

Point-Unet: A Context-aware Point-based Neural Network for Volumetric Segmentation

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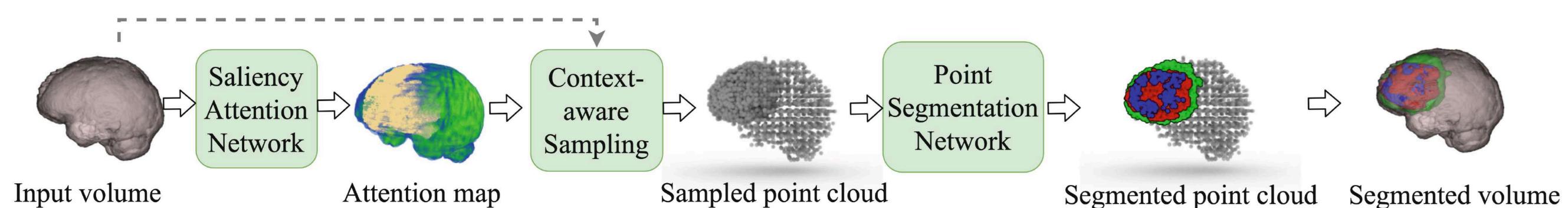
Binh-Son Hua^{1,2}



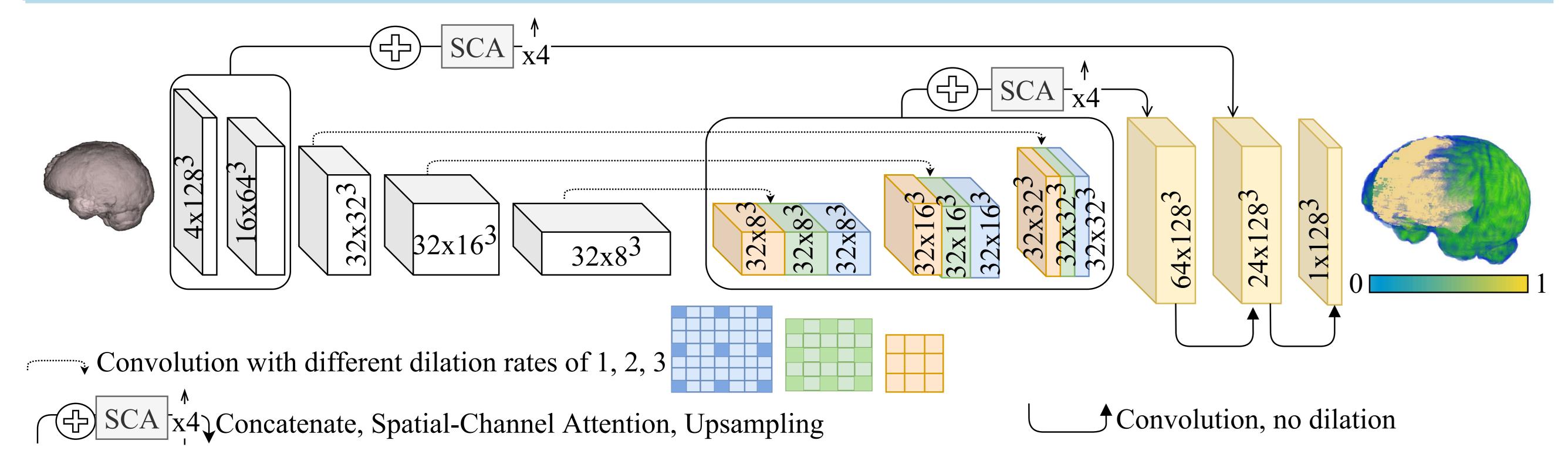
Contributions

- Point-Unet, a new network base on Point Cloud sloved 3D Medical Segmentation
- A saliency proposal network to extract an attentional probability map for an efficient point sampling
- The state-of-the-art accuracy and efficiency are achieved on 3D medical image semantic segmentation





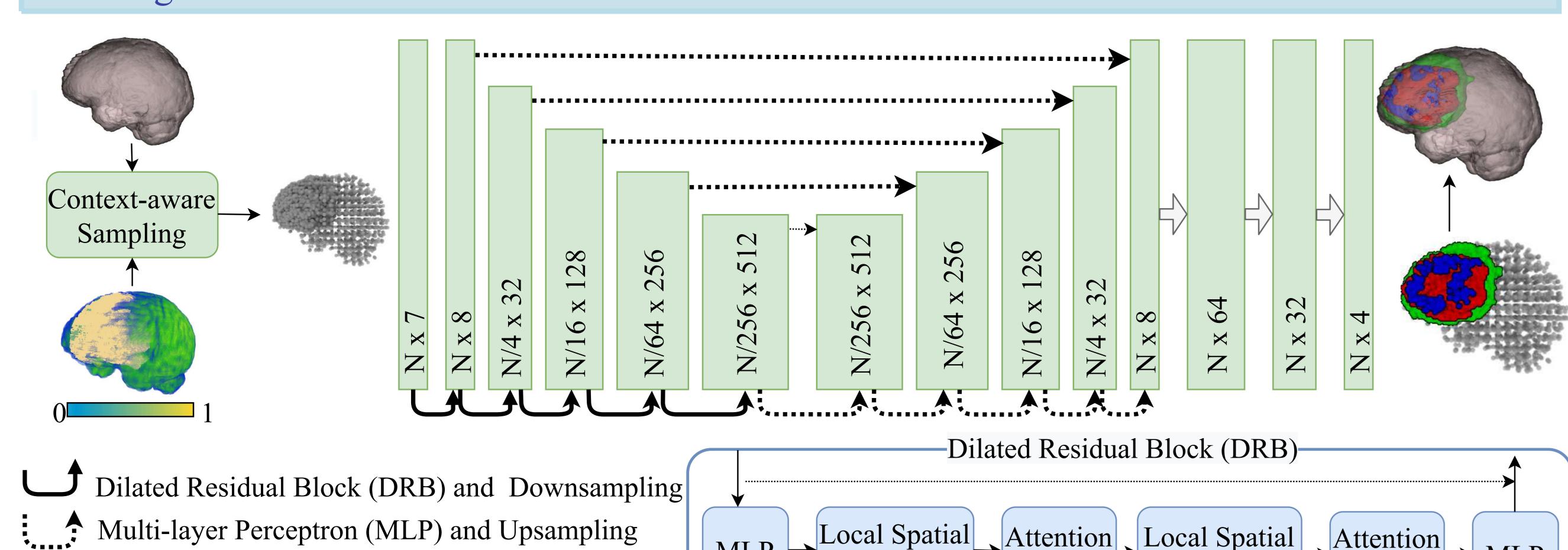
Saliency Attention Network



Point Segmentation Network

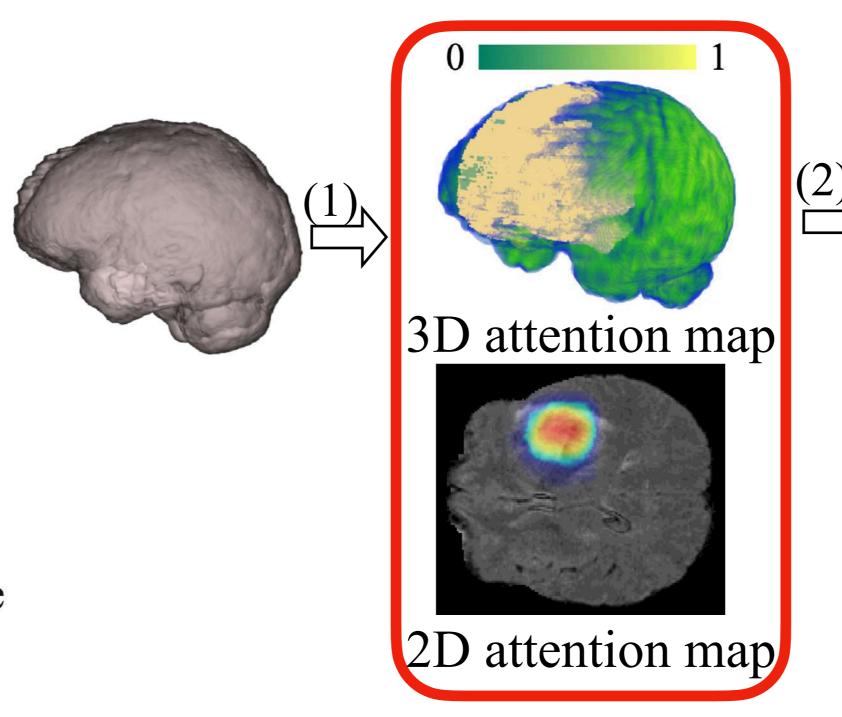
Skip connection

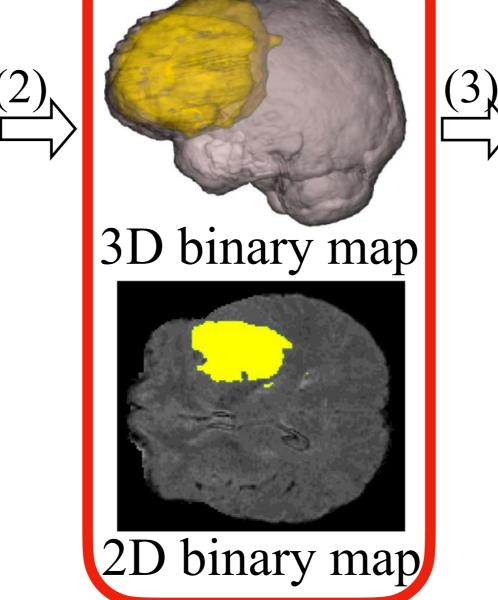
Fully connected layer



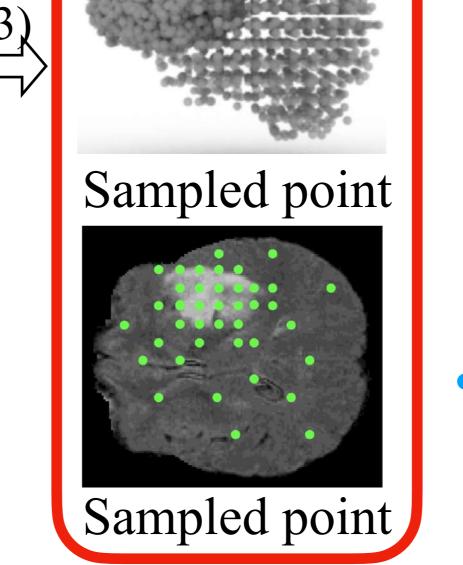
MLP Local Spatial Attention Local Spatial Attention MLP

Context-aware Sampling





(2) Binary map based



- Sampling based on output of saliency attention, so samples are focused on regions of interest

• Dense sampling in ROI on 3D attention map

Sparse sampling outside ROI

Quantitative Results

Saliency Attention
Network

$\operatorname{BraTS20}$	Offline validation set			Online validation set			
Methods	Dice score ↑		HD95 ↓	Methods	Dice score ↑		HD95 ↓
	ET/WT/TC	AVG	AVG		ET/WT/TC	AVG	AVG
3DUnet [15]	66.92/82.86/72.98	74.25	30.19	3DUNet [35]	67.66/87.35/79.30	78.10	21.16
nnNet [12]	73.64/80.99/81.60	78.74	14.33	$nnNet [12]^a$	68.69/81.34/78.06	78.03	24.30
aeUnet [25]	71.31/84.72/79.02	78.35	15.43	$nnUNet [10]^c$	77.67/90.60/84.26	84.18	15.30
				aeNet $[25]^a$	64.00/83.16/74.66	73.95	33.91
				Cascade [21] ⁴	$\frac{78.81}{89.92}$	<u>83.60</u>	<u>12.00</u>
				KiUNet [33]	73.21/87.60/73.92	78.24	8.38
RandLA [8]	$67.40/\underline{87.74}/76.85$	77.33	7.03	RandLA [8]	66.31/88.01/77.03	77.17	16.65
Ours	76.43/89.67/82.97	83.02	8.26	Ours	78.98 / <u>89.71</u> / <u>82.75</u>	83.81	11.73

- ^a Reproduce the results on the network trained with 100 epochs.
- We choose the model with as similar batch size as ours.
- ^c We choose single model with 190 epoches, stage 1. The best model at Brats2020.

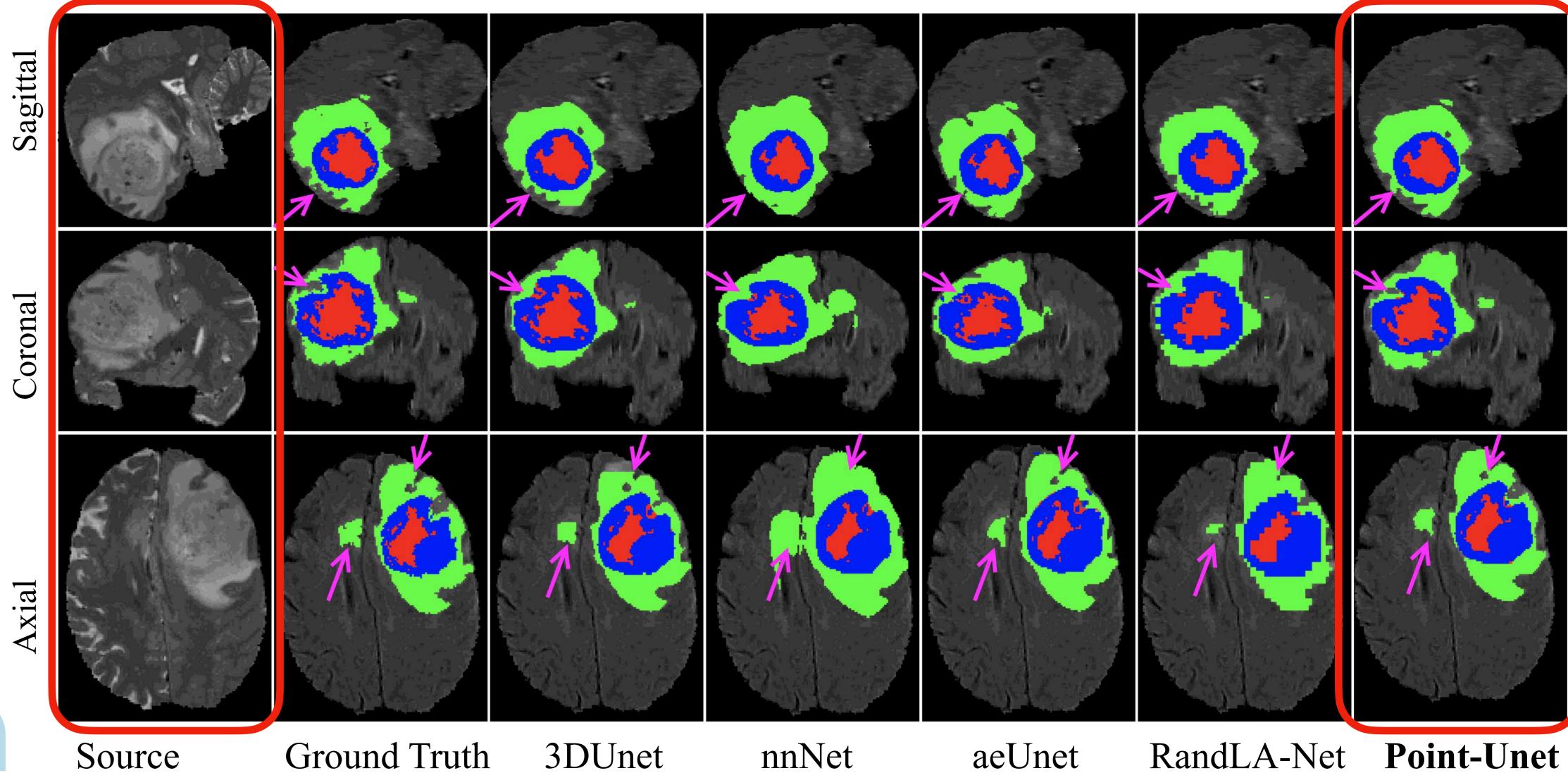
Comparison on BraTS20. The best, second best and third best are highlighted

Method	Average ↑	Method	Average ↑	
Oktay et al. [27]	83.10 ± 3.80	Yu et al. [40]	84.50 ± 4.97	
Zhu et al. [43]	84.59 ± 4.86	Ours	85.68 ± 5.96	

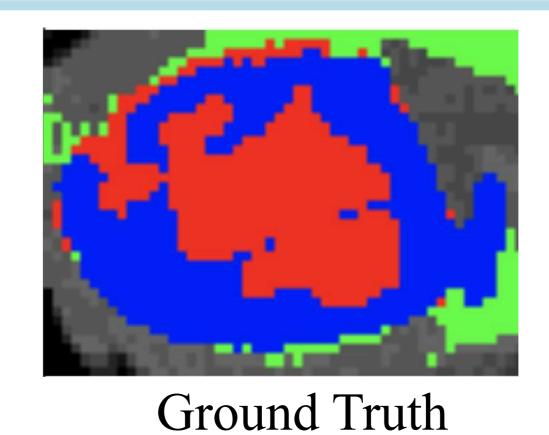
Dice score comparison on Pancreas dataset

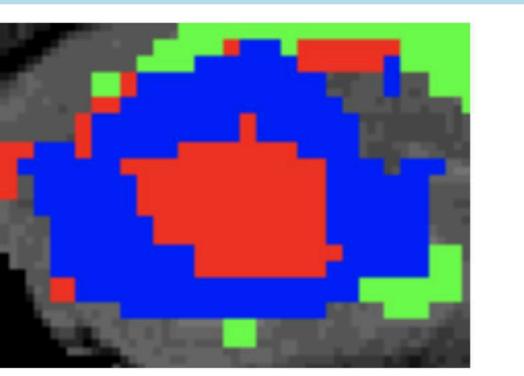
Code: https://github.com/VinAIResearch/Point-Unet

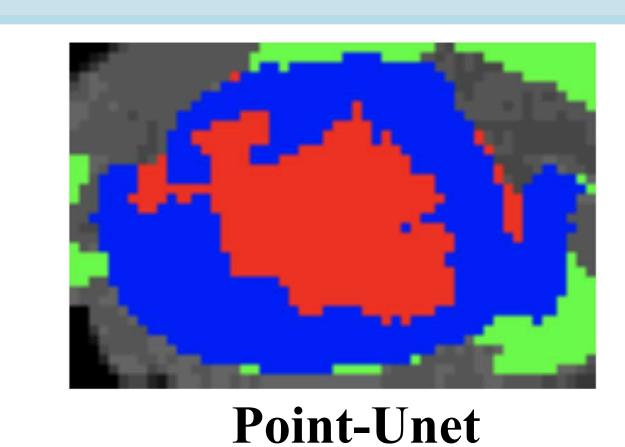
Quantitative Results



Efficiency of Context-aware Sampling

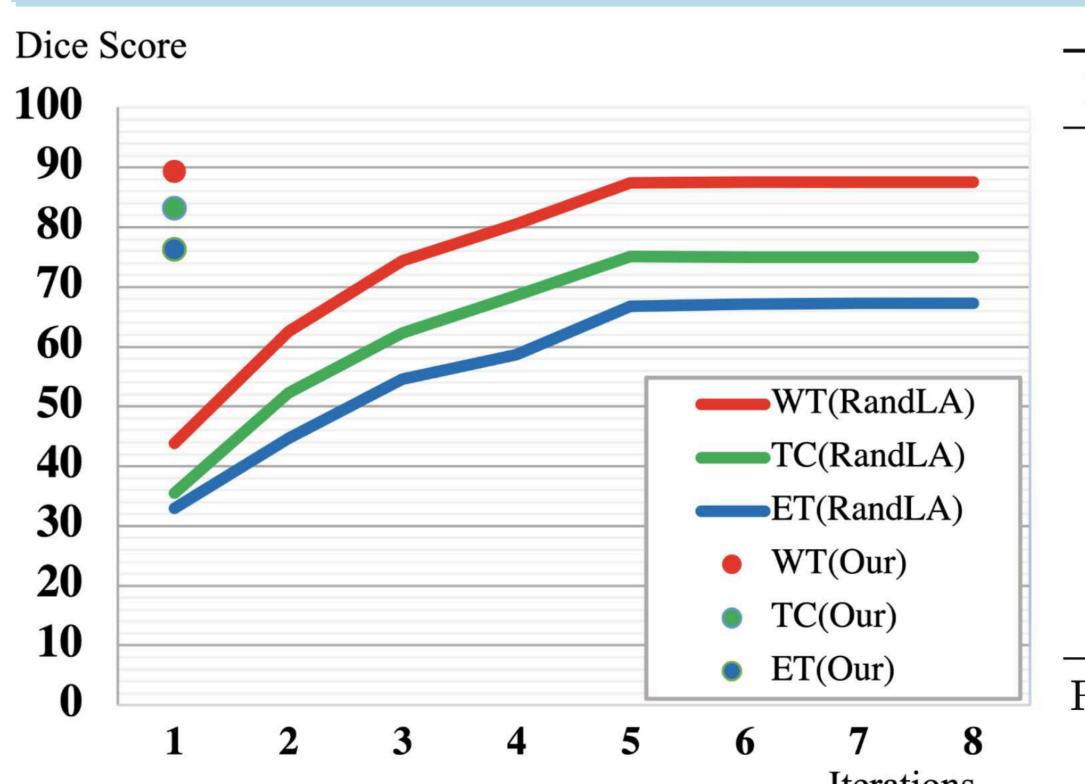






RandLA-Net Point-Unet has good boundaries. RandLA-Net has several zigzag artifact at boundaries

Performance Analysis



Networks	Patch size	Memory \downarrow	Inference \downarrow
3DUnet baseline [15]	$128 \times 128 \times 128$ $160 \times 192 \times 128$ $240 \times 240 \times 144$	8.75 GB 16.70 GB 32.00 GB	7.80 s 0.28 s 0.23 s
$\begin{array}{c} \mathrm{nnNet} \\ [12] \end{array}$	$128 \times 128 \times 128$ $160 \times 192 \times 128$ $240 \times 240 \times 144$	7.20 GB 11.10 GB 21.70 GB	55.30 s 26.50 s 2.30 s
aeUnet [25]	$128 \times 128 \times 128$ $160 \times 192 \times 128$ $240 \times 240 \times 144$	17.21 GB 31.42 GB >48.00 GB	110.40 s 78.80 s 7.10 s
RandLA[8]	$240\times240\times155$	$15.98~\mathrm{GB}$	8.00 s
(Ours)	$240\times240\times155$	17.22 GB	1.24 s
• 0			

Point-Unet requires just a single iteration for inference, having high accuracy and relatively low memory footprint.