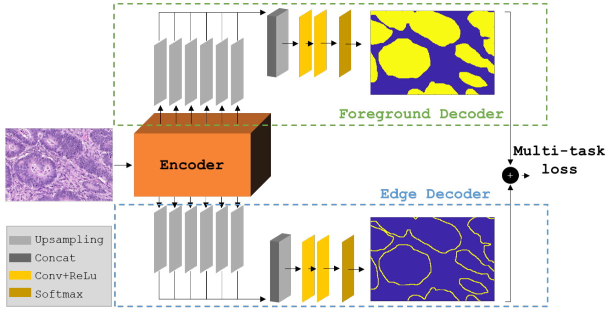
Softmax Cross Entropy
Loss Function
$L_{final} = L_{f/b} + L_{contour}$
Foreground Decoder
Encoder
Multi-task
loss
Edge Decoder
Upsampling
Concat
Conv+ReLu
Softmax

Questions

1. Does **loss weighting** influence the final performance?
2. How do we perform **instance segmentation**?
3. Do we really need **specialized networks**?

Methods

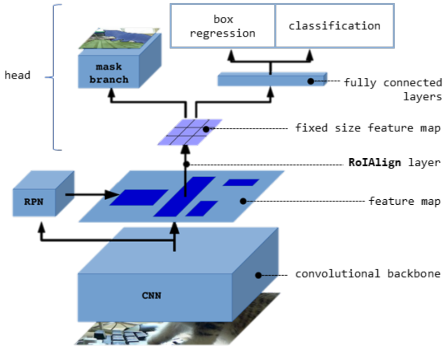
SA-FCN



SOTA on the
2015 MICCAI dataset

Domain specific model

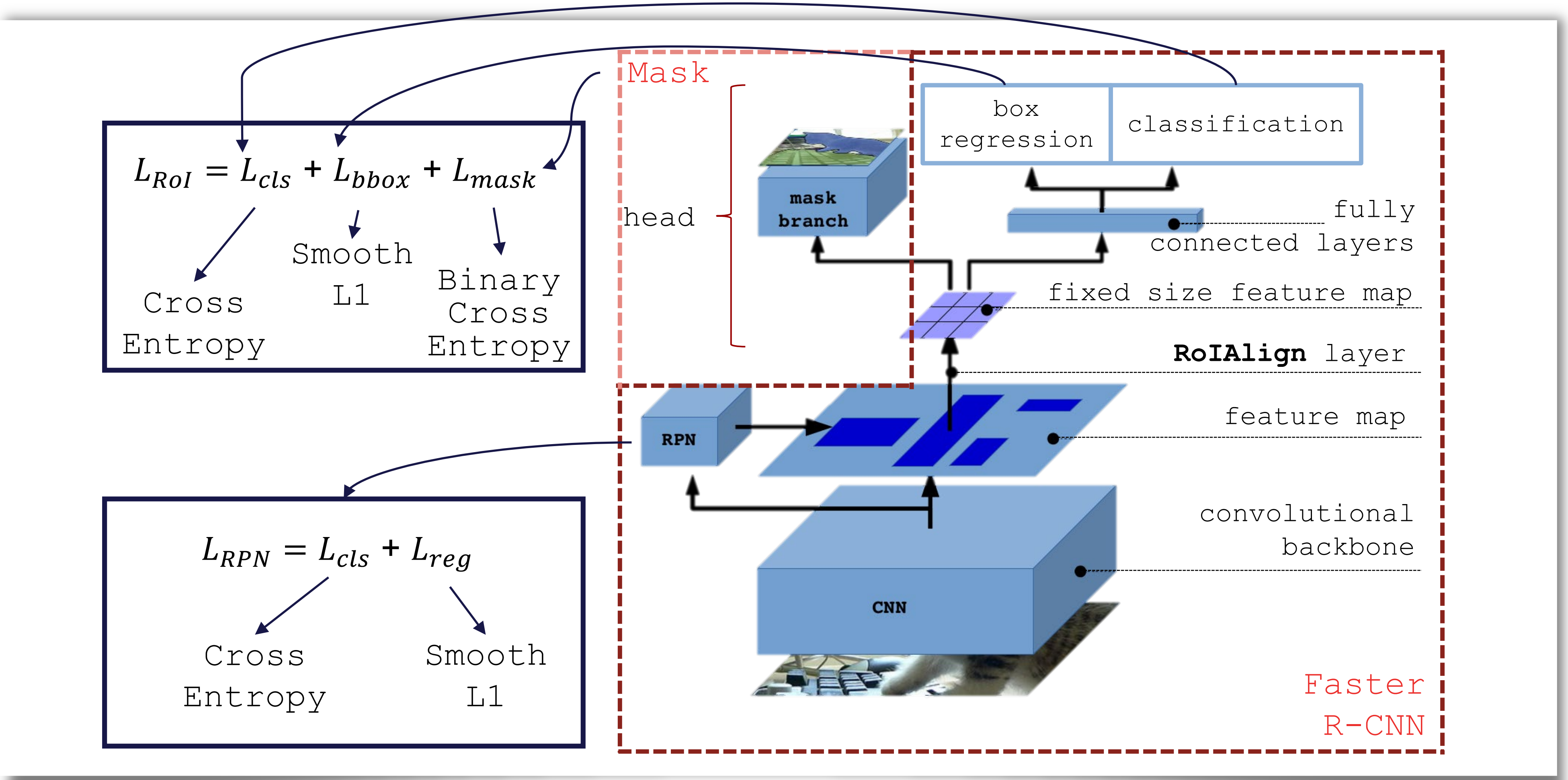
Mask R-CNN



SOTA on the
COCO dataset

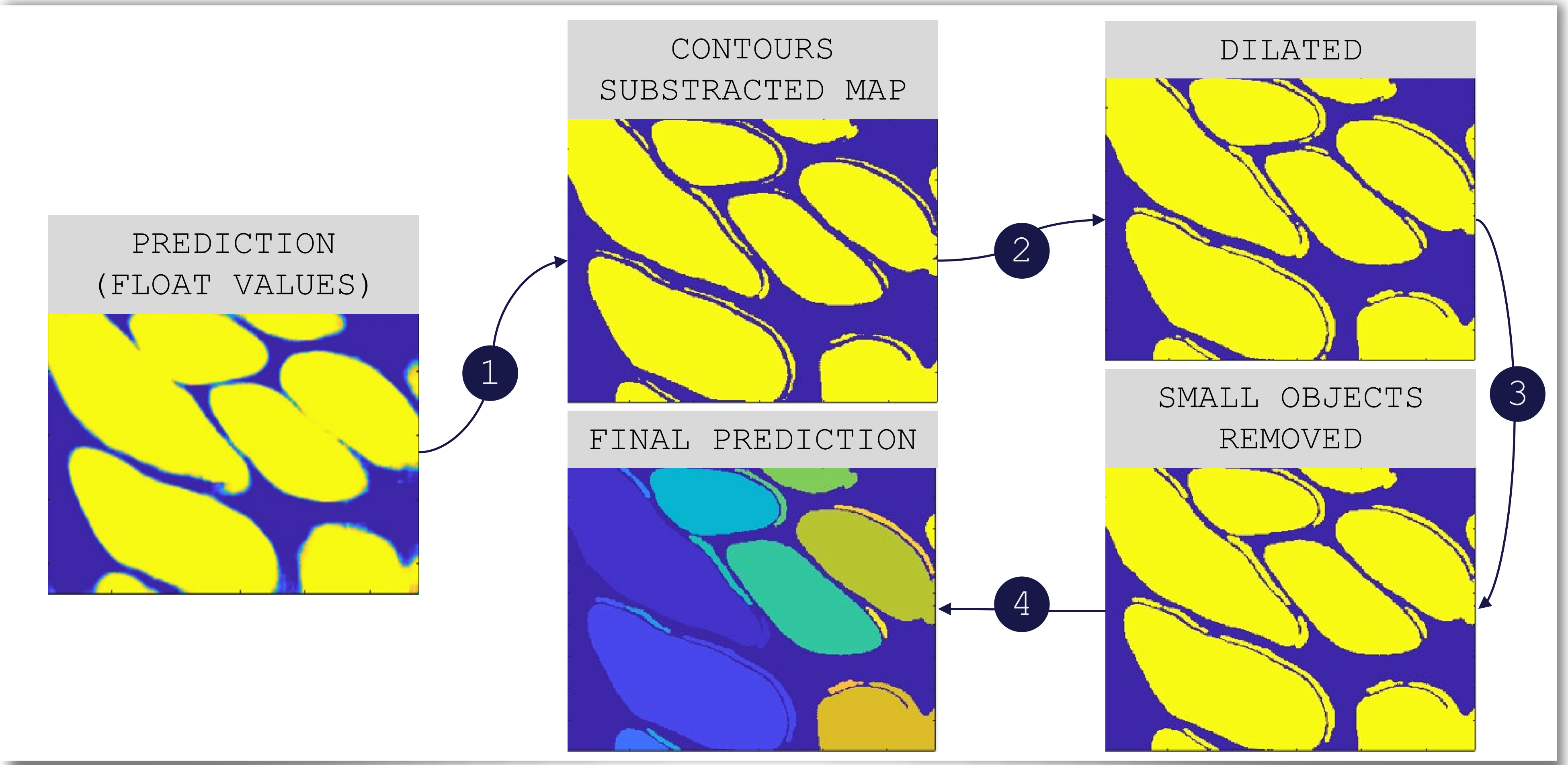
Generic model

Mask R-CNN



$L_{RoI} = L_{cls} + L_{bbox} + L_{mask}$
Cross Entropy
Smooth L1
Binary Cross Entropy
$L_{RPN} = L_{cls} + L_{reg}$
Cross Entropy
Smooth L1
Mask
head
mask branch
box regression
classification
fully connected layers
fixed size feature map
RoIAlign layer
feature map
RPN
convolutional backbone
CNN
Faster R-CNN

SA-FCN, post-processing



Our post-processing

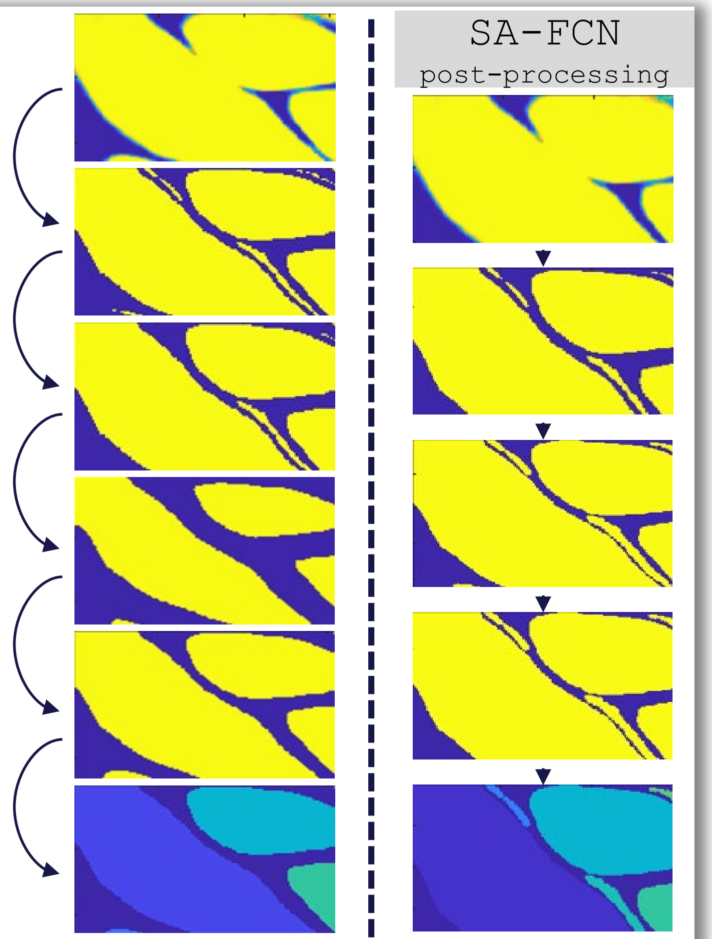
I. Contours subtracted from the f/b prediction.

II. Small elements removed.

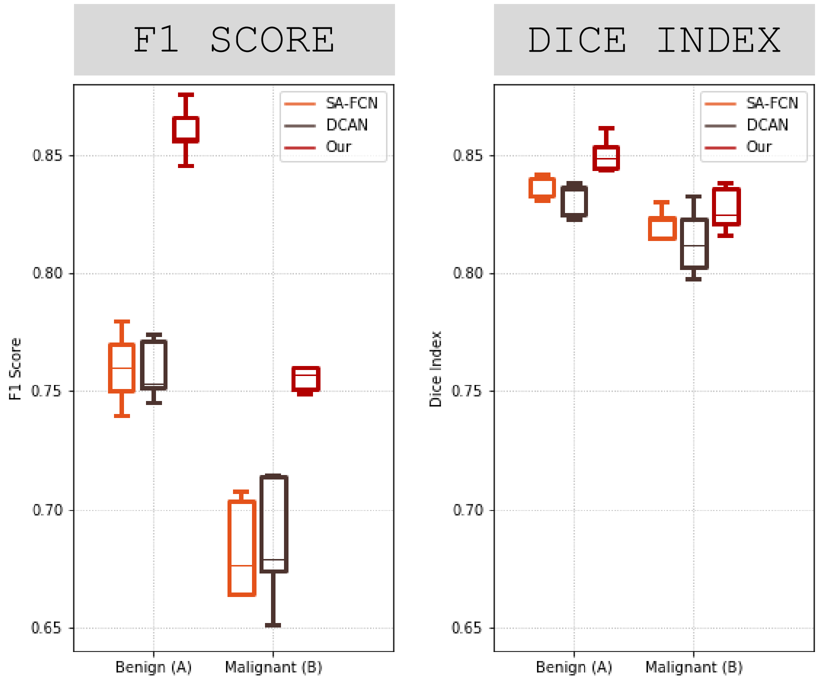
III. Opening operation – erosion.

IV. Opening operation – dilation, holes filled.

V. Connected-component labelling.



Comparison of post-processing



Comparison of post-processing

1. **Our post-processing** method, has significantly **improved** the final **performance.**

2. **SA-FCN** performance strongly **depends on** the **post-processing** techniques.

Multi-task learning,

loss weighting

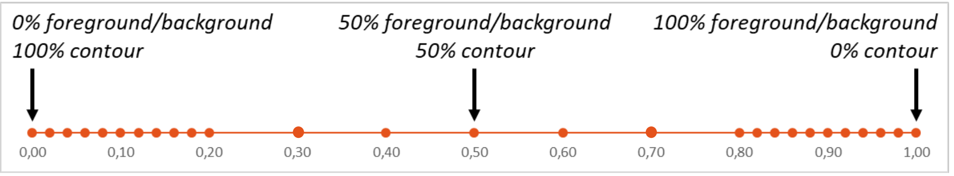
F/G LOSS

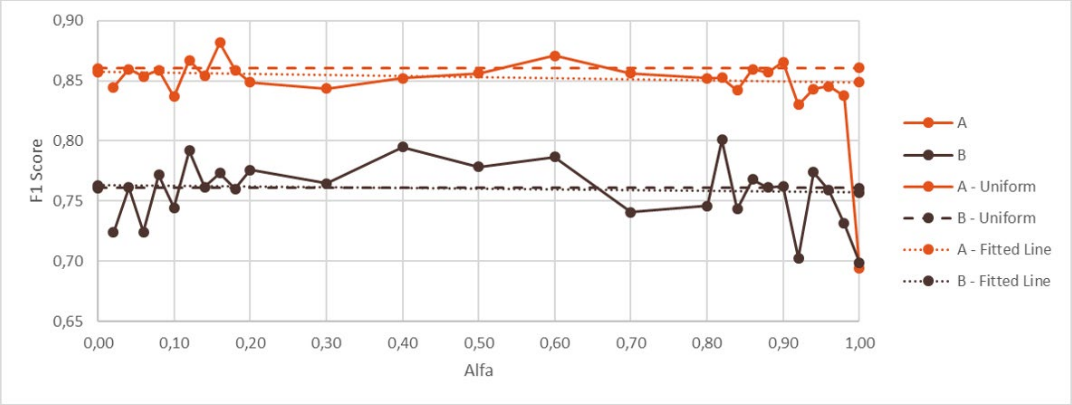
+

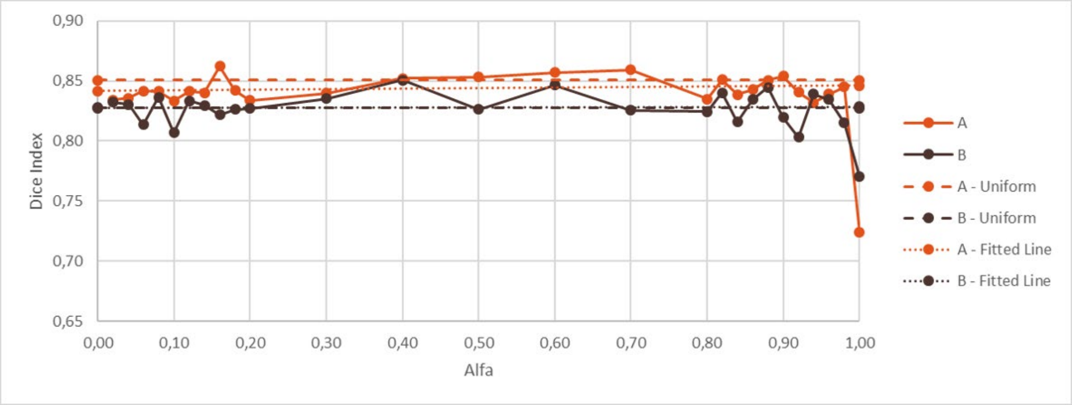
CONTOUR LOSS

=

FINAL LOSS







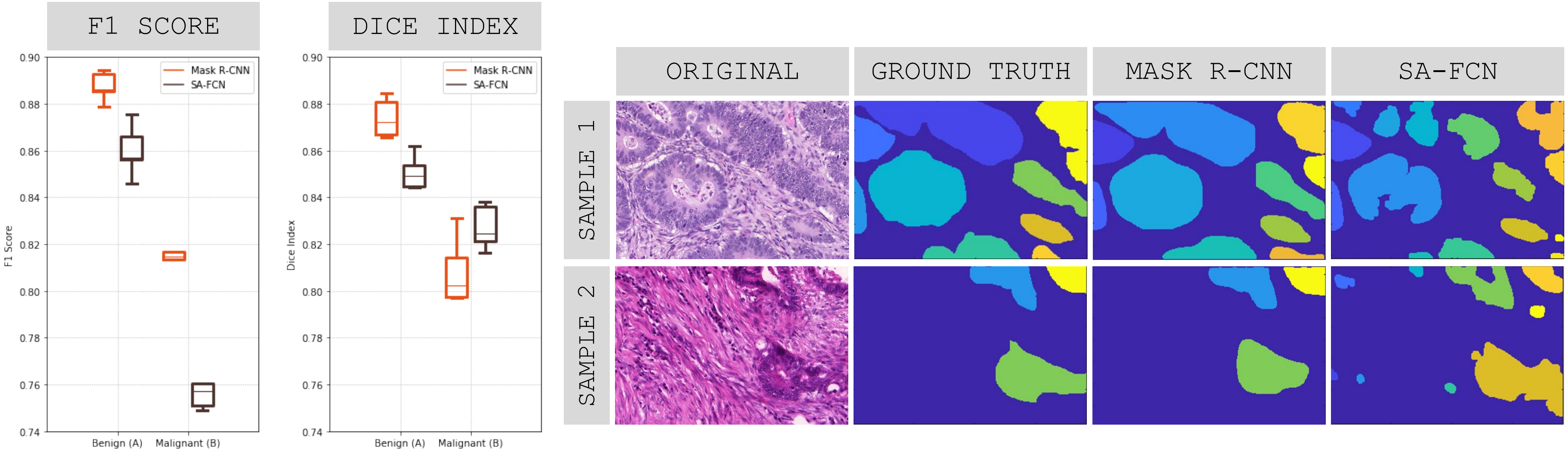
Multi-task learning

1. In this particular case, the ratio value for **loss weighting does not** significantly **affect** the performance of the model.

2. **Contour decoder helps** f/b decoder to ignore irrelevant parts of the image and improve the performance.

3. There is **no** visible **assistance from the f/b decoder** for the contour decoder.

SA-FCN versus Mask R-CNN



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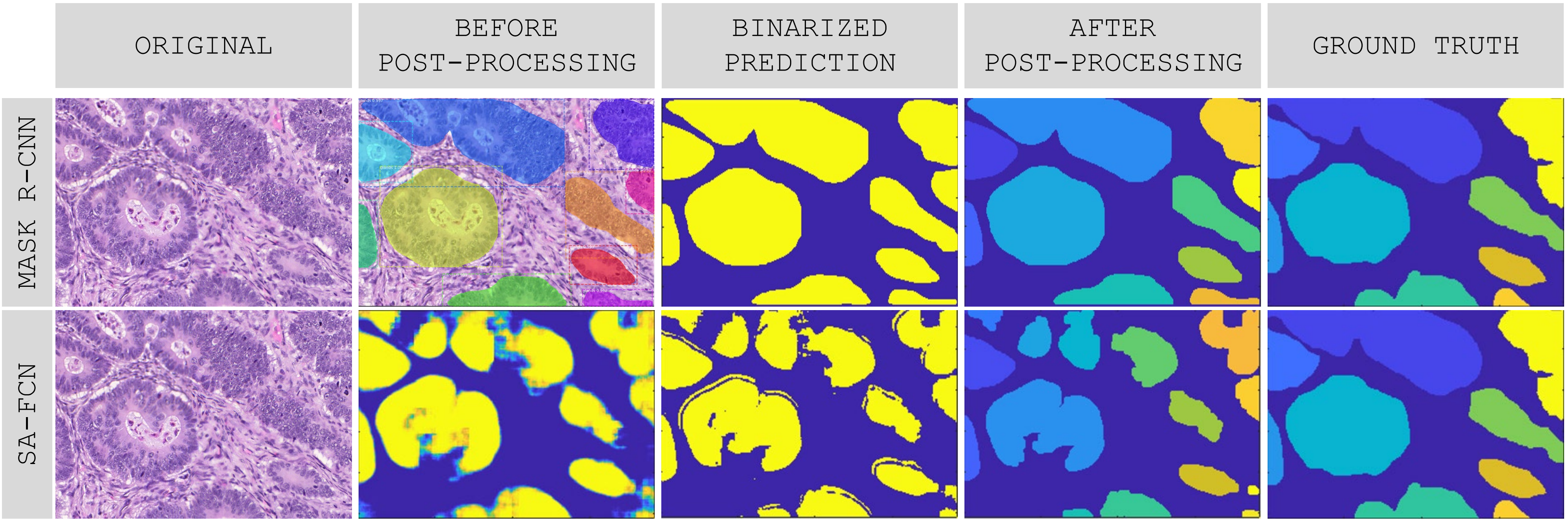
SA-FCN versus Mask R-CNN



SA-FCN versus Mask R-CNN

1. **Mask R-CNN** implementation **achieves higher performance** than our SA-FCN implementation.

2. **Mask R-CNN** implementation **requires less post-processing** actions as the SA-FCN implementation.

Conclusions

1. **Post-processing** can **have a great impact** on the final performance of the deep learning architecture.

2. **Mask R-CNN obtains comparable results** to current state-of-the-art, for gland segmentation task.

3. It is worth to **use generic models** instead of design complex architectures when tackling new domains.

Thank you

Comparison of Mask R-CNN and SA-FCN

	F1 Score				Dice Index				Hausdorff Distance				RS	WRS
	A		B		A		B		A		B			
	Score	R	Score	R	Score	R	Score	R	Score	R	Score	R		
Our Mask R-CNN	0.888	4	0.817	3	0.874	4	0.808	4	72.08	4	134.28	4	23	11.75
Our SA-FCN	0.860	6	0.761	6	0.851	6	0.827	3	77.33	6	119.13	3	30	16.5
SA-FCN from the article	**0.921**	**1**	**0.855**	**1**	0.904	2	**0.858**	**1**	44.73	2	**96.97**	**1**	**8**	**4.5**
CUMedVision1 (DCAN)	0.868	5	0.769	4	0.867	5	0.800	5	74.59	5	153.64	6	30	15
CUMedVision2 (DCAN)	0.912	2	0.716	7	0.897	3	0.781	7	45.41	3	160.34	7	29	11.25
Multichannel	0.893	3	0.843	2	**0.908**	**1**	0.833	2	**44.12**	**1**	116.82	2	11	5.25
FCN	0.788	7	0.764	5	0.813	7	0.796	6	95.05	7	146.24	5	37	19.75