New Boundary Constraint Loss to Facilitate Glands Segmentation

Weijia Lu, JianHua Yao, Xiao Han, Haocheng Shen
AI Lab, Tencent

2019.9

Problem

Pathologists normally use Hematoxylin & Eosin (H&E) stained image to determining grade of differentiation of carcinoma.

In histology, the area ratio of well differentiated glandulars to whole tissue is an important metric in evaluating carcinoma grade.

The degree of differentiation for a glandular is normally quantified by it's shape (formation) as indicated by Awan et al. Therefore a precise segmentation is required.

Nowadays, inter-pathologist disagreements can be 30-53% due to arbitrary annotation of glandulars, according Netto et al.'s research.

Multi-task network is normally used to pursue a precise boundary segmentation as well as a high-recall detection.
BUT this strategy increase the number of FLOPs, result a slower inference time.

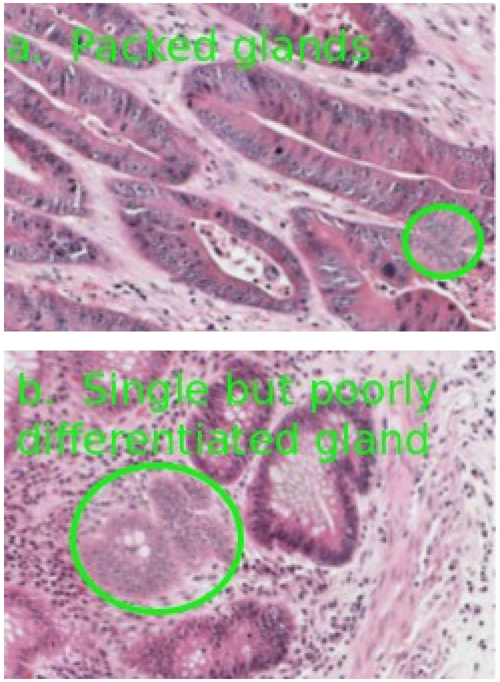
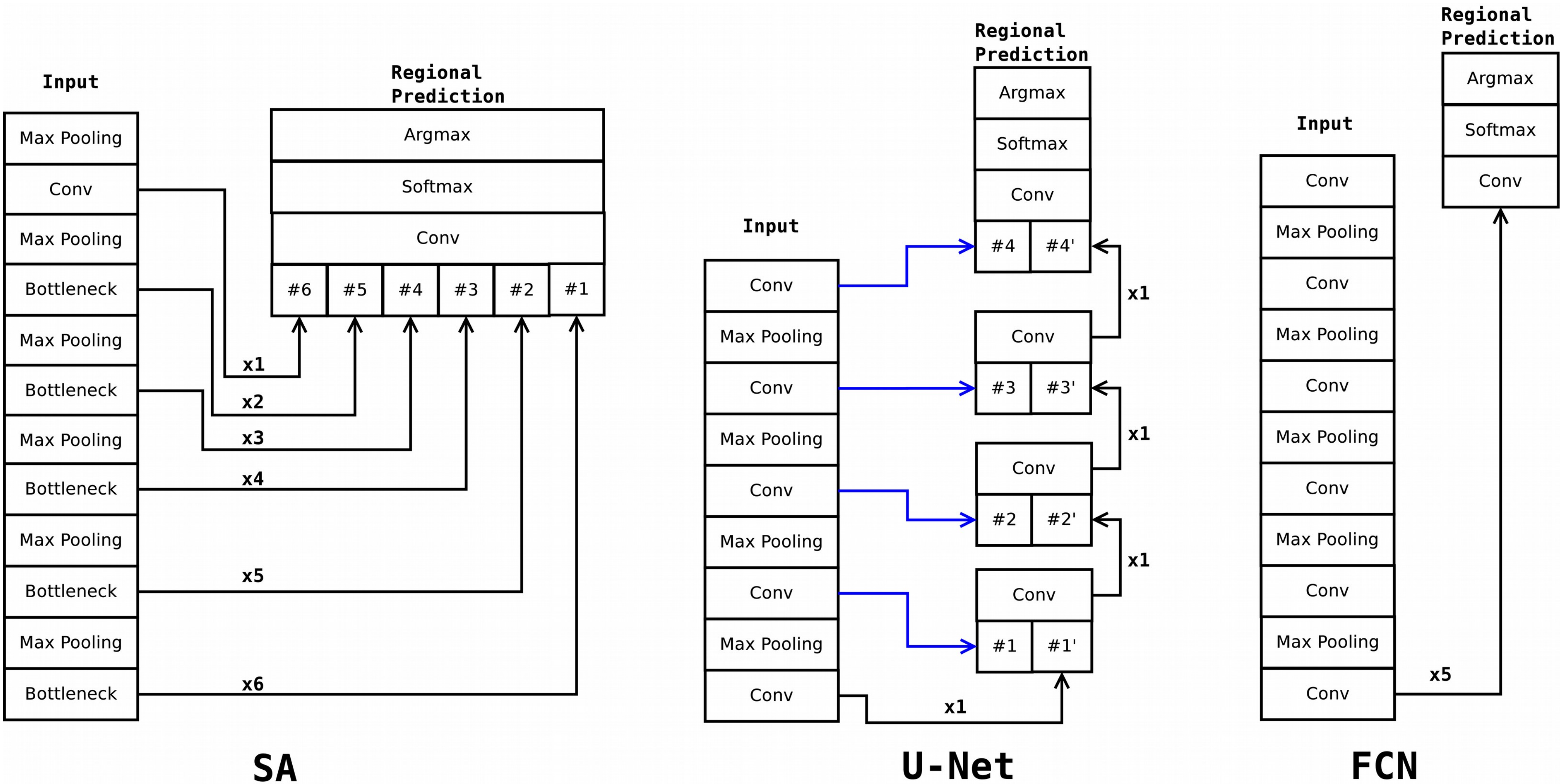


Fig. Demo H&E images reprinted from GlaS15 dataset

In this study, we proposed a boundary loss to tackle these problems. The proposed loss is enclosed into 3 single steam network, and tested on 2 dataset to verify its efficiency.

Single stream networks



Boundary loss formulation

Region logits before softmax normalization layer
MxN is size of feature map and K is total categories. $L_{reg} \in R^{MxNxK}$

Softmax normalization $S()$

Regional prediction $Y_{reg} = argmax(S(L_{reg}))$

Ground truth segmentation mask G

Extract boundary prediction by sobel operator or likely,
from regional prediction through convolution

$$B = \sum_{i \in (x, y)} \left| Soble_i \otimes Y_{reg} \right|$$

Boundary loss formulation

Calculate boundary potential map from G

$$\phi(G) = \omega_0 \circ \phi_{fg}(G) + \omega_1 \circ \phi_{bg}(G)$$

Where ϕ_{fg} is the distance map based on original regional binary mask and ϕ_{bg} based on the bitwise inverted mask, see following example

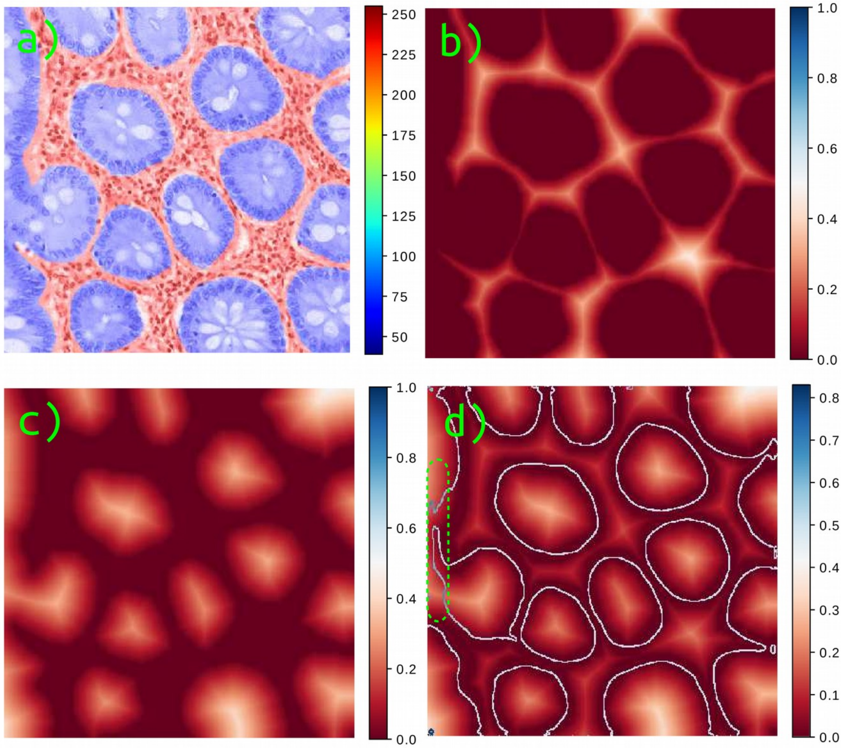


Fig. Potential map Φ and boundary B .

a) original H&E stained pathological image blended with ground truth segmentation mask (test A_58 in GlaS15);
b) and c) distance map retrieved from ground truth segmentation binary mask (Φ_fg) and its invert (Φ_bg);
d) Φ obtained by lumped 2 distance maps together

In d), B from regional prediction after a certain epoch is also shown (white contours).

Boundary loss formulation

Finally the proposed boundary loss

$$L_B = \frac{1}{M \times N} \sum \phi(G) \otimes B$$

Where $\otimes$ is a pixel wise multiplication

Transformation for differentiable solution and numerical stabilization

Problem

- argmax() is not differentiable. This will prevent training the model in an end-to-end manner.
- Get B from L_{reg} or $S(L_{reg})$ directly leading to fragmentary edge since they're defined in continuous real space

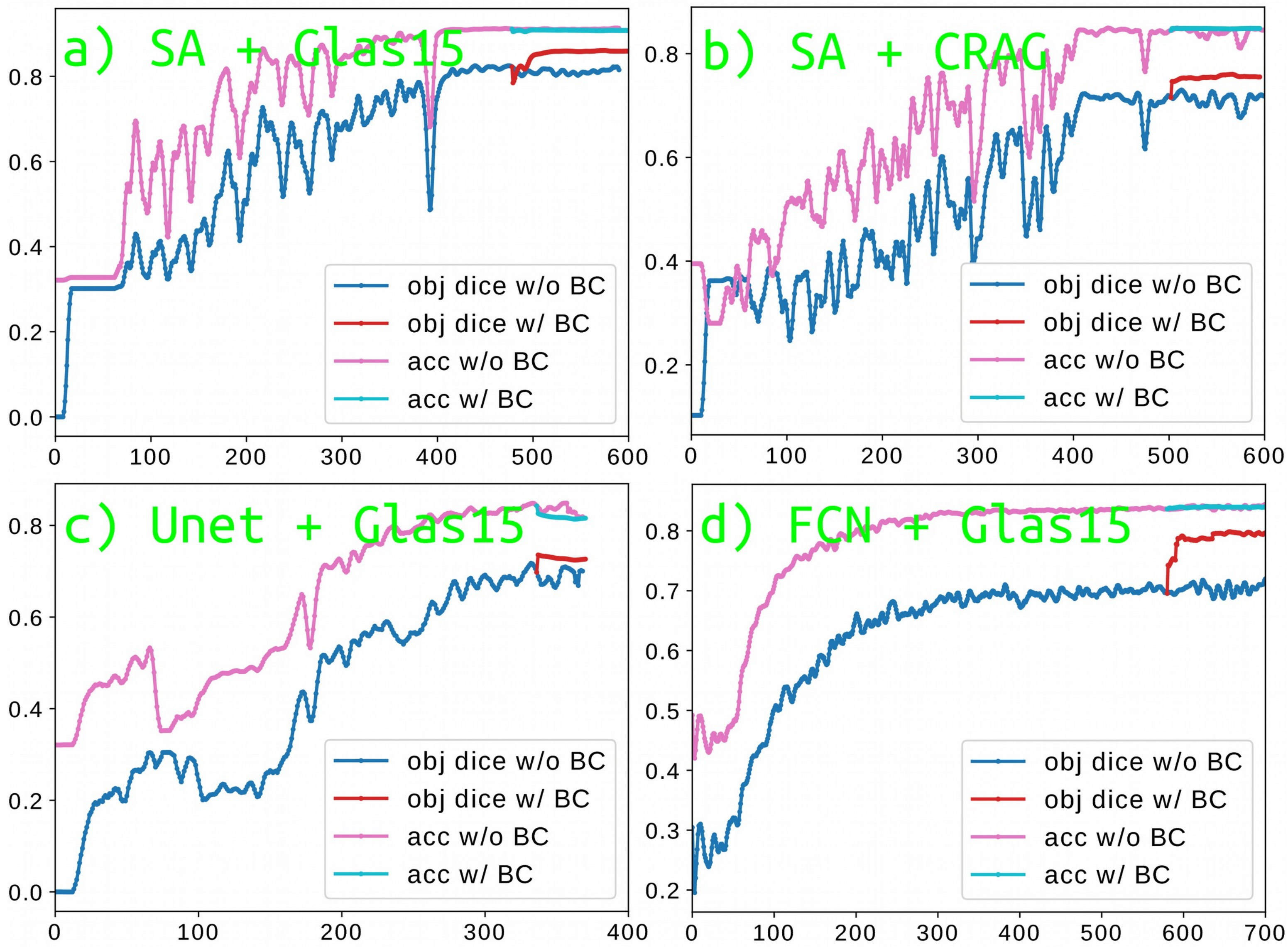
Solution

A soft argmax function defined as expectation of categories k

$$\widetilde{argmax}(S(\cdot)) \equiv E(k) = \sum_{k \in (0 \ldots K)} k \cdot S_k(\alpha(L_{reg}))$$

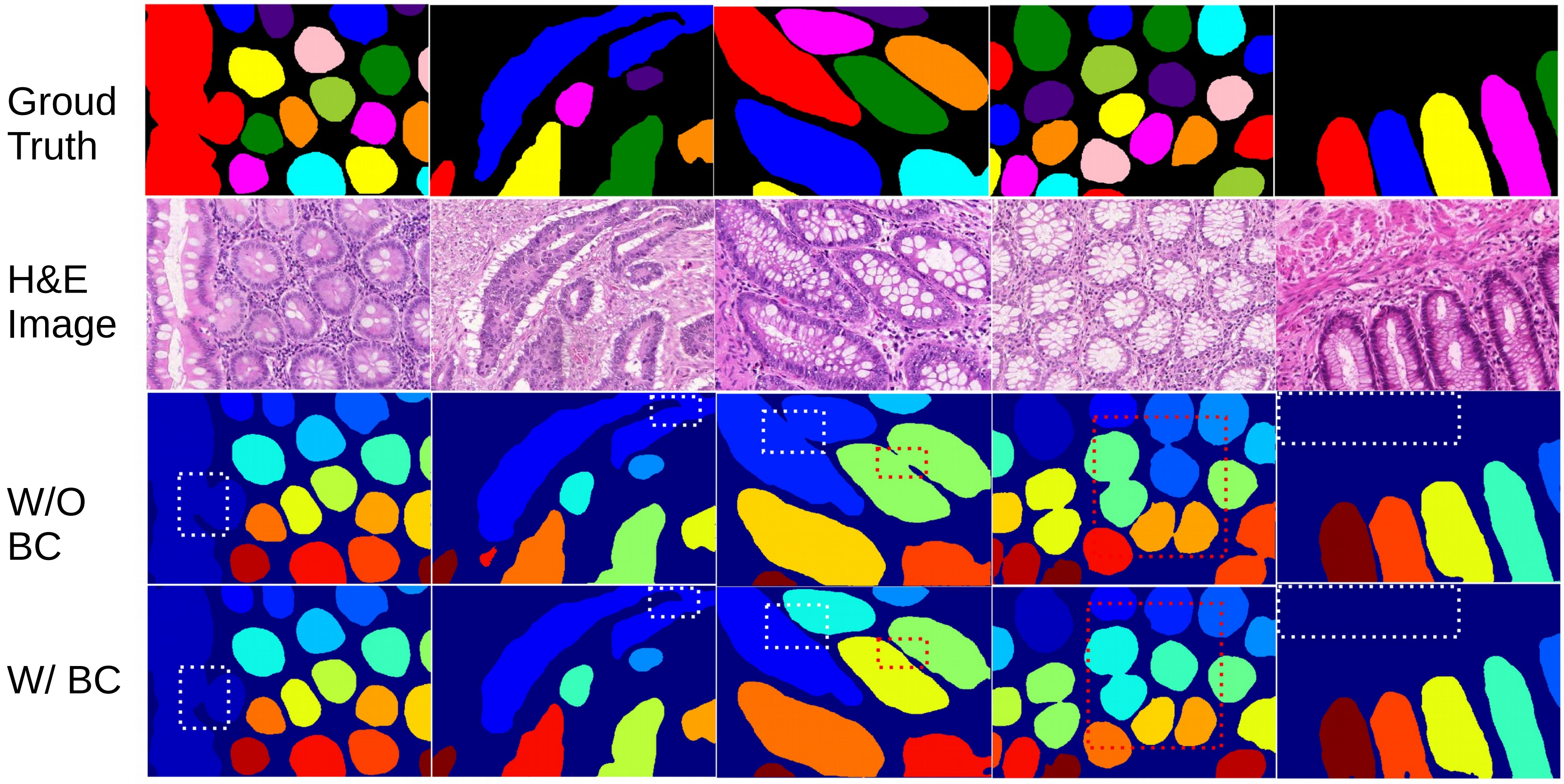
Since the output from softmax is a likelihood score drawn from 0-1

Results

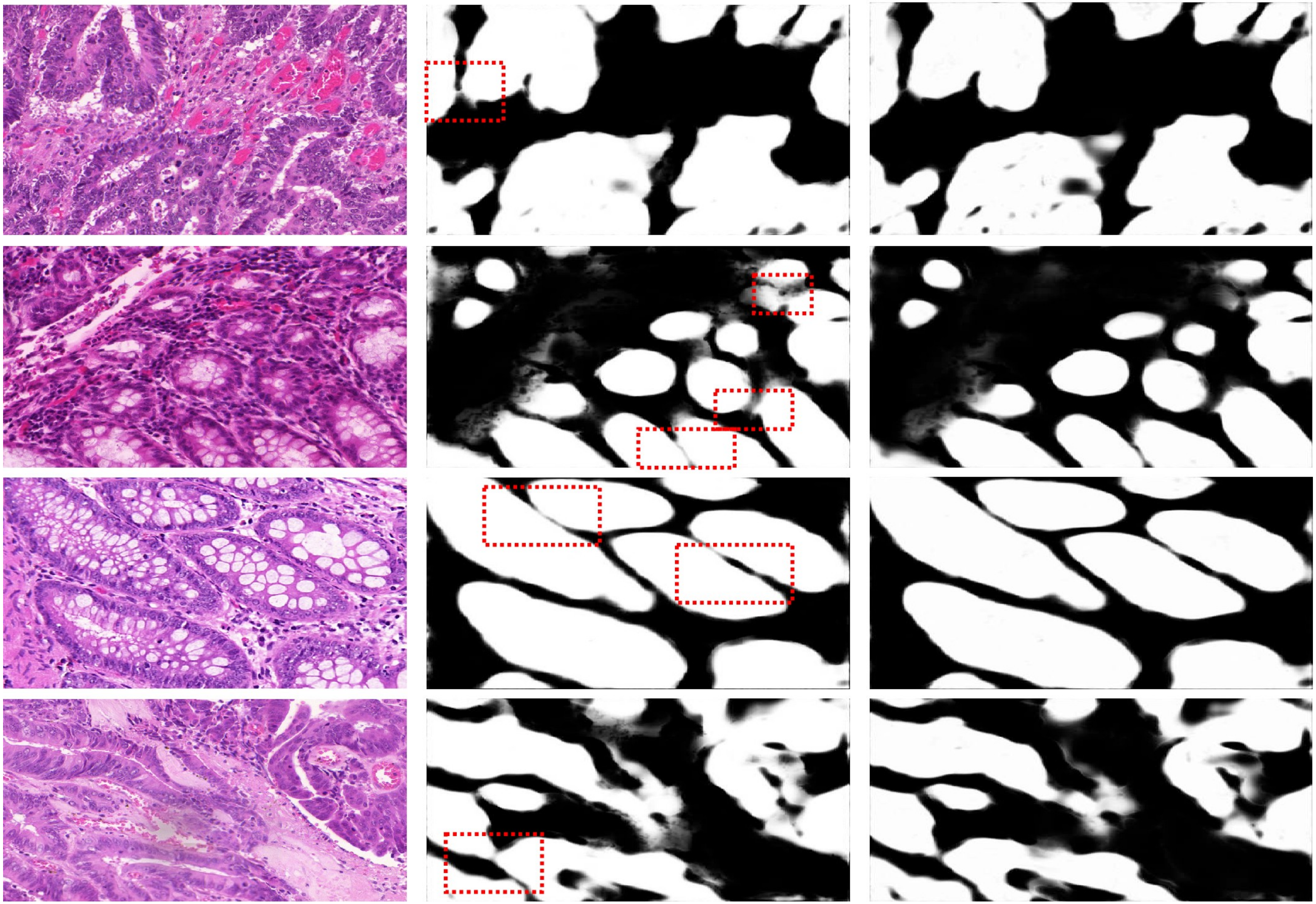


a) SA + Glas15
b) SA + CRAG
c) Unet + Glas15
d) FCN + Glas15
obj dice w/o BC
obj dice w/ BC
acc w/o BC
acc w/ BC

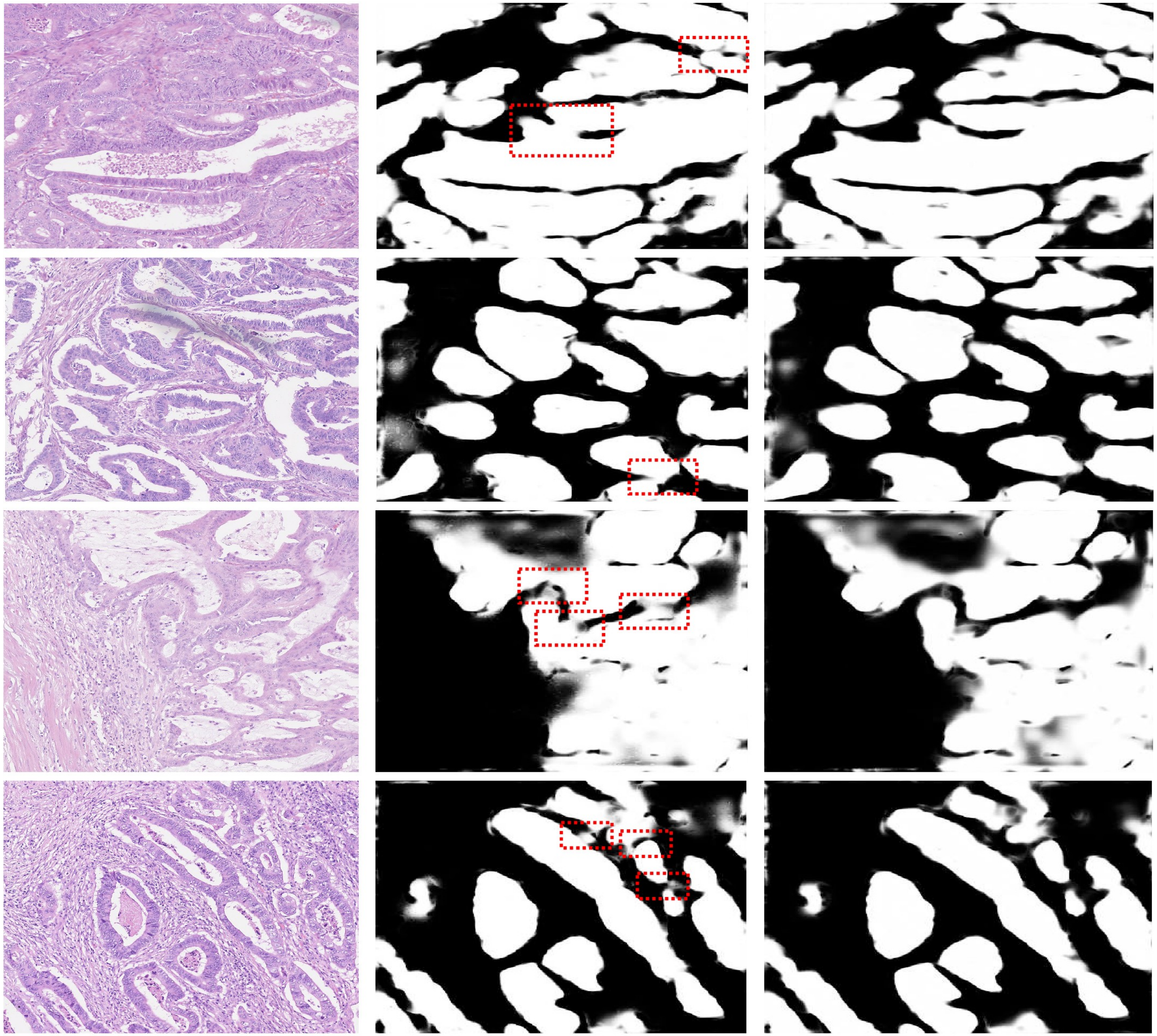
Result



Result



Result



Thanks !!

Question or suggestion please to

alfredwjlu at gmail.com