Paper Title

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Abstract

Graph Neural Networks (GNN) is an emerging field for learning on non-Euclidean data. Recently, there has been great interest in designing GNN that scales to large graphs. Most existing techniques use “graph sampling” or “layer-wise sampling” technique to reduce training time.

解决了什么问题？论文主要工作？效果如何？

1 Method

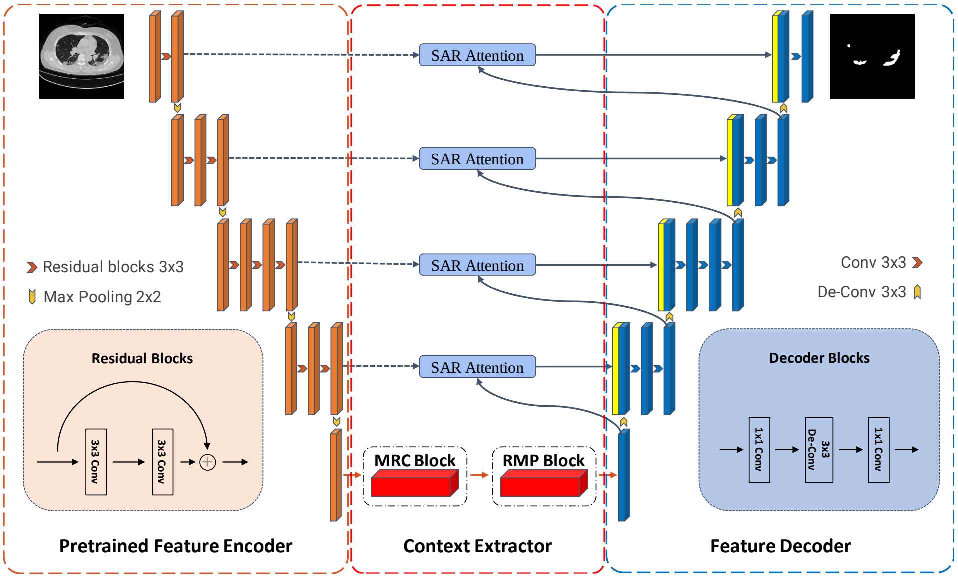

图 1: Illustration of our proposed network.

34th Conference on Neural Information Processing Systems (NeurIPS 2020), Vancouver, Canada.

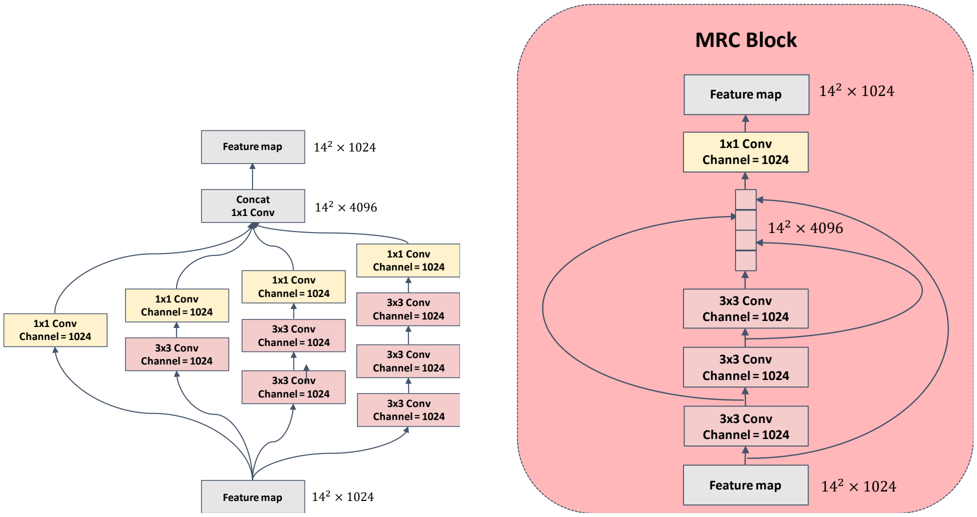

图 2: (1) is the illustration of DAC Block. (1) is the illustration of MRC Block.

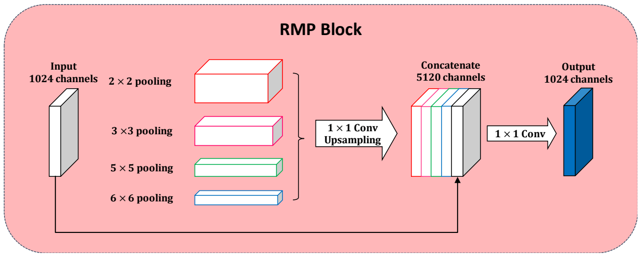

图 3: Illustration of RMP Block.

表 1: Memorize Cost Comparison With Different Methods In Bottleneck

Backbone	Components	Params	Params size
ResU-Net	SAR+DAC+RMP(CE-Net)	135,571,137	517.16
ResU-Net	SAR+ASPP	92,573,377	353.14
ResU-Net	SAR+MRC+RMP	94,669,505	361.14

2 Experiments

2.1 Baseline and implementation

We used a server equipped with an Intel Core i9-9980XE CPU @ 3.00GHz with 64GB RAM and 12GB of RTX2080Ti GPU for our proposed networks training. The operating system of the sever is 64-bits Ubuntu 18.04. The structure of the network is implemented under the open source deep learning library Pytorch with VSCode implementation.

2.2 Dataset

For this study, we conduct our experiments on four differents segmentation tasks. Covering lesions/organs from most commonly used medical imaging modalities including microscopy, computed tomography (CT), and magnetic resonance imaging (MRI). Table 2 summarize those datasets in our study.

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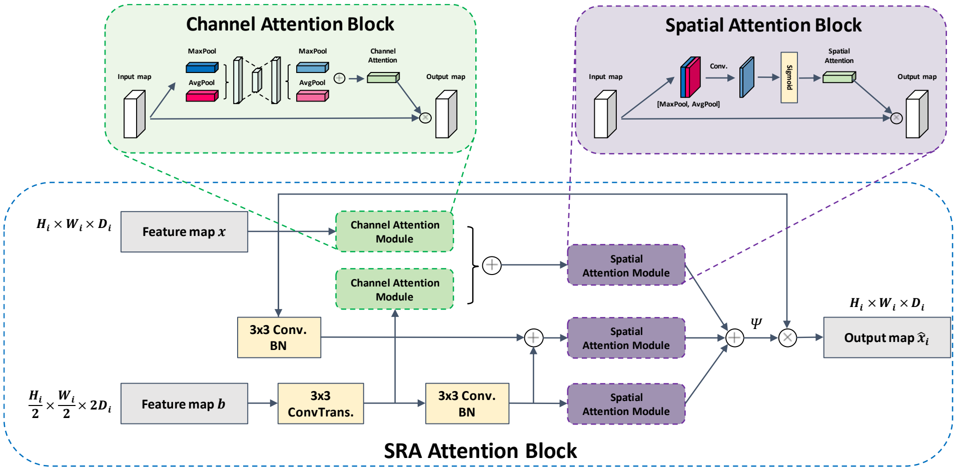

图 4: Illustration of SRA Attention Block

表 2: Summaey Of Biomedical Image Segmentation Datasets Used In Our Experiments

Dataset	Image	Input Size	Modality	Provider
Cell	30	512 × 512	EM	ISBI 2012[**?**]
Liver	4,000	512 × 512	CT	MICCAI 2017 LiTS[**?**]
DSB2018	670	256 × 256	EM	Kaggle[**?**]
COVID19	1,800	630 × 630	CT	Web[**? ?**]

Cell The datset is the segmentation of neuronal structures in electron microscopic recordings. The dataset is provided by the EM segmentation challenge[**?**] that is started at ISBI 2012. The data is a set of 30 images (512 × 512 pixels) from serial section transmission electron microscopy of the Drosophila first instar larva ventral nerve cord (VNC). Each image comes with a corresponding fully annotated ground truth segmentation map for cells (white) and membranes (black).

Liver Liver tumor Segmentation Challenge (LiTS)[**?**] contain 131 contrast-enhanced CT images provided by hospital around the world with 512 × 512 resolution. The ground truth segmentation provides two different labels: liver and lesion. For our experiments, we only consider liver as positive class and others as negative class.

COVID19 Dataset[**?**] includes whole volumes and includes, therefore, both positive and negative slices (373 out of the total of 829 slices have been evaluated by a radiologist as positive and segmented). Dataset[**?**] contains 20 CT scans of patients diagnosed with COVID-19 as well as segmentations of lungs and infections made by experts. These volumes are converted and normalized in a similar way as above, meanwhile we resize the data to 512 × 512.

2.3 Evaluation metrics

The experiments are implemented using the Pytorch framework. We use Adam optimizer[**?**] as our models' optimizer with a learning rate of 0.00001, batch size of 2. All of datasets are splitted into training set and validation set with the ratio of 8:2 using sklearn library. To numerically evaluate, we use five widely adopted metrics, *i.e.*, the Dice similarity coefficient(Dice.), F1 score., Sensitivity(Sen.), Iou. and hausdorff distance(Hd)., the expressions of them are defined as follows:

$$\text{Sensitivity } = \frac{TP}{TP + FN} \tag{1}$$

$$\mathrm{DSC}(G, S) = \frac{2|G \cap S|}{|G| + |S|} \tag{2}$$

$$\mathrm{IOU}(G, S) = \frac{|G \cap S|}{|G| \cup |S|} \tag{3}$$

$$F_1 = 2 \cdot \frac{\text{precision } \cdot \text{ recall}}{\text{precision } + \text{ recall}} \tag{4}$$

$$h(G, S) = \max_{g \in G} \left\{ \min_{c \in C} \|g - c\| \right\} \tag{5}$$

2.4 Medical image Segmentation Results

For comparsion, we use five origianl network FCN with 32s[**?**], U-Net[**?**], U-Net++[**?**] , CE-Net[**?**] and U-Net with Attention Gate[**?**] to evaluate our proposaed method.

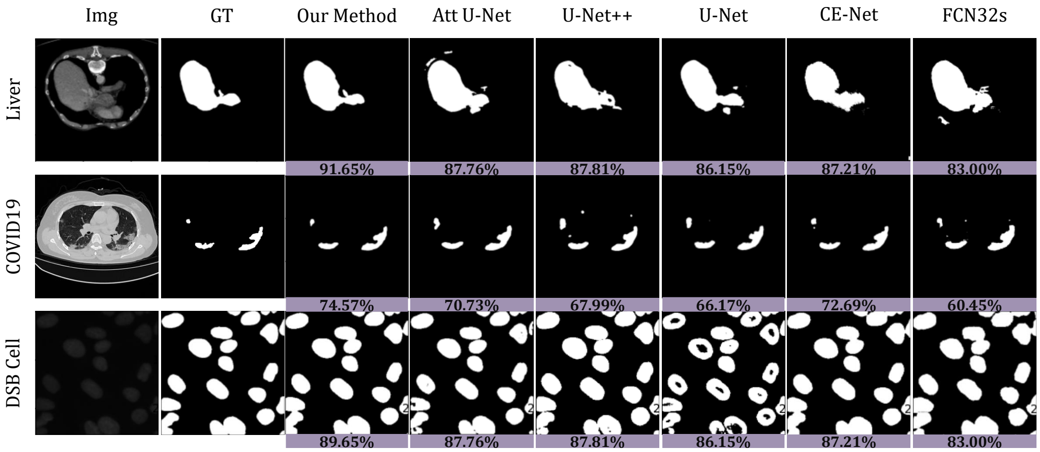

图 5: Medical image segmentation examples.

2.4.1 Performance in Cell segmentation task

Segmentation results of cell segmentation are shown in table3,

表 3: Comparsion With Other Methods In Cell[**?**] Dataset

Methods	Shape Loss	Dice.	F1 score.	Iou.	Sens.	Hd.
Our proposal	√	**0.8588**	**0.8588**	**0.7623**	**0.9296**	**4.6224**
CENet	×	0.8458	0.8458	0.7418	0.8316	5.2098
UNet++	×	0.8439	0.8439	0.7396	0.8643	5.5307
Attention UNet	×	0.8153	0.8153	0.7015	0.8557	5.3695
UNet	×	0.7977	0.7977	0.6893	0.8115	5.5049
FCN32s	×	0.6895	0.6895	0.5653	0.7760	7.1192

2.4.2 Performance in liver segmentation task

Segmentation results of cell segmentation are shown in table4,

表 4: Comparsion With Other Methods In Liver[?] Dataset

Methods	Shape Loss	Dice.	F1 score.	Iou.	Sens.	Hd.
Our proposal	√	**0.9551**	**0.9551**	**0.9165**	**0.9389**	**3.8854**
U-Net++	×	0.9351	0.9351	0.8781	0.9156	5.8218
Attention UNet	×	0.9346	0.9346	0.8776	0.9056	4.836
CENet	×	0.9315	0.9315	0.8721	0.9045	4.904
U-Net	×	0.9253	0.9253	0.8615	0.9106	6.6785
FCN32s	×	0.9065	0.9065	0.8300	0.9381	7.97

2.4.3 Performance in covid19 lesion segmentation task

Segmentation results of cell segmentation are shown in table5,

表 5: Comparsion With Other Methods In COVID19[?] Dataset

Methods	Shape Loss	Dice.	F1 score.	Iou.	Sens.	Hd.
Our proposal	√	**0.8489**	**0.8489**	**0.7457**	**0.8570**	**4.313**
CENet	×	0.8348	0.8348	0.7290	0.9359	4.7711
UNet++	×	0.8014	0.8014	0.6799	0.9426	5.0301
Attention UNet	×	0.8229	0.8229	0.7073	0.9435	4.8845
UNet	×	0.7874	0.7874	0.6617	0.9528	5.2231
FCN32s	×	0.7409	0.7409	0.6045	0.9935	5.8644

2.4.4 Performance in lung segmentation task

Segmentation results of cell segmentation are shown in table6,

表 6: Comparsion With Other Methods In Lung[?] Dataset

Methods	Shape Loss	Dice.	F1 score.	Iou.	Sens.	Hd.
Our proposal	√	**0.9392**	**0.9392**	**0.8965**	**0.9261**	**10.19714**
UNet++	×	0.9351	0.9351	0.8781	0.9156	5.8218
Attention UNet	×	0.9346	0.9346	0.8776	0.9056	4.836
CENet	×	0.9315	0.9315	0.8721	0.9045	4.904
UNet	×	0.9253	0.9253	0.8615	0.9106	6.6785
FCN32s	×	0.9065	0.9065	0.8300	0.9381	7.97

2.5 Ablation study

To justify the effectiveness of the pretrained U-Net[?], Res-UNet[?], MRC(multi residual convolution) block, RMP block and SAR(spatial channel and gateway) Attention block in our proposed method, we conduct the following ablation study using the COVID19 and Cell dataset as examples:

表 7: Comparsion With Other loss functions In COVID19[?] Dataset

Methods	Loss	Dice.	F1 score.	Iou.	Sens.	Hd.
Our proposal	BCE	0.8076	0.8076	0.6874	0.8772	5.0112
Our proposal	BCE+DiceLoss	0.8375	0.8375	0.7282	0.8827	4.7241
Our proposal	Ours	0.8489	0.8489	0.7457	0.8570	4.4313

表 8: Ablation study for each component on COVID19 dataset

Methods	Loss	Dice.	F1 score.	Iou.	Sens.	Hd.
U-Net	BCE	0.7874	0.7874	0.6617	0.9528	5.2231
ResU-Net	BCE	0.8105	0.8105	0.6923	0.9601	5.0248
ResU-Net + MRC + RMP	BCE	0.8185	0.8185	0.7030	0.9295	4.8931
ResU-Net + SAR	BCE	0.7988	0.7988	0.6846	0.7969	5.1522
ResU-Net+SAR+MRC+RMP	BCE	0.8076	0.8076	0.6874	0.8772	5.0112
ResU-Net+SAR+MRC+RMP	Ours	**0.8489**	**0.8489**	**0.7457**	**0.8570**	**4.313**

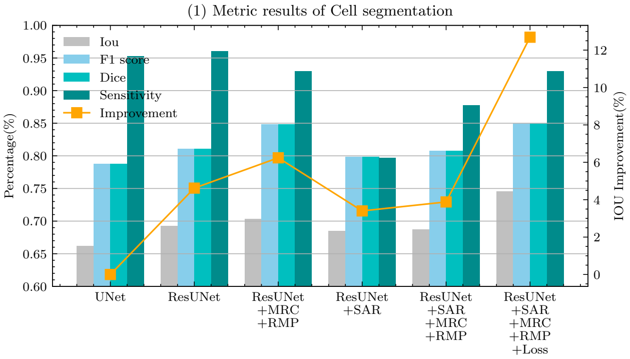

图 6: Fig 1 shows ; Fig 2 shows; Fig 3 shows; Fig 4 shows;Fig5 shows.

表 9: Ablation study for each component on Cell dataset

Methods	Loss	Dice.	F1 score.	Iou.	Sens.	Hd.
U-Net	BCE	0.7977	0.7977	0.6893	0.8115	5.5049
ResU-Net	BCE	0.8314	0.8314	0.7274	0.9685	5.5861
ResU-Net + MRC + RMP	BCE	0.8448	0.8448	0.7414	0.9714	5.0647
ResU-Net + SAR	BCE	0.8545	0.8545	0.7534	0.9669	4.9601
ResU-Net+SAR+MRC+RMP	BCE	0.8525	0.8525	0.7598	0.9744	4.9210
ResU-Net+SAR+MRC+RMP	Ours	**0.8588**	**0.8588**	**0.7623**	**0.9296**	**4.6224**

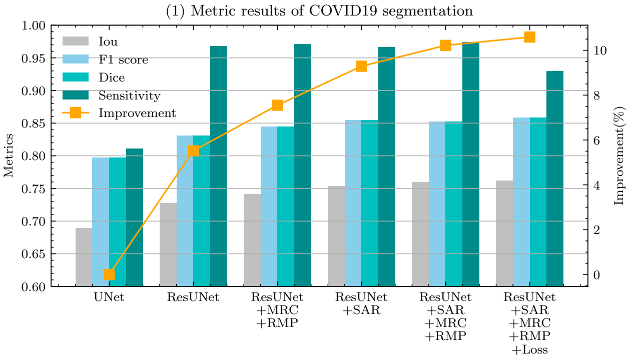

图 7: Fig 1 shows ; Fig 2 shows; Fig 3 shows; Fig 4 shows;Fig5 shows.

3 Conclusion

Acknowledgments