Unified Medical Lesion Segmentation via Self-referring Indicator

Supplementary Material

6. More Details of Experiments

6.1. Training Details

We present the implementation details of the "Separate BP - Average Update" in Algorithm 1. During the practical training phase, we set $B = 4$, *i.e.*, each image in the query uses the same reference set.

6.2. Training Details of Other Methods

In our experiments, we reproduce or fine-tune some other methods. For UNet [35], TransUNet [9], and RollingUNet [27], we adopt the same settings as ours. For Spider [61], we train it from scratch using the training settings from its paper. As for SegGPT [50], we initialize the model parameters with the weights provided, then fine-tune for 50 epochs on our dataset with a learning rate of 0.00001 and 1 reference image.

7. More Qualitative Results

For the sake of presentation, the prediction results shown in the paper all use one image as the reference set. In this section, we present more qualitative results with 4 reference images, as shown in Fig. 5 6 7 8.

Algorithm 1 "Separate BP - Average Update"

Training iteration with $N = 12$ *and* $B = 1$.

Require: A batch $D = \{D_t\}_{t=1}^{8}$ and $Q = \{Q_t\}_{t=1}^{8}$. D_t and Q_t are N and B image-mask pairs randomly selected from training set of task t.

create reference image tensor $I_r \in \mathbb{R}^{8\times N\times 3\times H\times W}$ from D
create reference mask tensor $M_r \in \mathbb{R}^{8\times N\times 1\times H\times W}$ from D
create query image tensor $I_q \in \mathbb{R}^{8\times B\times 3\times H\times W}$ from Q
create query mask tensor $M_q \in \mathbb{R}^{8\times B\times 1\times H\times W}$ from Q
$avg\_grads \leftarrow []$ // empty list
for each $param$ in $\texttt{SR-ICL}.parameters()$ **do**
    $zero\_tensor \leftarrow$ torch.zeros_like$(param)$
    $avg\_grads.append(zero\_tensor)$
end for
$L \leftarrow 0$
for $t \leftarrow 1, 8$ **do**
    $R_t^I \leftarrow I_r[t, ...]$ // reference images
    $R_t^M \leftarrow M_r[t, ...]$ // reference masks
    $P_t^I \leftarrow I_q[t, ...]$ // query images
    $P_t^M \leftarrow M_q[t, ...]$ // query masks
    $P_t \leftarrow \texttt{SR-ICL}(R_t^I, R_t^M, P_t^I)$ // get prediction
    $L \leftarrow \texttt{Loss}(P_t, P_t^M)$
    $\texttt{zero\_grad}(Optimizer)$
    $\texttt{backward}(L)$ // get gradients
    for each $(avg\_grad, param)$ in $(avg\_grads, \texttt{SR-ICL}.parameters())$ **do**
        $avg\_grad \leftarrow avg\_grad + param.grad$
    end for
end for
for each $(param, avg\_grad)$ in $(\texttt{SR-ICL}.parameters(), avg\_grads)$ **do**
    $param.grad \leftarrow \left(\frac{avg\_grad}{8}\right)$ // average gradients
end for
$\texttt{step}(Optimizer)$ // update parameters

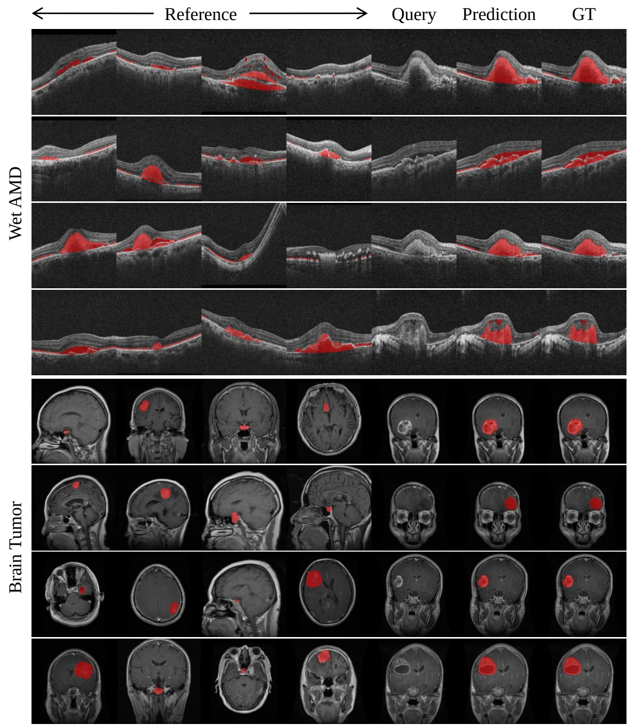

Figure 5. More results for Wet AMD and Brain Tumor.

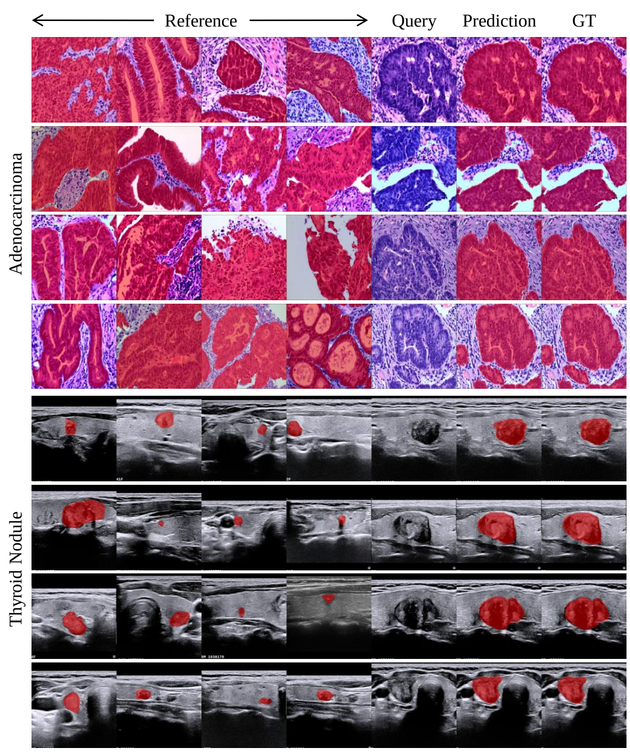

Figure 6. More results for Adenocarcinoma and Thyroid Nodule.

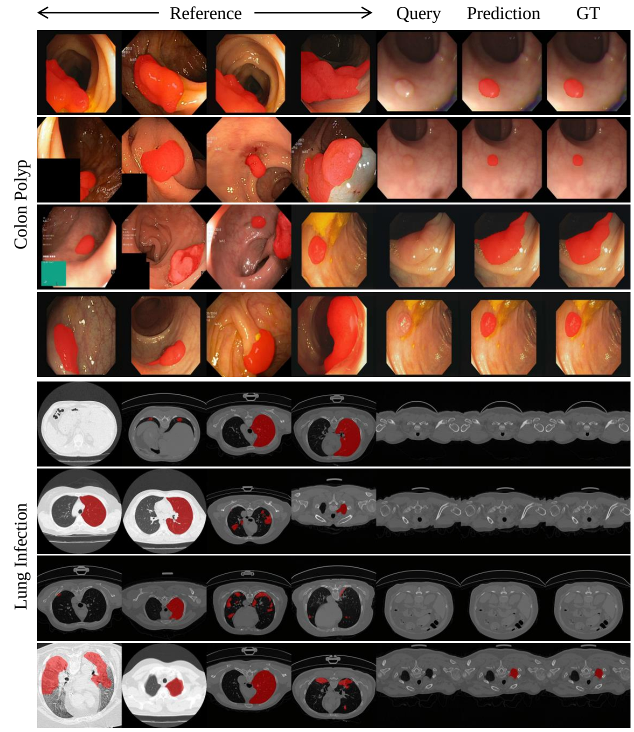

Figure 7. More results for Colon Polyp and Lung Infection.

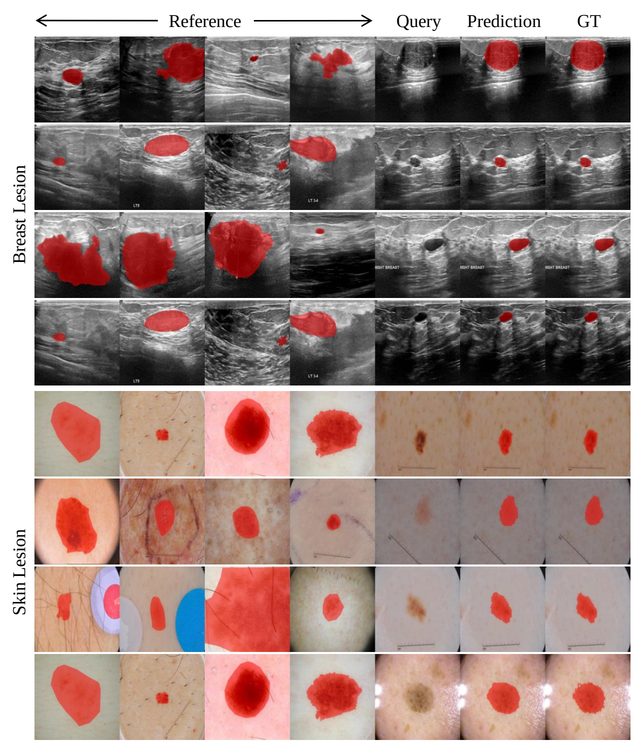

Figure 8. More results for Breast Lesion and Skin Lesion.