SEMI-SUPERVISED INFRARED MEIBOMIAN GLAND SEGMENTATION WITH INTRA-PATIENT REGISTRATION AND FEATURE SUPERVISION

1. SUPPLEMENTARY MATERIALS

Compared with the partial visualization graphs shown in the main body of the paper, Fig. 1 displays the complete visualization results of the semi-supervised segmentation methods:

In segmentation results, white pixels mean correct gland segmentation. Red pixels show background wrongly classified as glands, and green pixels indicate glands wrongly seen as background. For boxed regions:

- Red box: Marks the areas with specular highlights. High pixel values here can cause them to be easily mistaken as glands.
- Blue box: Highlights low-contrast areas with unclear boundaries, where single glands may be wrongly split or multiple ones wrongly merged.
- Yellow box: Marks the areas with abundant secretions. Similarity between secretions and gland appearances, making them prone to misclassification.

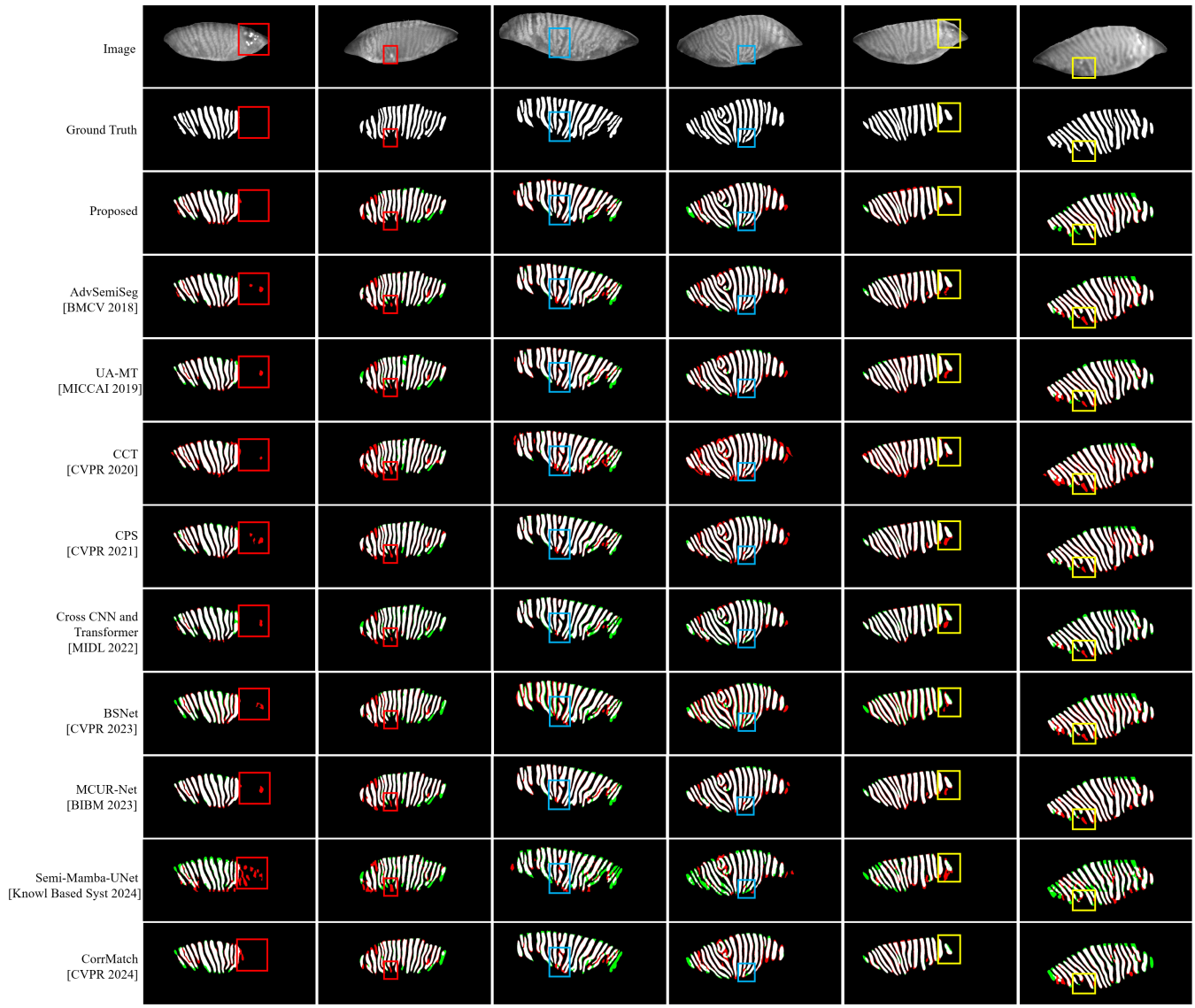
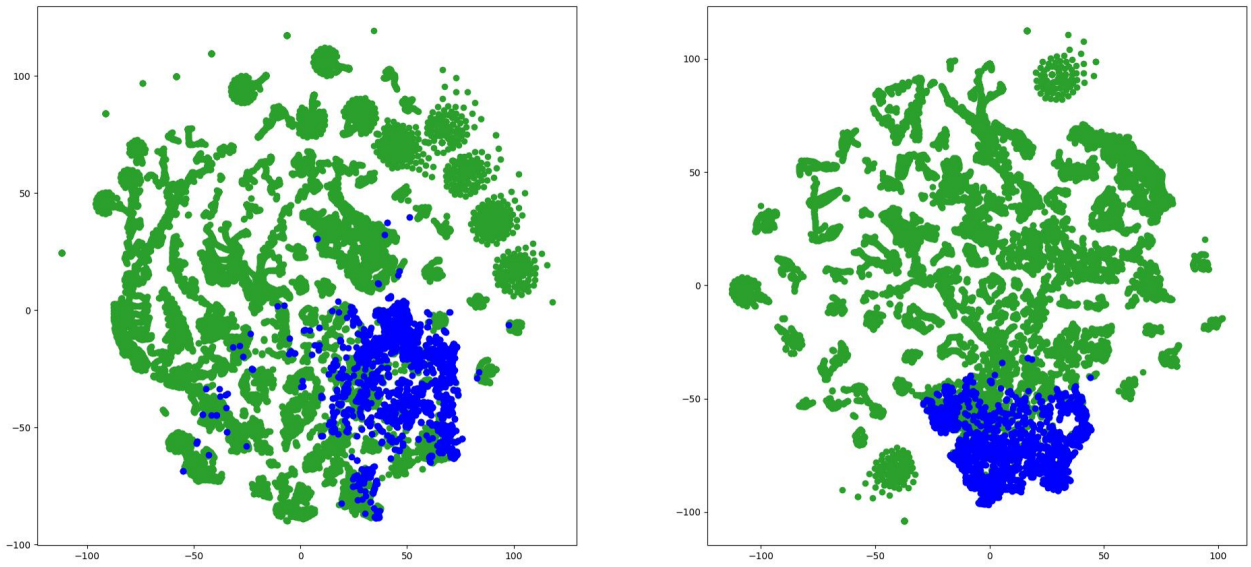


Fig. 1. Visualization results of several mainstream semi-supervised segmentation methods under 25% labeling ratio.

To further demonstrate that the separability at the feature level has been improved after introducing contractive learning, we applied the t-SNE algorithm to perform dimensionality reduction and visualization on the features obtained from the mapping head. The specific results are shown in Fig. 2.

As shown in Fig. 2(a), before the introduction of contrastive learning, the gland features and background features were intertwined in the original feature space. This made it difficult for the network to accurately distinguish the features of different class, resulting in poor class separability. This reflects the difficulty of the gland segmentation task from the feature level. As depicted in Fig. 2(b), through contrastive learning, the gland features (represented in blue) became more concentrated. The degree of interweaving among the features of different classes was further reduced, which improved the separability between glands and the background.



(a) Before Introducing Contractive Learning

(b) After Introducing Contractive Learning

Fig. 2. t-SNE visualization of the intermediate layer features before and after contractive learning at 25% labeling ratio (Blue: Glands, Green: Background).

Table 1 discussed the value of K for contractive learning with reliable negative sample filtering. It can be observed that when K is set to 250, the performance is the most outstanding, and thus K is set to 250 in the main text experiments. When K is small, the amount of information obtained by the model from negative samples is limited, and it cannot fully learn the subtle differences between features. This may cause the model to overfit specific negative samples and fail to generalize to a broader feature space, resulting in an unremarkable effect. As K increases, the amount of information that negative samples can provide gradually becomes richer, and the model gains a deeper understanding of complex features, so the performance improves step by step. However, when K exceeds a certain potential threshold, the model inevitably introduces some low-quality or even false negative samples, and the performance declines.

Table 1. Discussion of the value of K for the reliable negative sample filtering at the 25% labeling ratio.

K	**IoU(%)**↑	**Dice(%)**↑	**HD95**↓
0	81.1±0.6	89.5±0.4	6.281±0.810
50	81.1±0.6	89.4±0.4	6.252±0.675
150	81.2±0.7	89.5±0.5	6.228±0.758
250	**81.5±0.6**	**89.7±0.4**	**6.127±0.731**
350	81.3±0.6	89.6±0.4	6.347±0.712
450	80.9±0.6	89.4±0.4	6.385±0.810