

Leveraging Uncertainty for Deep Interpretable Classification and Weakly-Supervised Segmentation of Histology Images (Short#4)

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Context

Class Activation Maps (CAMs) methods allow a classifier to classify the image content and localize ROI using only image class as label.

Due to histology image properties such as visual similarity between foreground/background, these methods yield poor ROI localization results causing:

- CAMs under-activation, leading to high false negative.
- CAMs over-activation, leading to high false positive.

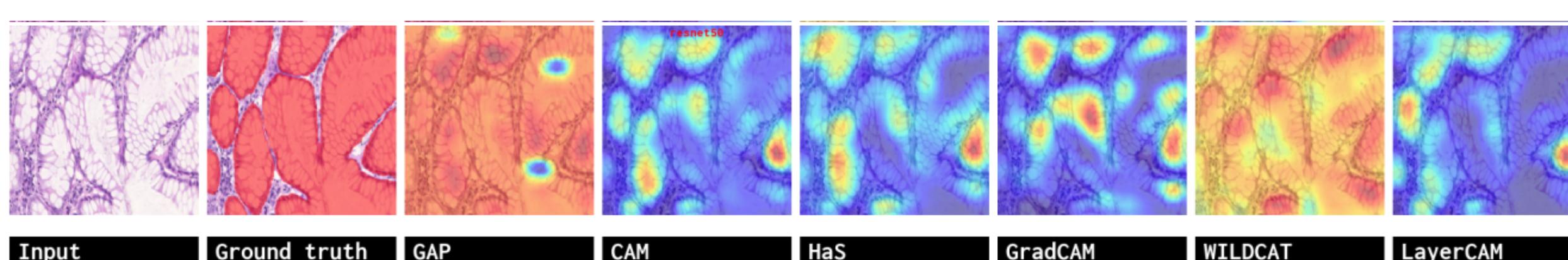


Figure 1. Example of a CAM ROI localization over histology images: under/over activation issue.

Our Proposal: Constraining CAMs using Priors

We constrain the CAMs to:

- Explicitly model foreground/background using a mask.
- Enforce the presence of both regions (foreground/background) using size priors.
- Ensure region' consistency using classifier response.

Proposed Approach: Architecture

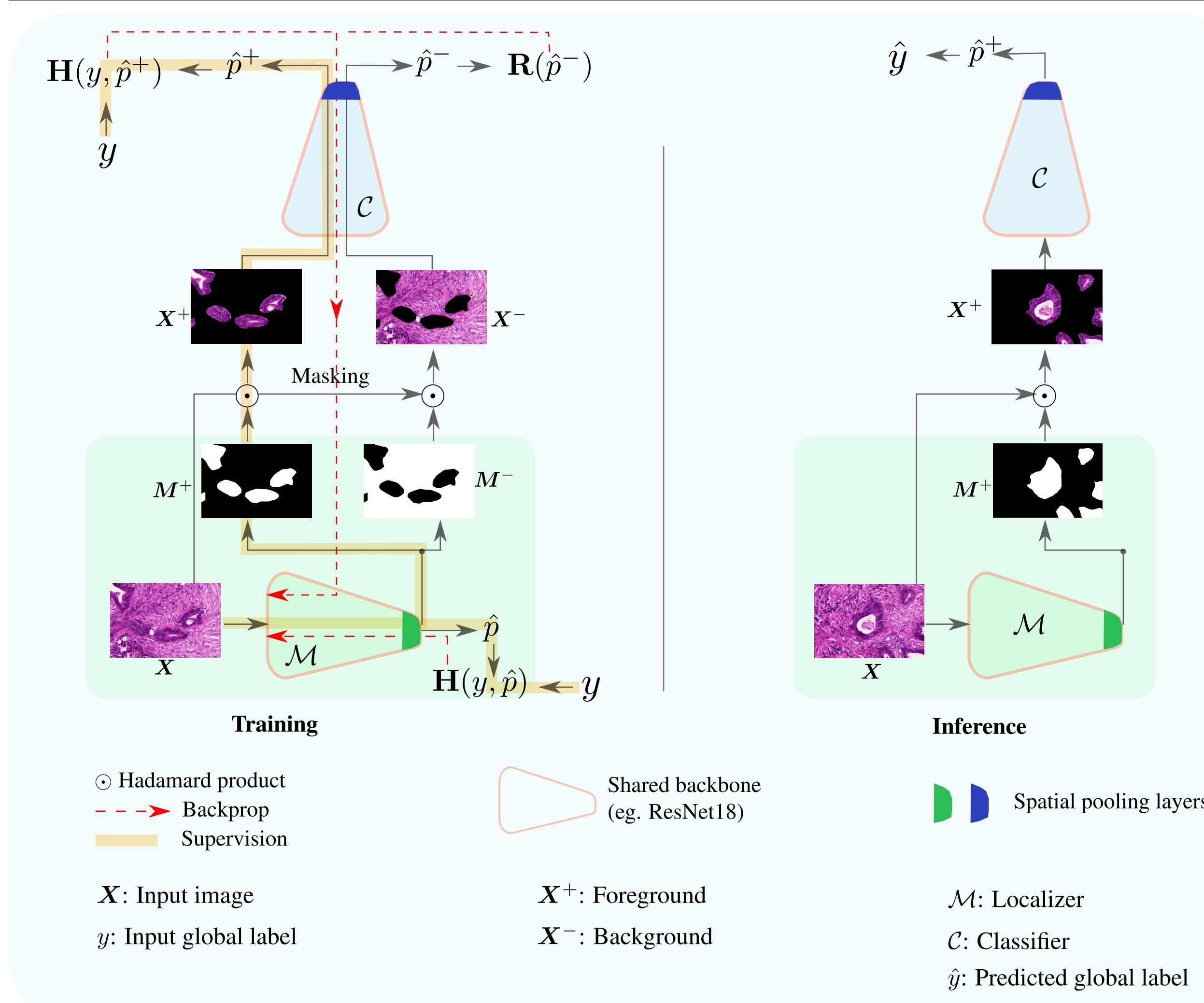


Figure 2. Our proposal. Left: training. Right: evaluation.

Proposed Approach: Training Loss

$$\min_{\theta_c} H(p, \hat{p}^+) + \lambda R(\hat{p}^-) - \frac{1}{t} [\log s^+ + \log s^-], \quad (1)$$

where $R(\hat{p}^-) = -H(\hat{p}^-)$; referred as Explicit Entropy Maximization (EEM), or, $R(\hat{p}^-) = H(q, \hat{p}^-)$, referred as Surrogate for explicit Entropy Maximization (SEM), q is a uniform distribution, λ is a balancing positive scalar, and $t > 0$ is a parameter that determines the accuracy of the approximation of the barrier method. We define the size of each mask as: $s^+ = \sum_{z \in \Omega} M^+(z)$, $s^- = \sum_{z \in \Omega} M^-(z)$, where Ω is the spatial image domain. We refer to the total size term as Absolute Size Constraints (ASC).

Results

Table 1. Image classification and pixel-level segmentation performances on the GlaS and Camelyon16 test sets. Cl: classification. The best performance is shown in bold.

Method	GlaS		Camelyon16-P512	
	Image level Cl. error (%)	Pixel level F1 ⁺ (%)	Image level Cl. error (%)	Pixel level F1 ⁺ (%)
All-ones (Lower-bound)	--	66.01	00.00	--
PN (media,2019)	--	65.52	24.08	--
ERASE (cvpr,2017)	7.50	65.60	25.01	8.61
Max-pooling (cvpr,2015)	1.25	66.00	26.32	10.06
CAM-LSE (cvpr,2016)	1.25	66.05	27.93	1.51
Grad-CAM (iccv,2017)	0.00	66.30	21.30	2.40
GAP (corr,2013)	0.00	66.90	17.88	2.40
WILDCAT (cvpr,2017)	1.25	67.21	22.96	1.48
Deep MIL (icml,2018)	2.50	68.52	41.34	1.93
Ours (EEM)	0.00	72.11	69.07	6.26
Ours (SEM)	0.00	71.94	69.23	6.95
U-Net (miccai,2015) (Fully supervised)	--	90.19	88.52	--
			71.11	89.68

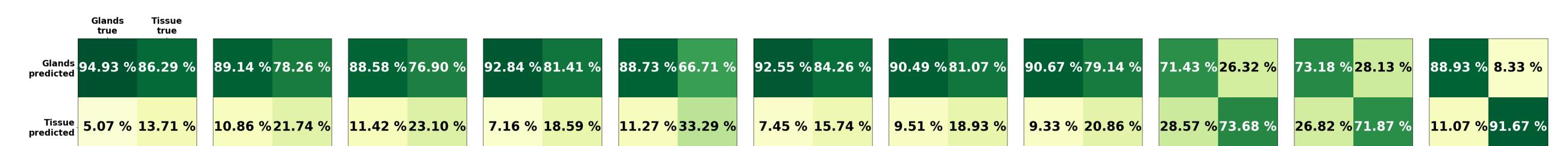


Figure 3. GlaS dataset: Confusion matrix over entire pixels of test set.

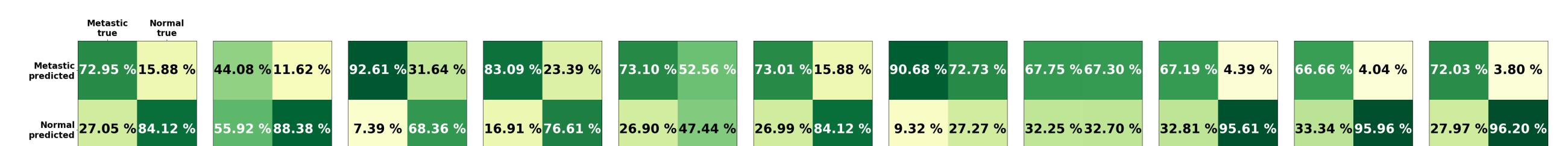


Figure 4. Camelyon16-P512 dataset: Confusion matrix over entire pixels of test set.

Visual results:

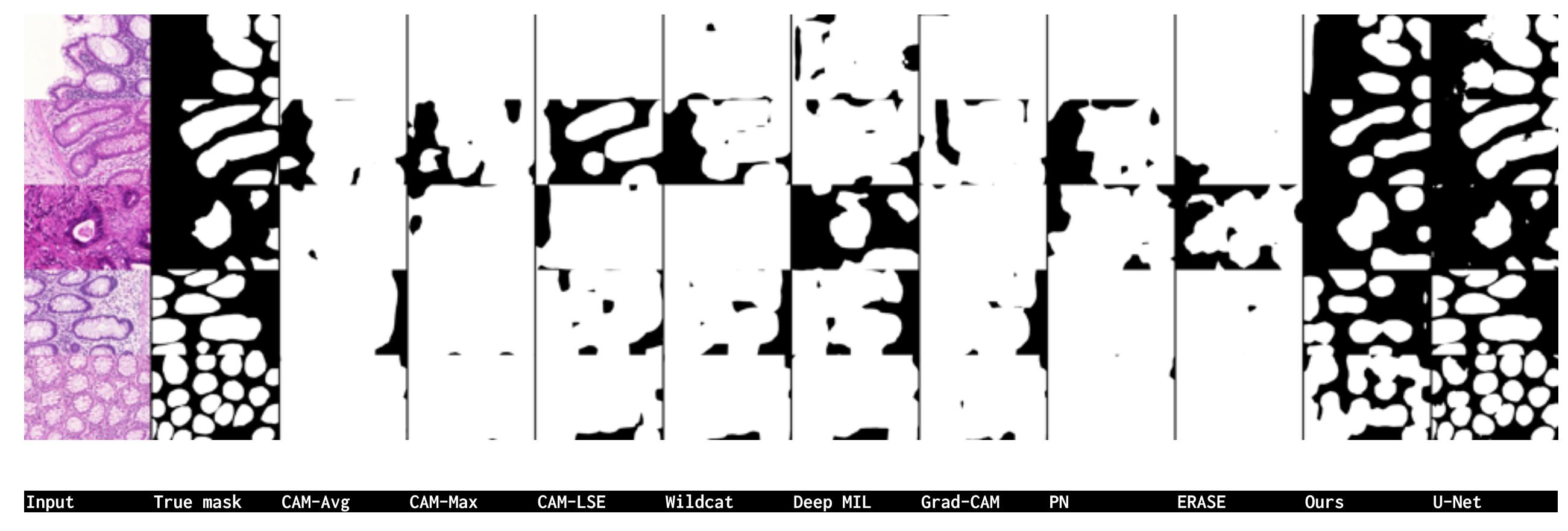


Figure 5. GlaS dataset: Qualitative results of the predicted binary mask for each method on several GlaS test images. Our method, referred to as Ours, is the SEM version with the ASC regularization term.

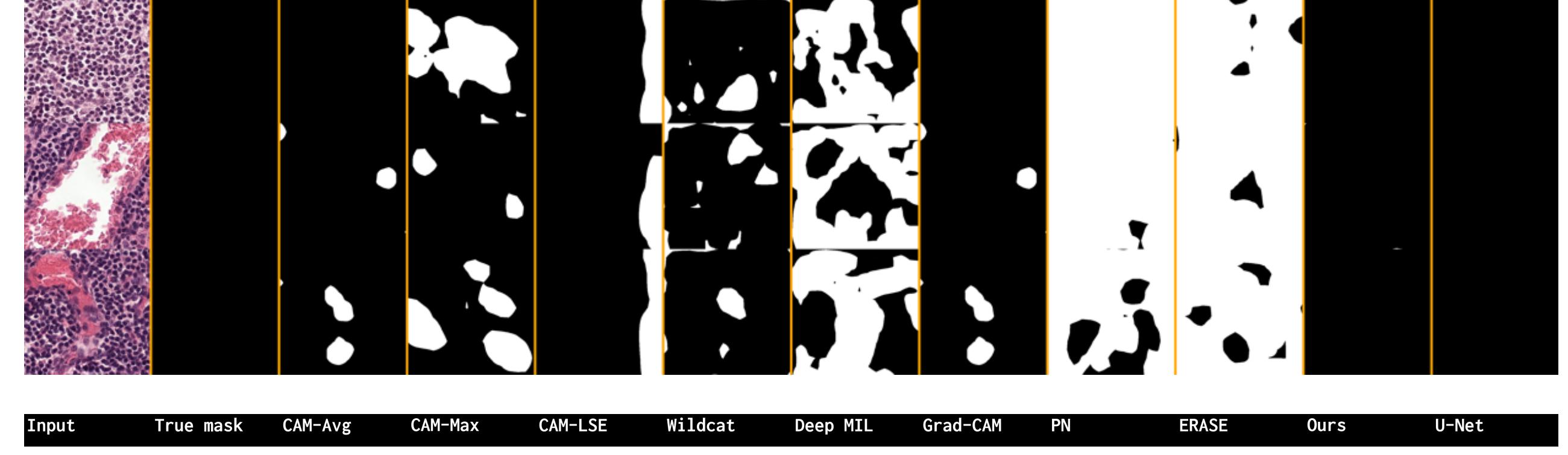


Figure 6. Camelyon16-P512 benchmark: Examples of mask predictions over normal samples from the testing set. White pixels indicate metastatic regions, while black pixels represent normal tissue. Ours is the SEM version with the ASC regularization.

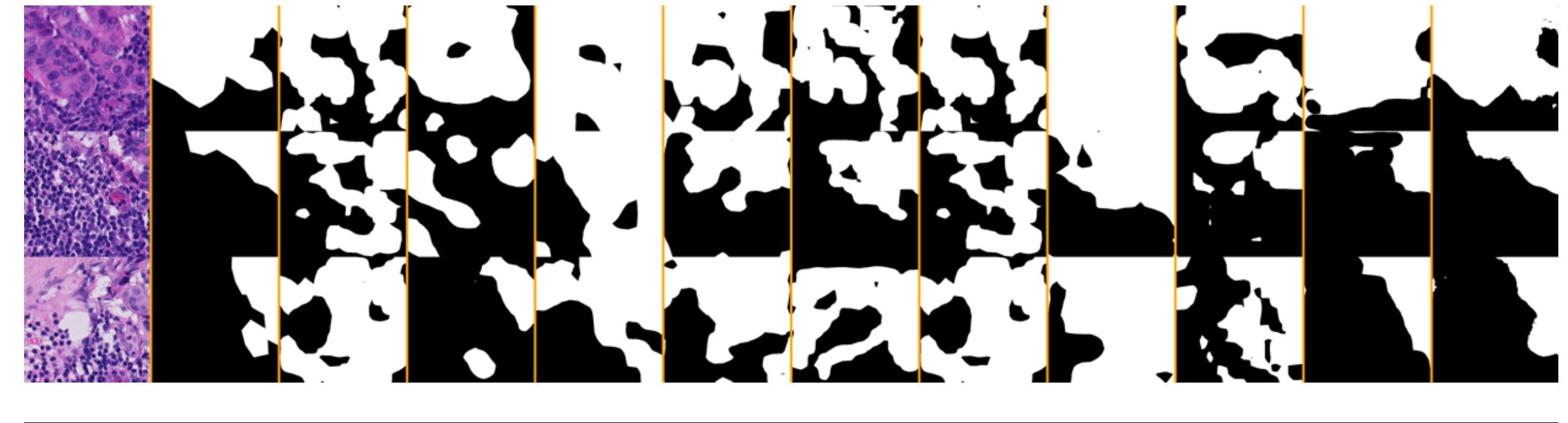


Figure 7. Camelyon16-P512 benchmark: Examples of predicted pixel-wise masks over metastatic samples from the test set. White pixels indicate metastatic regions, while black pixels represent normal tissue. Ours is the SEM version with the ASC regularization.

Ablation studies: see paper.