# PH-Net: Semi-Supervised Breast Lesion Segmentation via Patch-wise Hardness

Supplementary Material

## 1. More hyper-parameters analysis

**Different weights for losses.** The impact of our proposed adaptive patch augmentation and hard-patch contrastive learning modules depends on the weights $\lambda_u$ and $\lambda_c$ of the unsupervised loss $\mathcal{L}_u$ and contrastive loss $\mathcal{L}_c$. Networks with low $\lambda_u$ and $\lambda_c$ cannot effectively utilize the effects of our modules, while high $\lambda_u$ and $\lambda_c$ might disrupt the training of the model on labeled data. Moreover, coordination between them is also necessary to prevent negative effects. Therefore, setting the weights for losses is quite significant for our method's effectiveness. Tab. 1 shows our ablation study for different $\lambda_u$ and $\lambda_c$. Our method obtains the best performance when both $\lambda_u$ and $\lambda_c$ are set to 1.

| $\lambda_u$ | $\lambda_c$ | UDIAT | | BUSI | |
|---|---|---|---|---|---|
| | | Dice(%) | IoU(%) | Dice(%) | IoU(%) |
| 0.5 | 0.5 | 85.06 | 74.02 | 75.88 | 61.10 |
| 0.5 | 1 | 85.58 | 74.80 | 75.97 | 61.23 |
| 1 | 1 | **86.23** | **75.80** | **76.84** | **62.39** |
| 1.5 | 1 | 86.10 | 75.60 | 76.47 | 61.88 |
| 1 | 1.5 | 85.44 | 74.59 | 76.09 | 61.38 |
| 1 | 0.5 | 85.61 | 74.85 | 75.92 | 61.15 |

Table 1. Ablation study of loss function weights based ResNet-50 on the UDIAT and BUSI datasets under 1/4 partition protocol.

**Different epochs for pre-training.** We pre-train the model before formal training, feeding only labeled data for the first few epochs. Too large pre-training epochs will make the model overly rely on labeled data and lead to poor generalization, while small epochs will make the pre-training insufficient and prevent the model from having basic segmentation ability before formal training. Therefore, the setting of the pre-training epoch is important for the subsequent training of the model. We ablate different pre-training epochs in Tab. 2, which shows that our method achieves the best results when the pre-training epoch is taken as 10.

| Epochs | UDIAT | | BUSI | |
|---|---|---|---|---|
| | Dice(%) | IoU(%) | Dice(%) | IoU(%) |
| 0 | 84.59 | 73.31 | 75.17 | 60.19 |
| 5 | 86.04 | 75.51 | 76.40 | 61.77 |
| 10 | **86.23** | **75.80** | **76.84** | **62.39** |
| 15 | 85.83 | 75.17 | 76.36 | 61.74 |
| 20 | 85.47 | 74.64 | 76.10 | 61.38 |

Table 2. Ablation study of pre-training epochs based ResNet-50 on the UDIAT and BUSI datasets under 1/4 partition protocol.

## 2. More ablation studies on BUSI

**Ablation of different components.** Tab. 3 illustrates the effectiveness of our method for each component on the BUSI dataset with ResNet-50 [4] as the backbone. It is obvious that Method III with all components superior to the other methods, fully demonstrating the validity of each component in our method.

| Method | APA | HPC | MB | Dice(%) | IoU(%) |
|---|---|---|---|---|---|
| SupOnly | | | | 73.69 | 58.34 |
| I | ✓ | | | 75.61 | 60.76 |
| II | ✓ | ✓ | | 76.59 | 62.04 |
| III | ✓ | ✓ | ✓ | **76.84** | **62.39** |

Table 3. Ablation study of different components on BUSI dataset under 1/4 partition protocol. APA: Adaptive Patch Augmentation. HPC: Hard-Patch Contrastive Learning. MB: Memory Bank.

**Ablation of hyper-parameters.** We conduct more ablation experiments on the BUSI dataset with ResNet-50 [4] as the backbone for the hyperparameters. For the patch shielding parameter $\beta$, the best performance is obtained when $\beta = 30\%$ as shown in Tab. 4. For the confidence threshold $\gamma$, it can be seen from Tab. 5 that taking 0.9 gives the best results for our method.

| $\beta$ | 0 | 10% | 20% | 30% | 40% |
|---|---|---|---|---|---|
| Dice(%) | 75.14 | 75.49 | 76.03 | **76.84** | 76.33 |
| IoU(%) | 60.15 | 60.60 | 61.30 | **62.39** | 61.70 |

Table 4. Ablation study of patch shielding parameter $\beta$ on the BUSI dataset under 1/4 partition protocol.

| $\gamma$ | 0.70 | 0.80 | 0.85 | 0.90 | 0.95 |
|---|---|---|---|---|---|
| Dice(%) | 75.91 | 76.39 | 76.51 | **76.84** | 76.60 |
| IoU(%) | 61.15 | 61.77 | 61.93 | **62.39** | 62.05 |

Table 5. Ablation study of confidence threshold $\gamma$ on the BUSI dataset under 1/4 partition protocol.

## 3. More visual comparison results

We perform more visual comparison with SupOnly and other eight state-of-the-art methods including CPS [2], PS-MT [6], U$^2$PL [8], iMAS [9], AugSeg [10], BCP [1], PDF-UNet [5] and RA-UGMT [3] on the UDIAT and BUSI datasets, with ResNet-50 [4] and U-Net [7] as the backbone, as shown in Fig. 1 and Fig. 2.

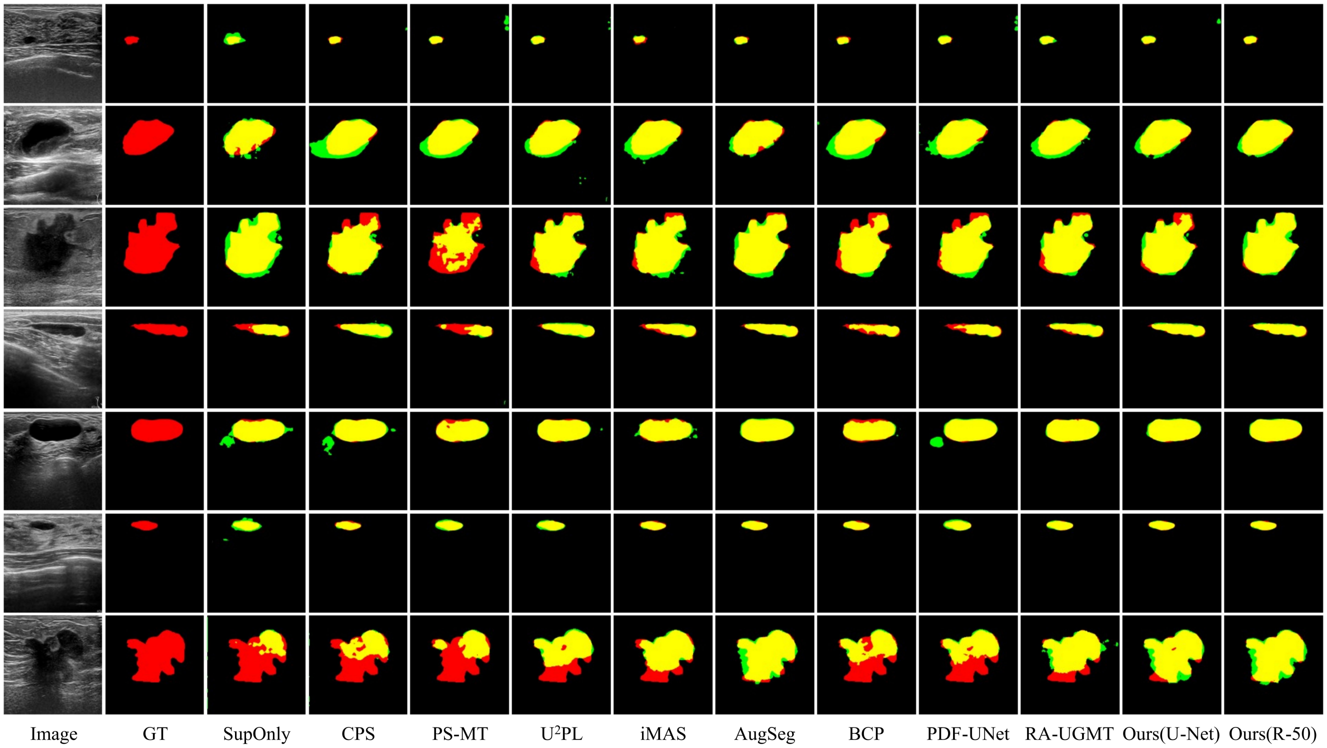


Figure 1. More visual comparison with different state-of-the-art methods on the UDIAT dataset under 1/4 partition protocol. Red, green and yellow regions represent ground truth, prediction and overlapping regions, respectively.

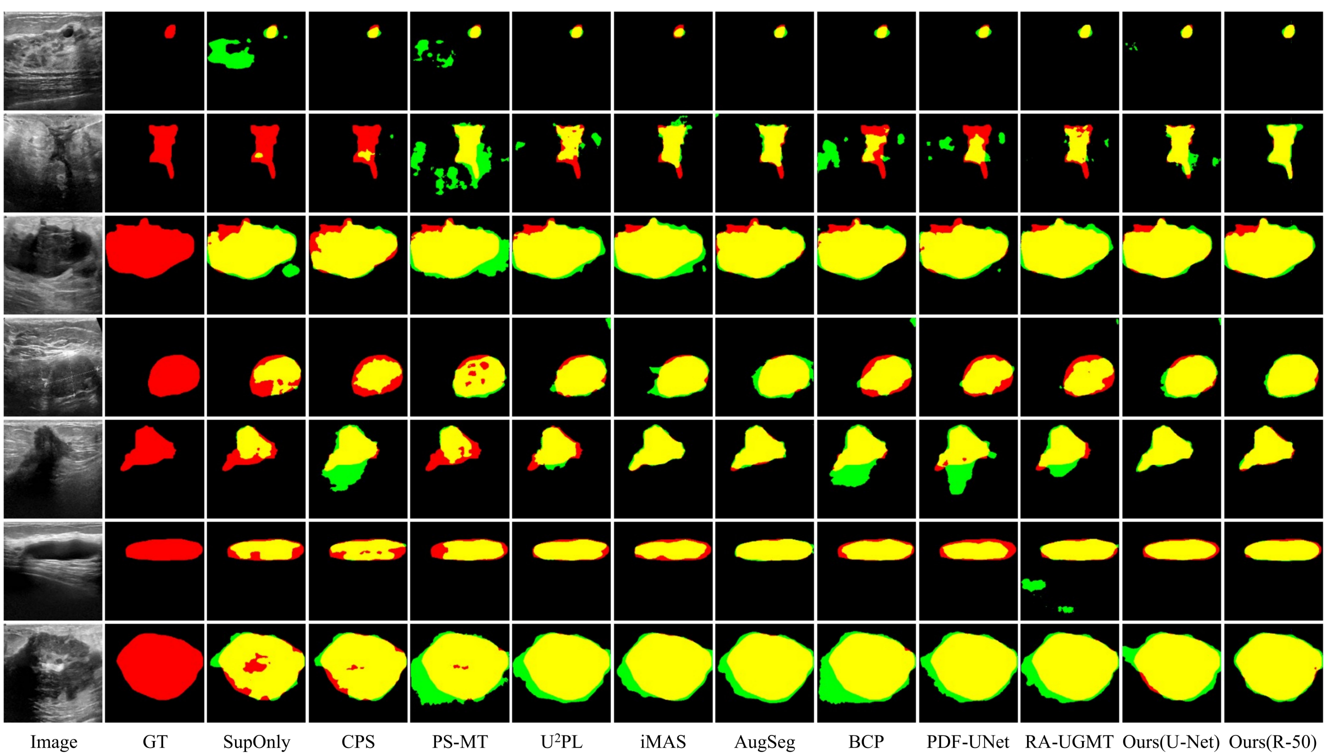


Figure 2. More visual comparison with different state-of-the-art methods on the BUSI dataset under 1/4 partition protocol. Red, green and yellow regions represent ground truth, prediction and overlapping regions, respectively.

## References


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