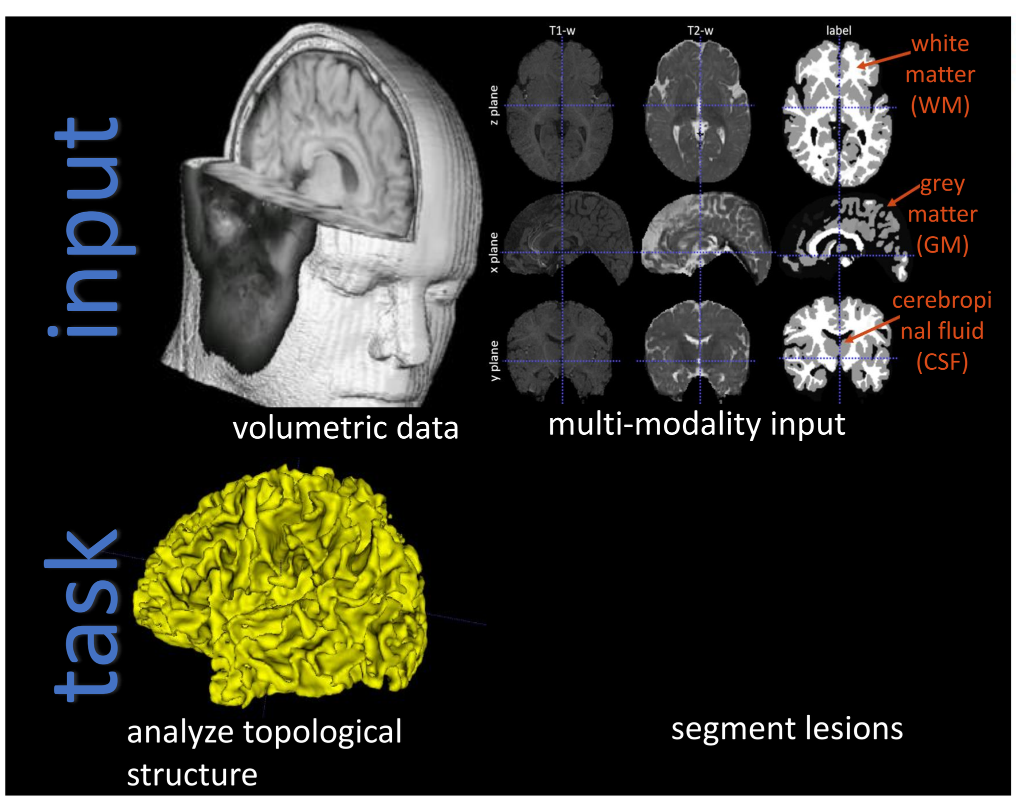
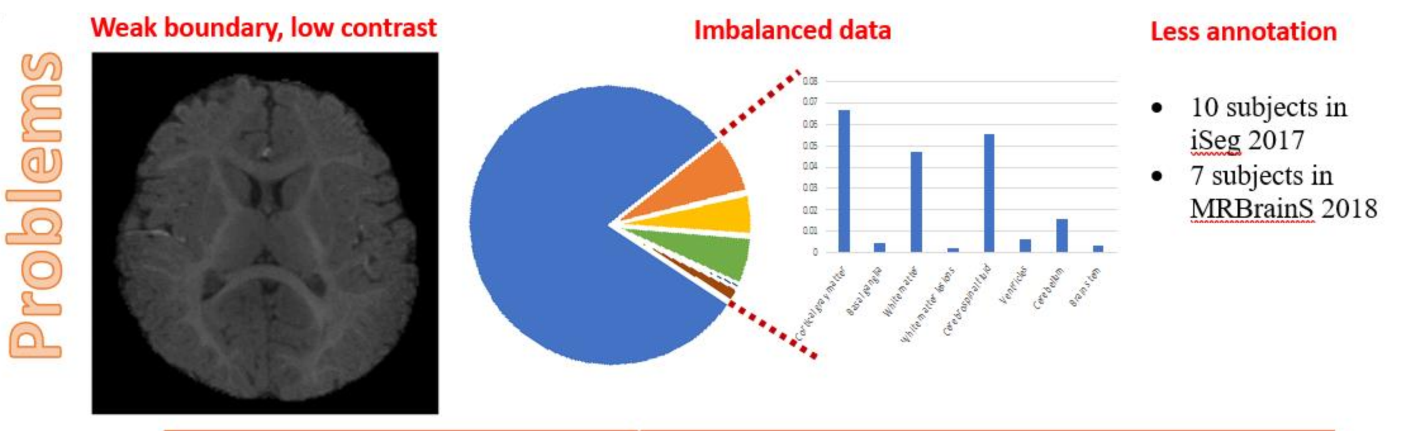
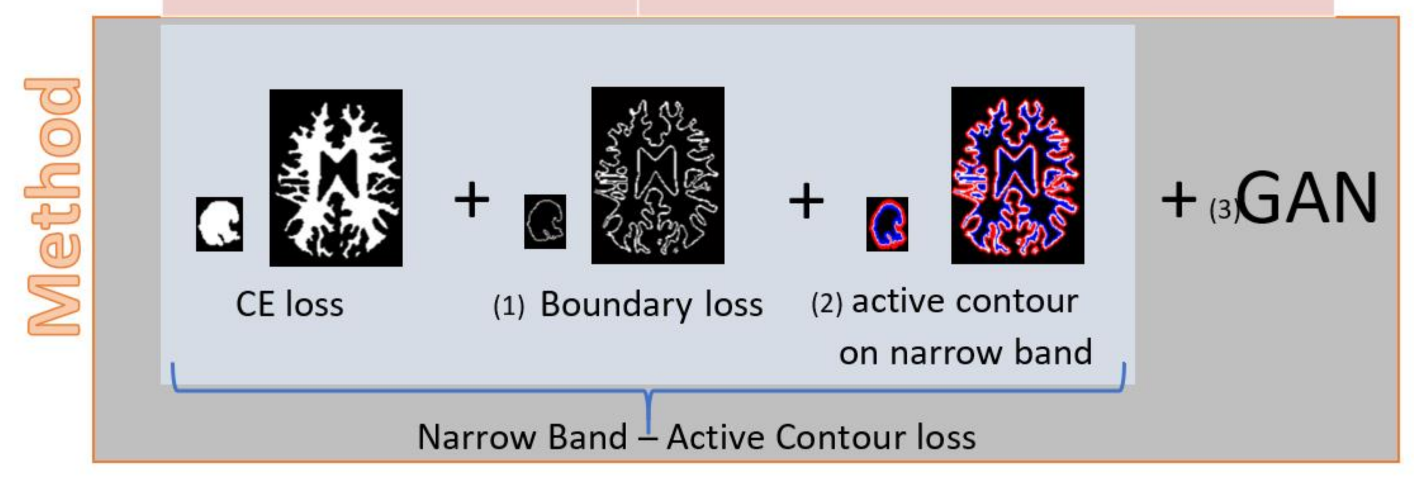
Active Contour Unet with Transfer Learning for Medical Image Segmentation

Different tissues segmentation has been considered as one of the most challenging works in medical image processing (the problem considered here is for the brain), even with the effective support of deep learning methods. Given the 3D multi-modality MRI images, we have to analyze based on the intensity contrast of these input images. These MRI images will try to capture the brain cross-sectional anatomy under different MRI machine settings at the time of capture, leading to the multi-modality input. The figure below shall illustrate this:



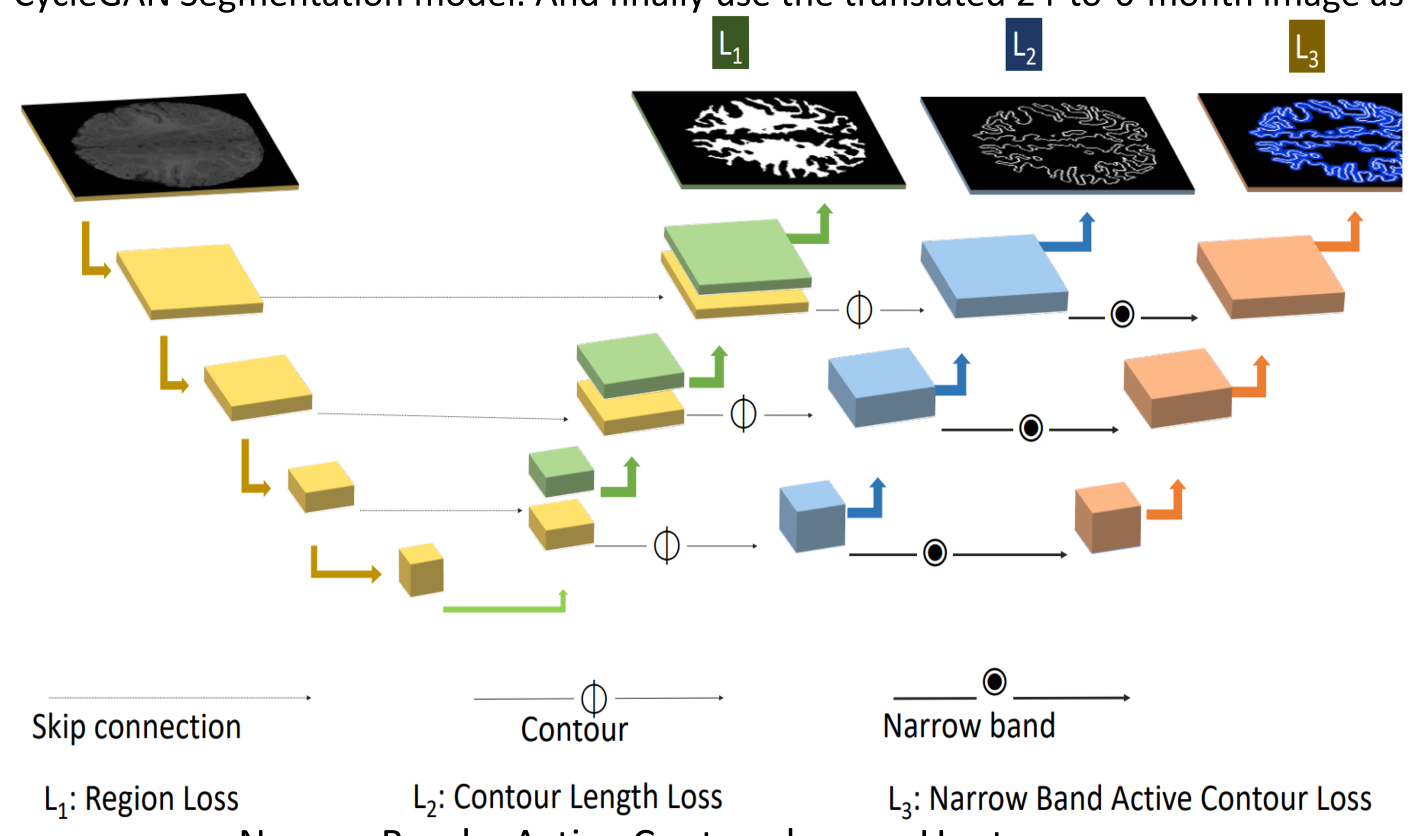


Problems	Our Solutions
Weak boundary, low contrast	(1) **Attention gate** on the edge
Imbalanced data	(2) Focus on narrow band around the contour under **level set energy minimization**
Less annotation	(3) **Transfer learning** by GAN

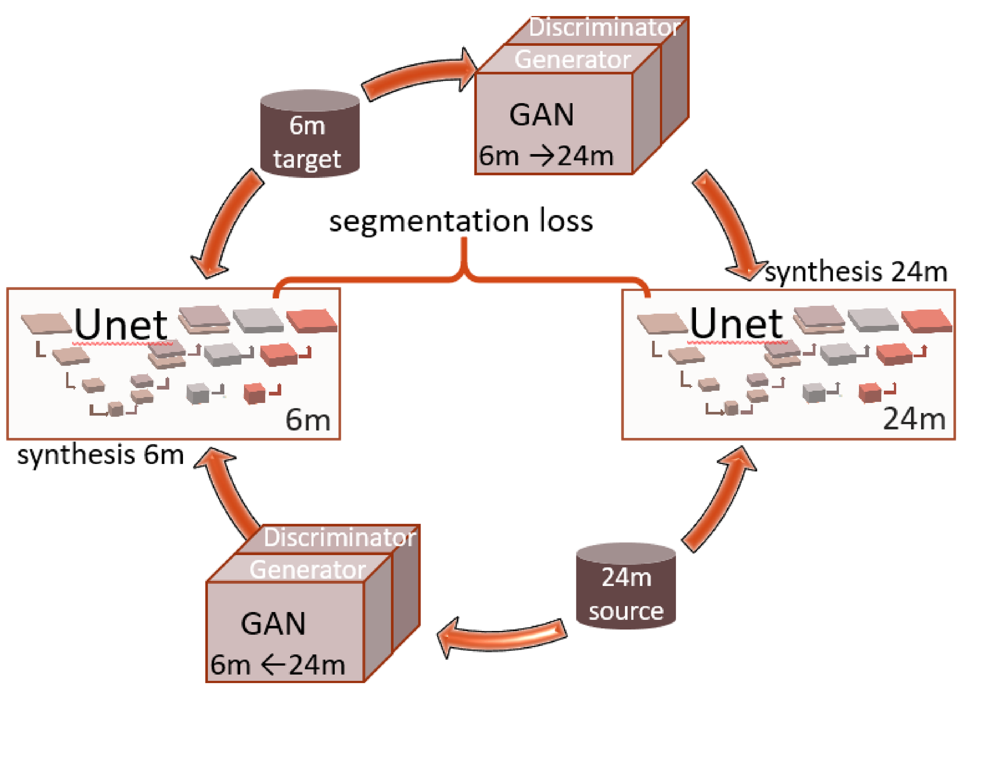


As shown above, the two main tasks here in brain image segmentation are to (1) distinguish different parts of the human brain (e.g. grey matter, white matter, cerebrospinal fluid, etc.) for a deeper understanding of the topological structure and to (2) determine exact pixels of lesion or brain tumors (e.g. whole tumor, core tumor, enhancing tumor). Here, the **commonly** encountered **problems** are (1) weak boundary, low contrast, (2) imbalanced data, (3) less annotation. For the corresponding problems, our proposed **solutions** respectively are (1) **attention gate** on the edge, (2) focus on the narrow band around the contour under **level set energy minimization**, (3) **transfer learning** by GAN. We ***proposed a loss function*** named **Narrow Band – Active Contour (NB-AC) loss**, a combination of solutions 1 and 2, able to use as an objective function and train as an end-to-end network.

However, due to the limitation in the number of available MRI brain images, especially those with ground truth annotations, several tasks suffer the less annotation problem. For these task, for instance in iSeg, we have only a few subjects with labels for the 6-month target dataset, while more are available for 24-month. Hence, we adapt the model from Toan Duc Bui et al. trying to translate image from 24 month to 6 month assuming that the topological structure remain. So, we will first need to train independent 6 month and 24 month AC Unets, then train the CycleGAN Segmentation model. And finally use the translated 24-to-6-month image as an augmentation method for the 6-month Unet.



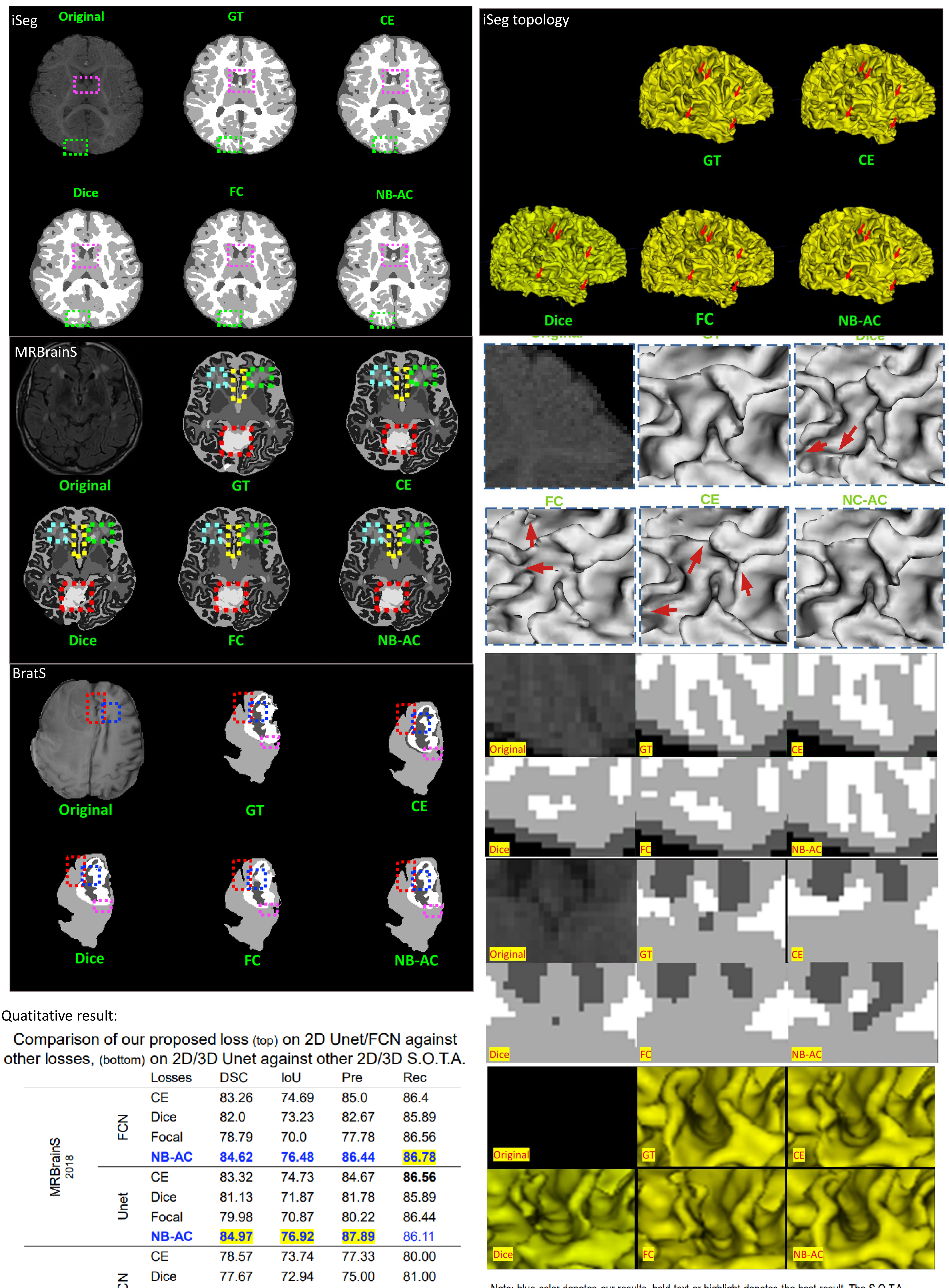
Narrow Band – Active Contour loss on Unet



Cycle GAN Segmentation

We also conducted several **experiments**: (1) an level set post-processing method to check whether it is promising on our collected dataset; (2) experiments and comparison of NB-AC loss (with cross-entropy loss, dice score, focal loss) trained using 2D/3D Unet and FCN on three datasets (iSeg 2019, MRBrainS18, BRATS 2018), evaluated with different metrics (dice score coefficient, intersection over union, precision, recall) for an overview performance of the proposed loss, with qualitative and quantitative results as well as the topology view; (3) transfer knowledge from Cycle GAN Segmentation model to the proposed 3D dense Unet with NB-AC loss. The figures on the next pages show the overview of this work. Also, this work is currently under review as "*Narrow Band Active Contour Attention Model for Imbalanced-Class and Weak Boundary in Medical Segmentation*", at IEEE Transactions on Image Processing, IF: 6.79.

Qualitative result:



Quatitative result:

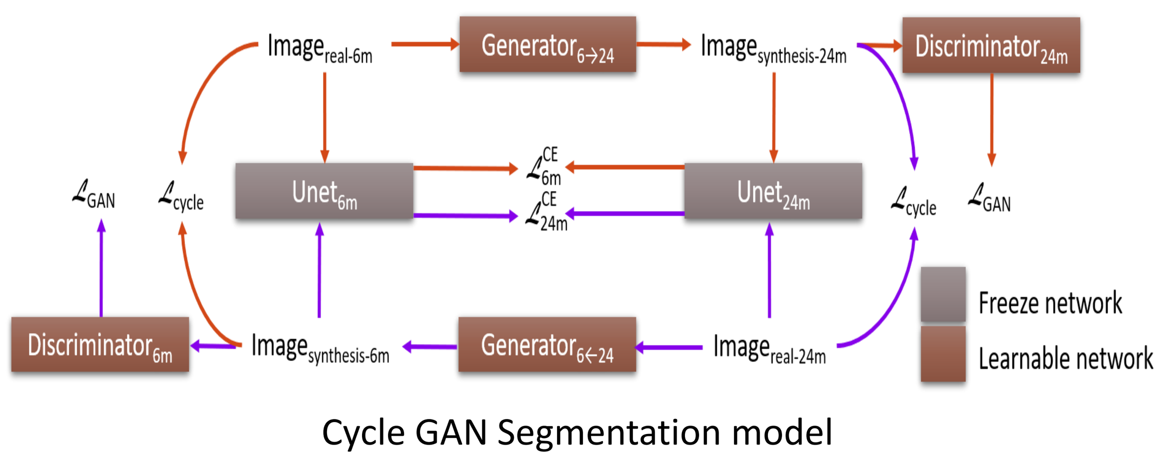
Comparison of our proposed loss (top) on 2D Unet/FCN against other losses, (bottom) on 2D/3D Unet against other 2D/3D S.O.T.A.

Dataset	Network	Losses	DSC	IoU	Pre	Rec
MRBrainS 2018	FCN	CE	83.26	74.69	85.0	86.4
		Dice	82.0	73.23	82.67	85.89
		Focal	78.79	70.0	77.78	86.56
		NB-AC	**84.62**	**76.48**	**86.44**	**86.78**
	Unet	CE	83.32	74.73	84.67	**86.56**
		Dice	81.13	71.87	81.78	85.89
		Focal	79.98	70.87	80.22	86.44
		NB-AC	**84.97**	**76.92**	**87.89**	86.11
BRATS 2018	FCN	CE	78.57	73.74	77.33	80.00
		Dice	77.67	72.94	75.00	81.00
		Focal	72.33	68.08	69.00	78.00
		NB-AC	**79.96**	**75.16**	**79.66**	**80.33**
	Unet	CE	79.40	74.59	78.33	81.00
		Dice	78.21	73.44	77.33	78.67
		Focal	76.38	**78.93**	68.00	**87.00**
		NB-AC	**80.38**	75.48	**81.25**	82.19
iSeg 2019	FCN	CE	87.95	83.91	90.25	91.75
		Dice	86.44	82.14	89.50	90.25
		Focal	83.19	78.51	87.25	88.00
		NB-AC	**88.95**	**85.11**	**91.50**	**92.25**
	Unet	CE	88.91	85.06	91.25	**92.25**
		Dice	87.19	83.01	90.03	90.50
		Focal	87.07	82.90	89.75	91.00
		NB-AC	**89.73**	**86.05**	**92.25**	92.00

	Datasets	DSC	Recall
2D	Brats18 [[1]/**Ours**]	77.75 / **80.38**	80.1 / **82.19**
	MRBrainS18 [[2]/**Ours**]	82.48 / **84.97**	– / **86.11**
	iSeg19 [[3]/**Ours**]	89.00 / **89.73**	– / **92.00**
3D	Brats18 [[4]/**Ours**]	84.87/**85.67**	– / **86.47**
	MRBrainS13 [[5]/**Ours**]	**87.17**/87.02	– / **87.89**
	iSeg19 [[6]/**Ours**]	92.55 / **93.07**	92.64 / **93.16**

Note: blue color denotes our results, bold text or highlight denotes the best result. The S.O.T.A. methods above are:

1. Shengcong Chen, Changxing Ding, and Minfeng Liu. Dual-force convolutional neural networks for accurate brain tumor segmentation. Pattern Recognition, 88:90–100, 2019.
2. Reuben Dorent, Wenqi Li, Jinendra Ekanayake, Sebastien Ourselin, and Tom Vercauteren. Learning joint lesion and tissue segmentation from taskspecific hetero-modal datasets. arXiv preprint arXiv:1907.03327, 2019.
3. Kevin Pham, Xiao Yang, Marc Niethammer, Juan C Prieto, and Martin Styner. Multiseg pipeline: automatic tissue segmentation of brain mr images with subject-specific atlases. In Medical Imaging 2019: Biomedical Applications in Molecular, Structural, and Functional Imaging, volume 10953, page 109530K. International Society for Optics and Photonics, 2019.
4. Richard McKinley, Raphael Meier, and Roland Wiest. Ensembles of densely-connected cnns with label-uncertainty for brain tumor segmentation. In Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries, pages 456–465, 2019.
5. Hao Chen, Qi Dou, Lequan Yu, Jing Qin, and Pheng-Ann Heng. Voxresnet: Deep voxelwise residual networks for brain segmentation from 3d mr images. NeuroImage, 170:446 – 455, 2018.
6. Toan Duc Bui, Jitae Shin, and Taesup Moon. 3d densely convolutional networks for volumetric segmentation. arXiv preprint arXiv:1709.03199, 2017.



Cycle GAN Segmentation model