Healthcare Technology Innovation Centre

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Psi-Net: Shape and boundary aware joint multi-task deep network for medical image segmentation

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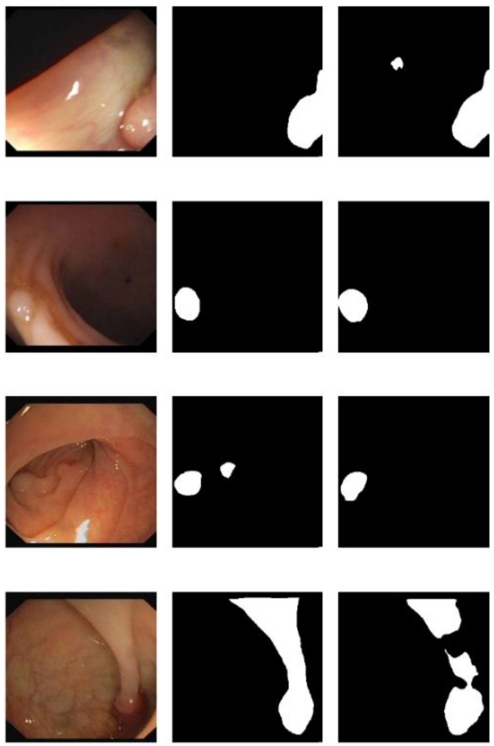
Outline

Deep learning : Medical image segmentation challenges

- The segmentation network should be shape-aware
- The segmentation output produced by the network should ideally have no outliers.
- The boundary of segmentation outputs produced by networks should be smooth
- The network should be able to handle class-imbalance
- The network should work for multi-instance object segmentation

Deep learning : Medical image segmentation challenges



Outliers

Non-smooth boundaries.

Multi instance object segmentation

Shape information

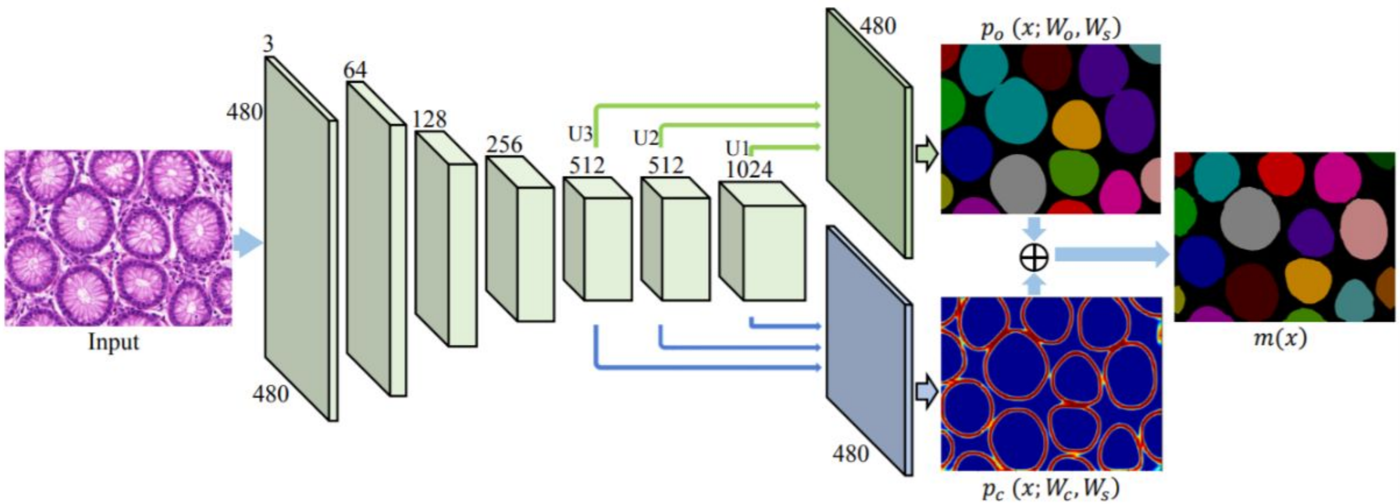
Related Work (U-Net) [1]

- U-Net is the most commonly used deep learning network.
- U-Net
  - Encoder decoder type of network
  - Input - Image, Output - Probability segmentation map
  - Loss function - Cross entropy

- Shape information : Network not aware of shape
- Outliers/non smooth boundaries : Pixel-wise classification
- Class imbalance - Cross entropy is used

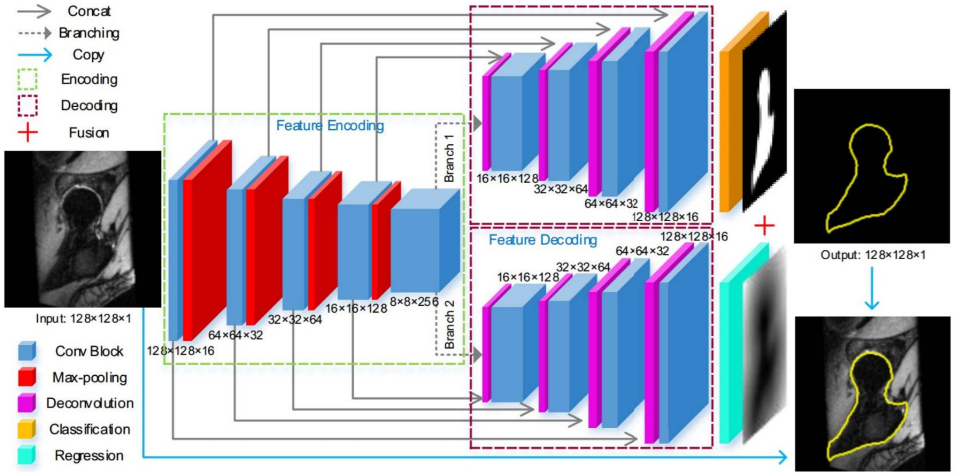
Related work (DCAN: Deep Contour-Aware Networks for Accurate Gland Segmentation) [2]

- Architecture : Single encoder and two parallel decoders
- Decoders are used for mask and contour prediction
- Loss function - Cross entropy for mask and contour
- Shape information - Contour is used to provide shape information
- Class imbalance - Cross entropy has difficulty in handling class imbalance
- Outliers/uneven mask boundaries - Pixel wise classification will result in outliers.



Related work (Deep multi-task and task-specific feature learning network for robust shape preserved organ segmentation (DMTS)) [3]

- Architecture : Single encoder and two parallel decoders
- Decoders are used for mask prediction and distance estimation
- Loss function - Cross entropy for mask and Mean square error for distance map
- Shape information - Distance map is used to provide shape information
- Class imbalance - Learning regression map helps to alleviate the problem
- Outliers/non smooth boundaries - Distance map acts as regularizer to provide smooth boundaries with reduced outliers



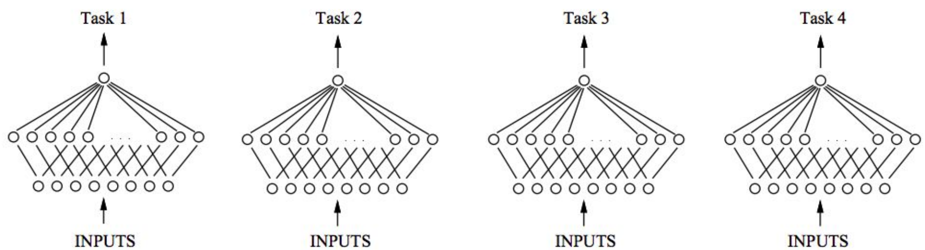
Comparison of related work

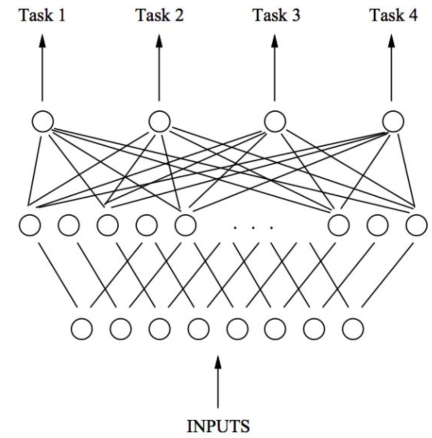
Multiple object instances - DMTS treats small object as outliers and removes the correct prediction

	Shape information	Class imbalance	Smooth boundary	Multiple object instances
U-Net	X	X	X	✓
DCAN	✓	X	X	✓
DMTS	✓	✓	✓	X
Ours	✓	✓	✓	✓

Multi task learning (MTL) [4]

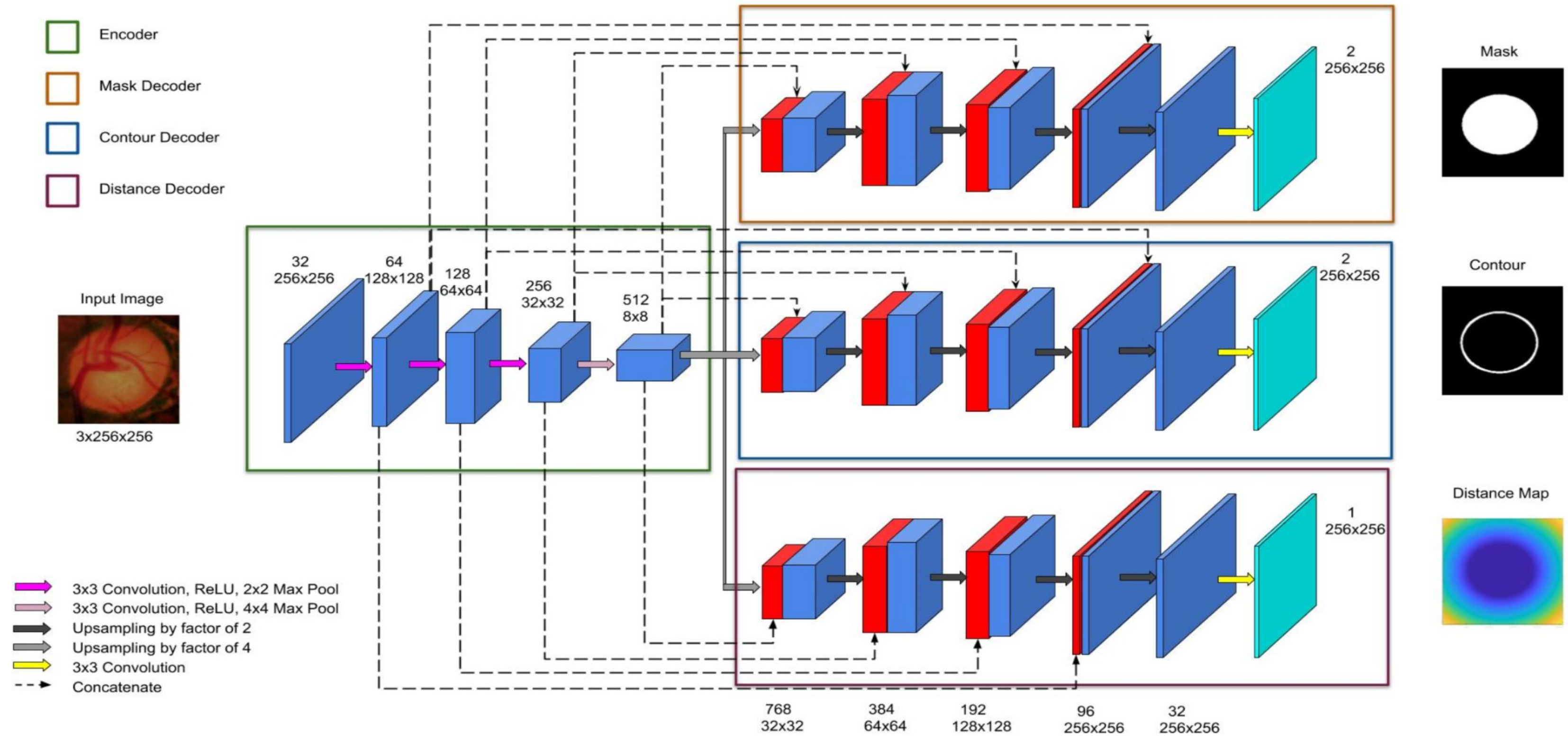
- Learning multiple related tasks together will help the model generalize better for the intended task.





- The generalization performance for tasks 1,2,3 and 4 is better for model trained together compared to training it for each task separately.
- MTL is a form of inductive transfer.
- L1 regularization is common form of inductive bias
- In case of MTL, inductive bias is provided by auxiliary tasks.

Proposed Network - Psi-Net



- Single encoder, three decoders
- Three decoders learn three tasks : Mask, Contour and Distance in parallel
- Intended task: Mask, Auxiliary task: Contour, Distance

Psi-Net Loss function

$$\mathcal{L}_{total} = \lambda_1 \mathcal{L}_{mask} + \lambda_2 \mathcal{L}_{contour} + \lambda_3 \mathcal{L}_{distance}$$

$$\mathcal{L}_{mask} = \sum_{\boldsymbol{x} \,\epsilon\, \Omega} log\, p_{mask}(\boldsymbol{x}; l_{mask}(\boldsymbol{x}))$$

$$\mathcal{L}_{contour} = \sum_{\boldsymbol{x} \,\epsilon\, \Omega} log\, p_{contour}(\boldsymbol{x}; l_{contour}(\boldsymbol{x}))$$

$$\mathcal{L}_{distance} = \sum_{\boldsymbol{x} \,\epsilon\, \Omega} (\hat{D}(\boldsymbol{x}) - D(\boldsymbol{x}))^2$$

Dataset and Preprocessing

Optic cup and disc segmentation [5]

- ORIGA dataset for the task of optic disc and cup segmentation
- 650 color fundus image with train and test
- Image dimension : 256 x 256

Polyp segmentation [6]

- MICCAI 2018 Gastrointestinal Image Analysis(GIANA)
- 912 images with train and test
- Image dimension : 256 x 256

Preprocessing

- Contour map - Estimating boundary of connected components
- Distance map - Euclidean distance transform to the mask

Evaluation metrics

Segmentation evaluation

$$Jaccard(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

$$Dice(A, B) = \frac{2|A \cap B|}{|A| + |B|}$$

Shape similarity

$$H(A, B) = max\left\{ \sup_{x \epsilon A} \inf_{y \epsilon B} ||x - y||, \sup_{y \epsilon B} \inf_{x \epsilon A} ||x - y|| \right\}$$

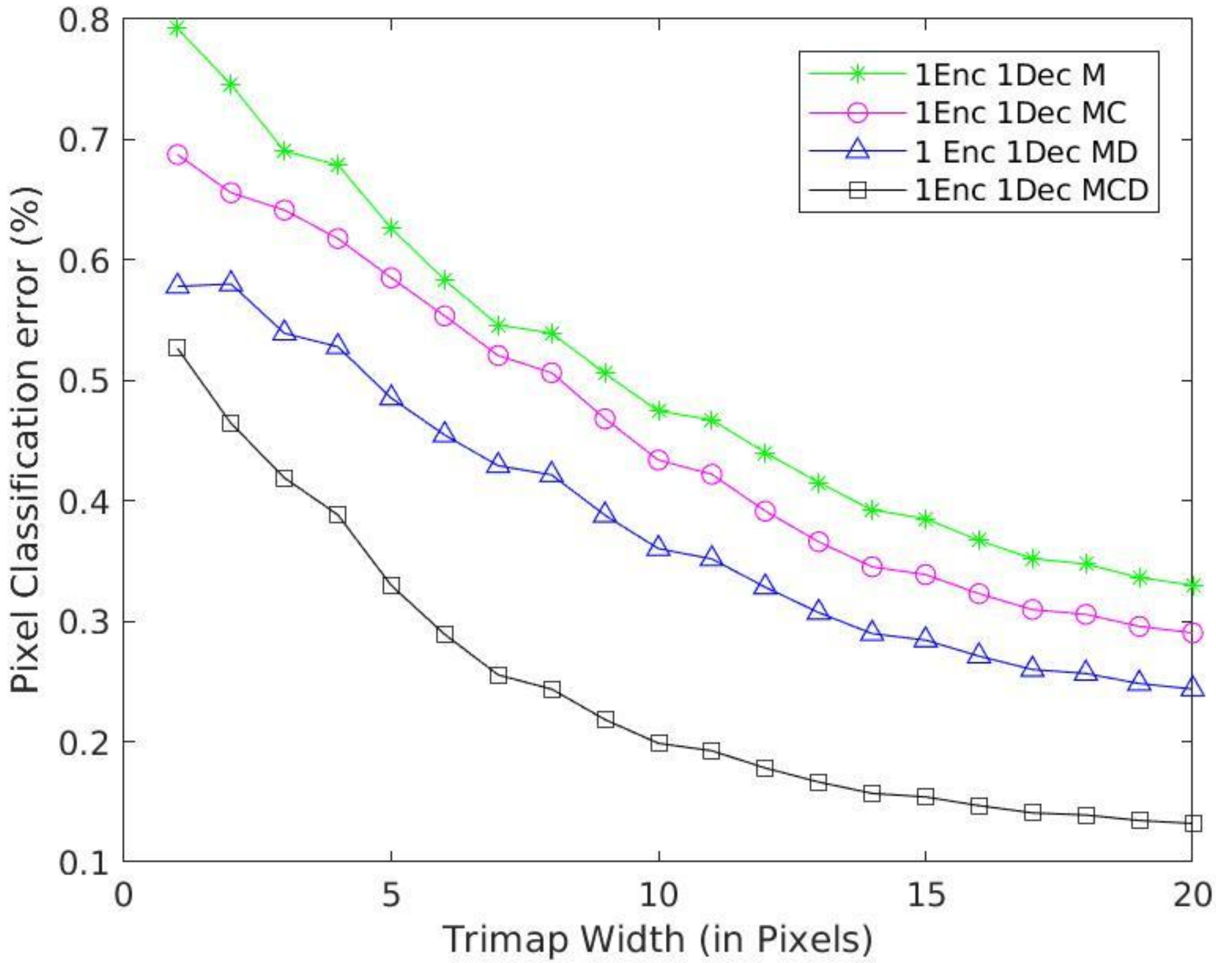
Evaluation : Segmentation and shape similarity

Architecture		Cup			Disc	
	Dice	Jaccard	Hausdorff	Dice	Jaccard	Hausdorff
U-Net	0.8655	0.7712	14.832	0.9586	0.9215	8.802
DCAN	0.8715	0.7803	14.775	0.9646	0.9324	8.992
DMTS	0.8723	0.7807	14.814	0.9665	0.9358	9.538
Psi-Net (Ours)	**0.8745**	**0.7848**	**14.541**	**0.9665**	**0.9358**	**7.268**

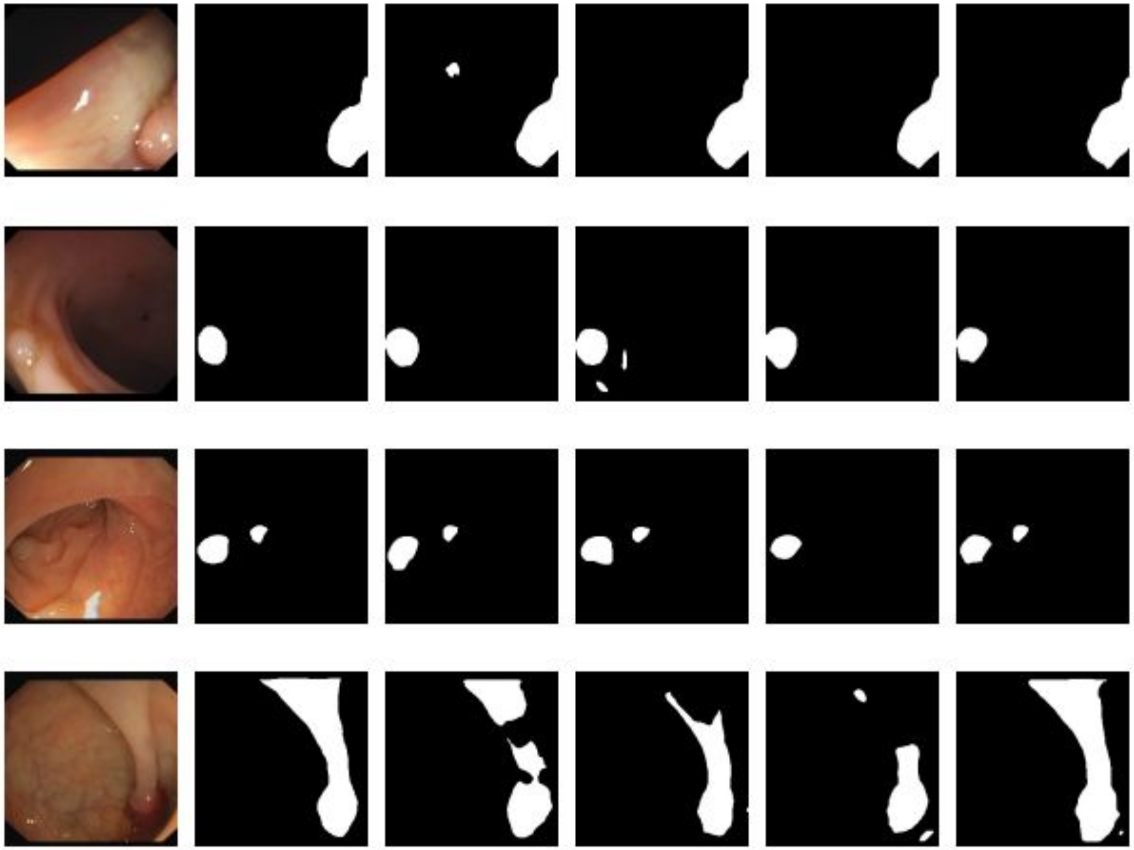
Architecture		Polyp	
	Dice	Jaccard	Hausdorff
U-Net	0.8125	0.7323	24.133
DCAN	0.8151	0.7391	22.737
DMTS	0.8283	0.7482	22.686
Psi-Net (Ours)	**0.8462**	**0.7721**	**21.143**

Note: The performance improvement is significant in Polyp followed by Cup and Disc. This corresponds to the difficulty of dataset.

Evaluation: Segmentation around boundaries [7]



Qualitative results



Image, GT, U-Net, DCAN, DMTS, Psi-Net(ours)

References

1. O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” in Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. Springer International Publishing, 2015, pp. 234–241.
2. H. Chen, X. Qi, L. Yu, and P. Heng, “DCAN: Deep Contour-Aware Networks for Accurate Gland Segmentation,” in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jun 2016, pp. 2487–2496.
3. C. Tan, L. Zhao, Z. Yan, K. Li, D. Metaxas, and Y. Zhan, “Deep multi-task and task-specific feature learning network for robust shape preserved organ segmentation,” in 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), Apr 2018, pp. 1221–1224.
4. Caruana, Rich. 1993. “Multitask Learning: A Knowledge-Based Source of Inductive Bias.” in ICML.
5. Z. Zhang, F. S. Yin, J. Liu, W. K. Wong, N. M. Tan, B. H. Lee, J. Cheng, and T. Y. Wong, “Origa-light: An online retinal fundus image database for glaucoma analysis and research,” in Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE. IEEE, 2010, pp. 3065–3068.
6. Vázquez, David, Jorge Bernal, F. Javier Sánchez, and et al. 2017. “A Benchmark for Endoluminal Scene Segmentation of Colonoscopy Images.” Journal of Healthcare Engineering 2017.
7. Krähenbühl, Philipp and Vladlen Koltun. 2011. “Efficient Inference in Fully Connected CRFs with Gaussian Edge Potentials.” Pp. 109–17 in Advances in Neural Information Processing Systems 24.