Transformer Based Multi-model Fusion for Medical Image Segmentation

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Abstract

We present our solutions to the MedAI for all the three tasks: polyp segmentation task, instrument segmentation task, and transparency task. We use the same framework to process the two segmentation tasks of polyps and instrument. The key improvement over last year is new state-of-the-art vision architectures, especially transformers which significantly outperform ConvNets for the medical image segmentation tasks. Our solution consists of multiple segmentation models, and each model uses a transformer as the backbone network. we get the best IoU score of 0.915 on instrument segmentation task and 0.836 on polyp segmentation task after submitting. Meanwhile, we provide complete solutions in <https://github.com/dongbo811/MedAI-2021>.

Keywords: polyp segmentation; surgical instrument segmentation; vision transformer

Introduction

Colorectal cancer is one of the deadliest cancers in the world. Colonoscopy is the standard method for locating and removing colorectal polyps. However, there is a high missed diagnosis rate for polyps. Therefore, an automatic and accurate polyp segmentation [1] method during colonoscopy can help clinicians eliminate missed lesions and prevent the development of colorectal cancer. Meanwhile, surgical instruments [1] can be used for robot-assisted surgical tasks to reduce surgical risks and workload of doctors, which has important clinical significance.

Materials and Methods

Following the official regulations, we train our models on the Kvasir-seg [2] with 1000 images and Kvasir-instrument [3] containing 590 images to complete the

polyp segmentation and instrument segmentation tasks, respectively. Our method is the ensemble of three sub-models, namely Polyp-PVT, Sinv2-PVT, and Transfuse-PVT. The official Polyp-PVT [4] is designed for polyp segmentation and achieves SOTA segmentation capability and generalization performance. Here, we adopt its standard structure without any modification. For the Transfuse [5], which is also designed for polyp segmentation, we improve it by replacing the transformer part with the pyramid vision transformer (PVT) [6, 7] to enhance its performance. The official Sinv2 [8] proposes an end-to-end network for searching and recognizing the concealed object, which achieves considerable segmentation performance. Due to the similarity of segmentation tasks, we employ it and replace the original backbone of Res2Net [9] with a stronger PVT transformer [6, 7] to extract more powerful features.

Hyperparameter Settings

We use Adam optimizer to optimize our models with the initial learning rate of $1e-4$. In addition, we resize the input image to 352×352 , and set the batch size to 16. To adapt to the images with different sizes, we use multi-scale strategy in the training phase.

Training Stage

We use the same training strategy to train Polyp-PVT, Sinv2-PVT, and Transfuse-PVT. Specifically, we first divide the dataset into 5 groups (folds). At each time, we use 4 groups of dataset as the training set and the remaining one as the validation set. During training, we choose the model weights with the best IoU on the validation set. After 5-fold training, each of Polyp-PVT, Sinv2-PVT, and Transfuse-PVT has 5 model weights, and a total of 15 different model weights are obtained.

Table 1: 5-fold cross-validation results of surgical instrument segmentation and polyp segmentation. Intersection-Over-Union (Jaccard index), Dice coefficient, and the pixel accuracy are abbreviated as IoU, Dice, PA respectively. The best mean score of each metrics in the three methods are marked in **bold**. The last line is the best score we got after submitting.

		Surgical Instrument Segmentation						Polyp Segmentation					
models	Metrics	Flod-1	Flod-2	Flod-3	Flod-4	Flod-5	Mean	Flod-1	Flod-2	Flod-3	Flod-4	Flod-5	Mean
Polyp-PVT	IoU	0.901	0.874	0.931	0.953	0.952	0.922	0.842	0.846	0.863	0.863	0.851	0.853
	Dice	0.943	0.923	0.962	0.975	0.975	0.955	0.902	0.905	0.917	0.921	0.908	0.911
	PA	0.992	0.990	0.994	0.994	0.993	0.993	0.967	0.968	0.974	0.973	0.969	0.970
Sinv2-PVT	IoU	0.897	0.876	0.931	0.952	0.952	0.922	0.850	0.849	0.867	0.865	0.857	0.858
	Dice	0.939	0.924	0.962	0.975	0.975	0.955	0.908	0.909	0.921	0.922	0.912	0.914
	PA	0.991	0.990	0.994	0.994	0.993	0.992	0.970	0.967	0.974	0.972	0.971	0.971
Transfuse-PVT	IoU	0.903	0.869	0.931	0.950	0.951	0.921	0.841	0.852	0.872	0.855	0.856	0.855
	Dice	0.944	0.921	0.961	0.973	0.974	0.955	0.903	0.911	0.925	0.914	0.913	0.913
	PA	0.992	0.989	0.993	0.993	0.993	0.992	0.967	0.968	0.977	0.970	0.969	0.970
Submission Score		IoU:0.915			Dice:0.950			PA: 0.989			IoU:0.836		
											Dice:0.893		
											PA: 0.959

Figure 1: Qualitative description of our predication.

Figure 2: Some failure cases in surgical instrument segmentation.

Inference Stage

In the inference stage, we only resize the input images to 352×352 without any data enhancement. For the output, we upsample it to the original image size. So, we can obtain 15 different prediction results. In order to obtain a more robust prediction, we merge the 15 prediction results with a voting strategy where the minority obeys the majority. Because the voting strategy will produce many independent noise pixels on the edge of polyps or surgical instruments, we use the open operation and counting to remove tiny independent noise points. Then, the area of each block in the prediction image is counted to remove relatively small noise blocks in the prediction image.

Result

Due to space limitations, we only show the results of surgical instrument segmentation. We show the qualitative results in Figure 1, and give the results of evaluations in Table. 1. At the same time, we illustrate our failure cases in Figure 2.

Discussion

In the 5-fold cross-validation, the three results are relatively stable. There are results above 0.92 on the IoU, and we also give some visual results in Figure 1.

As shown in the Figure 1 and Table. 1, we have achieved great results in the surgical instrument segmentation, but there are still some failure cases as shown in Figure 2. Our results almost correctly segment the instruments, while introduce some noise. One characteristic of these noise is that they are biased towards black. This is due to the fact that there are many black instruments in the entire dataset. Therefore, small black areas (food residuals, etc.) in the colonoscope are identified as surgical instruments. These noises can be filtered by the size of the area to achieve the purpose of noise removal.

Conclusion

In this paper, we propose a robust generalized medical image segmentation framework, which is composed of multiple models, and uses the pyramid vision transformer backbone as an encoder to explicitly extract more powerful features. Meanwhile, for the transparency task, we provide a complete description of our method, data, open source code and results for easy reproduction.

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