# Recurrent Mask Refinement for Few-Shot Medical Image Segmentation

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## 1. Supplementary #1

Regarding the selection of support and query images, we used randomly chosen pairs of support and query images, instead of one fixed support, in order to make sure that our results are not biased by a particular choice of support/query pairs in Table 1. Among the three datasets (ABD-110, ABD-30 and ABD-MR) we tested, the selection of support/query images on ABD-110 are exactly the same for all compared methods. We ensured the same sequence of support/query pairs (albeit random) were used by fixing the seed of the random number generator. Our selection of support/query images was different for ABD-30 and ABD-MR from [1], which used a fixed support image. To ensure the results are directly comparable, we reran our method following exactly the same selection of support as in [1]. Our conclusion remains the same (Supplementary Table 1). Our result (labeled "RP-Net (fixed support)") shows the proposed method still outperforms the SOTA method by a large margin.

## References

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[3] Kaixin Wang, Jun Hao Liew, Yingtian Zou, Daquan Zhou, and Jiashi Feng. Panet: Few-shot image semantic segmentation with prototype alignment. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9197–9206, 2019. 2

| Dataset | Method | Spleen | Kidney L | Kidney R | Liver | mean |
|---|---|---|---|---|---|---|
| ABD-110 | PANet-init [3] | 30.95±1.09 | 19.24±0.37 | 17.64±0.71 | 49.91±0.34 | 29.43 |
| | PANet [3] | 35.89±1.75 | 40.22±1.71 | 41.54±0.82 | 52.36±0.60 | 42.50 |
| | SE-Net [2] | 29.48±1.07 | 37.48±2.08 | 37.53±1.97 | 19.09±0.36 | 30.89 |
| | SSL-ALPNet [1] | 64.90±1.62 | 61.58±2.53 | 64.05±2.27 | 71.83±1.81 | 65.59 |
| | Affine | 50.42±0.91 | 53.04±1.57 | 52.025±2.17 | 66.99±1.20 | 55.62 |
| | RP-Net (Ours) | **78.77±0.64** | **81.89±1.45** | **85.12±0.98** | **81.88±0.63** | **81.91** |
| ABD-30 | SE-Net [2] | 0.23 | 32.83 | 14.34 | 0.27 | 11.91 |
| | PANet-init [3] | 23.82 | 13.97 | 14.17 | 50.27 | 25.55 |
| | PANet [3] | 25.59 | 32.34 | 17.37 | 38.42 | 29.42 |
| | SSL-ALPNet [1] | 60.25 | 63.34 | 54.82 | 73.65 | 63.02 |
| | Affine | 48.99±1.48 | 43.44±2.04 | 45.67±1.45 | 68.93±0.88 | 51.75 |
| | RP-Net (Ours) | **69.85±2.34** | **70.48±2.55** | **70.00±0.89** | **79.62±0.91** | **72.48** |
| | RP-Net (fixed support) | 68.27 | 71.59 | 70.27 | 80.51 | 72.66 |
| ABD-MR | SE-Net [2] | 51.80 | 62.11 | 61.32 | 27.43 | 50.66 |
| | PANet-init [3] | 34.59 | 18.63 | 22.50 | 47.43 | 30.78 |
| | PANet [3] | 50.90 | 53.45 | 38.64 | 42.26 | 46.33 |
| | SSL-ALPNet [1] | 67.02 | 73.63 | 78.39 | 73.05 | 73.02 |
| | Affine | 62.87±1.80 | 64.70±4.71 | 69.10±1.15 | 65±1.65 | 65.41 |
| | RP-Net (Ours) | **76.35±0.66** | **81.40±2.10** | **85.78±1.12** | **73.51±1.55** | **79.26** |
| | RP-Net (fixed support) | 75.96 | 80.18 | 86.63 | 73.52 | 78.99 |

Supplementary Table 1: DSC comparison with other methods on ABD-110, ABD-30 and ABD-MR (unit: %).