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Fused Lasso Application for Gastric Cancer Image Segmentation

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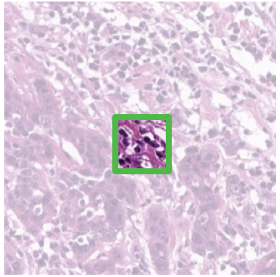
Introduction

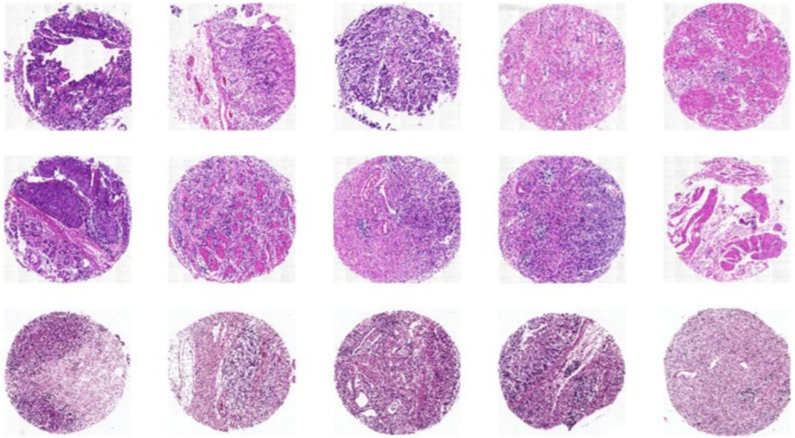
- Tumor segmentation on digitalized slide images has been plagued by problems related to the patch-based approach attributable to the narrow and limited field-of-views.

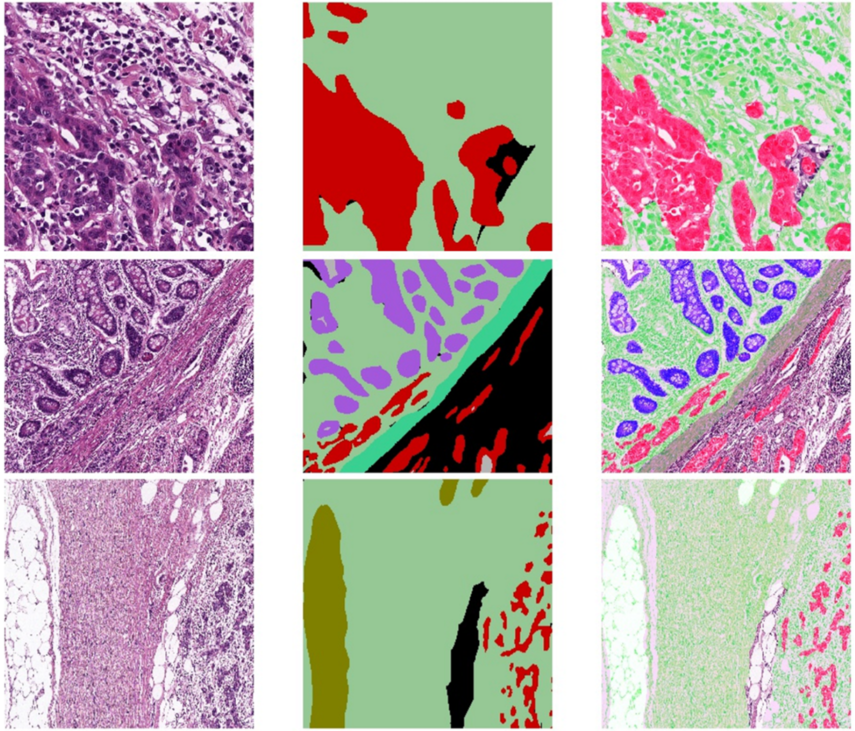


- Our goal is to develop a speedy tumor segmentation algorithm that overcomes performance degradation arising from the limitations of the patch-based approach.
- To achieve our goal, we explored the effect of the fused lasso regularization on segmentation performance using gastric cancer pathology images.

Materials and methods (Data)

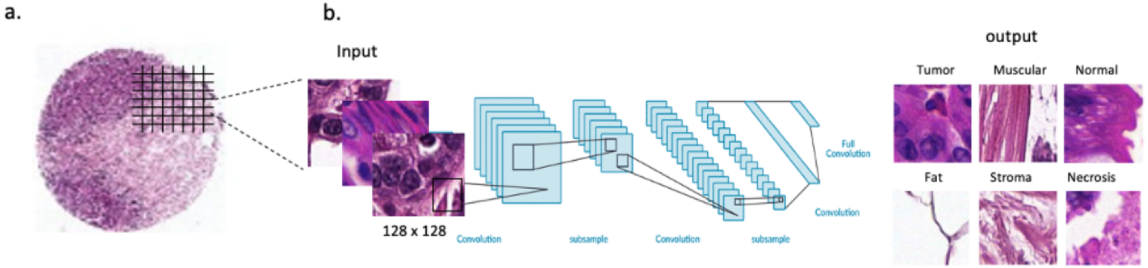
- We used 27 specimens with partial annotation from tissue-microarrays (TMAs) with gastric cancer from Asan Medical Center.





Class labels: tumor, stroma, benign epithelial, fat, muscle

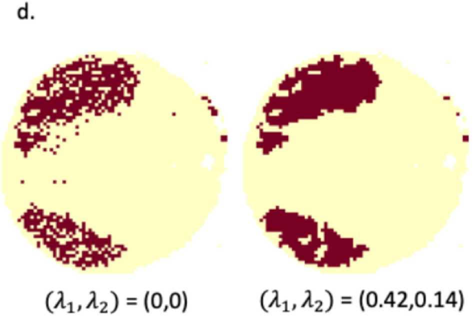
Materials and methods (Workflow)



c.

Manually annotated specimens				
Training data				Test data
Fold 1	Fold 2	Fold 3	Fold 4	Final evaluation
Fold 1	Fold 2	Fold 3	Fold 4	
Fold 1	Fold 2	Fold 3	Fold 4	
Fold 1	Fold 2	Fold 3	Fold 4	

Validation	Training	Test



- Our segmentation adjustment method was tested on multiple renowned deep learning architectures to detect malignancy on tissue slides.

Materials and methods (Formula)

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$$\operatorname*{argmin}_{\boldsymbol{\beta}} \frac{1}{2}\sum_{j=1}^{n_c}\sum_{i=1}^{n_r}(y_{i,j}^C - \beta_{i,j}^C)^2 + \lambda_1 \sum_{j=1}^{n_c}\sum_{i=1}^{n_r}|\beta_{i,j}^C| + \lambda_2 \sum_{\substack{|i-i'|+|j-j'|=1 \\ i\geq i',j\geq j'}} |\beta_{i,j}^C - \beta_{i',j'}^C|$$

- In our fused lasso application, these penalties were adopted to regularize variables with ℓ_1-norms based on both the patchwise prediction probabilities (for all $\beta_{i,j}$'s) and their pairwise differences between adjoining patches (e.g., $\beta_{i,j}$ and $\beta_{i+1,j}$)
- Tuning-parameters, λ_1 and λ_2, control the degree of regularizing effect.

Materials and methods (Tuning-parameters)

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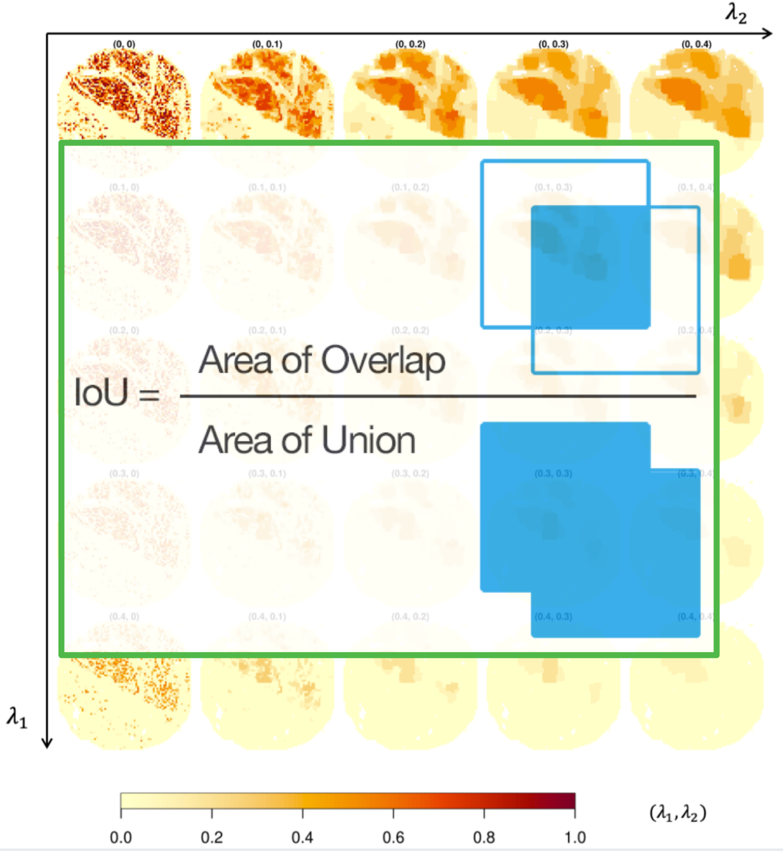

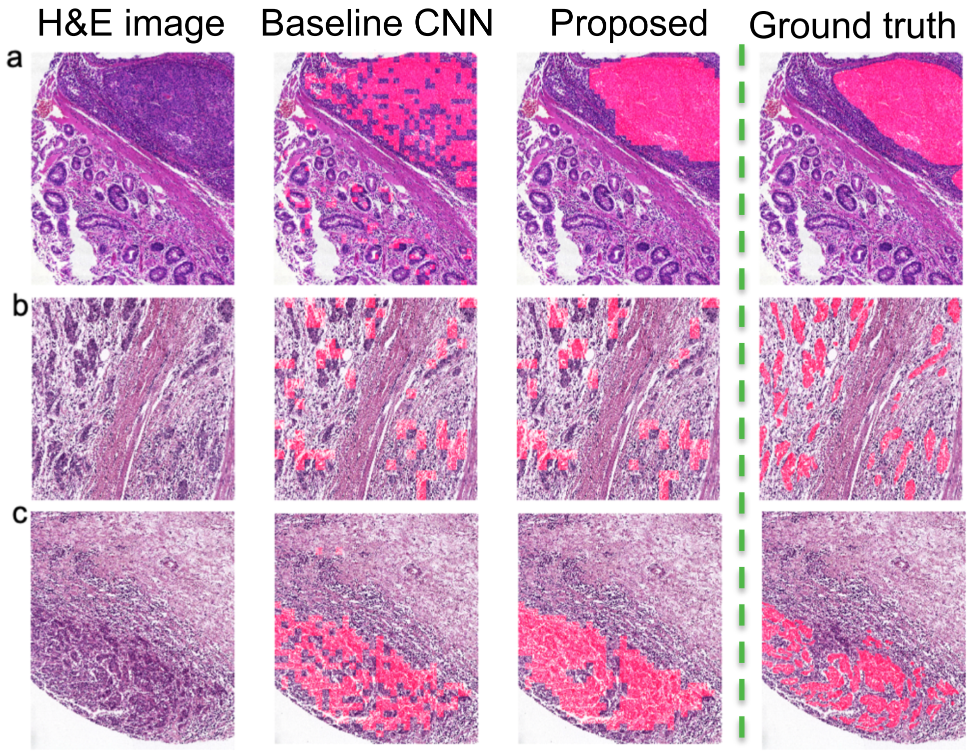

Results

- The average test performance in terms of IOU, dice, accuracy, precision, recall, and AUROC increased by a degree of 3.74%p, 3.27%p, 0.93%p, 5.32%p, 3.20%p , and 1.58%p, respectively.

Architecture	Method (λ_1, λ_2)	IOU	Dice	Accuracy	Precision	Recall	AUROC
AlexNet	$(0, 0)$	0.521022	0.685095	0.913913	0.691466	0.678840	0.946606
	$(0.29, 0.06)$	0.617225	0.763314	0.928878	0.705561	**0.831364**	0.969972
DenseNet-121	$(0, 0)$	0.592014	0.743730	0.930360	0.755260	0.732546	0.970133
	$(0.42, 0.14)$	**0.660262**	**0.795371**	**0.942362**	0.779381	0.812030	**0.977791**
ResNet-18	$(0, 0)$	0.550442	0.710046	0.924730	0.757613	0.668099	0.964167
	$(0.48, 0.27)$	0.447368	0.618182	0.915988	**0.828520**	0.493018	0.975162
ResNet-50	$(0, 0)$	0.295495	0.456189	0.884131	0.646943	0.352309	0.952945
	$(0.37, 0.13)$	0.338249	0.505510	0.893614	0.704415	0.394200	0.961517
SqueezeNet	$(0, 0)$	0.430973	0.602350	0.904727	0.709913	0.523093	0.944146
	$(0.36, 0.15)$	0.513692	0.678727	0.923692	0.809524	0.584318	0.972626

(Optimized on a single GPU Titan X Pascal processor)

Conclusions

- We demonstrated that adoption of fused lasso penalties can produce segmentation close to that generated by experts without a significant increase in computing time.

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