MASK-EMBEDDING AND FEATURE-FUSED NETWORK FOR MEDICAL IMAGE SEGMENTATION

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Annotation. Medical image segmentation has a vital role in disease diagnosis and treatment. The feature enhancement module and a mask embedding block for medical image segmentation is proposed. This method utilizes an encoder-decoder architecture with attention mechanism and residual connections to adaptively adjust the importance of each layer of features. The proposed network achieves stronger feature transfer and reconstruction, enhancing multi-scale expressive capabilities and context-awareness иy introducing dense skip connections Experimental results on three datasets demonstrate significant improvements in segmentation accuracy and robustness, particularly in handling segmentation details and boundaries.

Medical image segmentation is crucial for accurate disease diagnosis and treatment planning. It's known the manual segmentation is time-consuming and prone to errors. To solve this problem the feature enhancement and mask embedding modules has proposed. This approach aims to improve segmentation accuracy and efficiency in medical imaging. The existing methods for medical image segmentation, including classical U-Net [1] with its variants and other SOTA methods are reviewed.

In our paper, we present our feature enhancement module, which enhances the encoder-decoder architecture by incorporating additional feature-fused blocks, which enables the network to capture more detailed and discriminative features, leading to improved segmentation performance. Meanwhile, we introduce the mask embedding technique, which involves embedding the mask information into the feature maps at each layer of our proposed structure. This integration helps the network focus on relevant regions and suppress noise, leading to improved accuracy in medical image segmentation.

To train and validate the proposed blocks, this study uses three publicly available biomedical image datasets: Kvasir-SEG[2], CVC-ClinicDB, and 2018 Data Science Bowl (2018 DSB).

Then, several standard evaluation metrics are utilized to validate the usefulness of proposed blocks and network, including precision, dice coefficient (DSC) (a.k.a F1), recall and mean intersection over union[2].

The results show the accuracy of proposed network can reach up to 91.57 %, 94.92 % and 98.60 % on three data sets respectively. Storage is very important in actual clinical testing. And the proposed network achieves recall rates of 90.35 %, 94.84 % and 93.95 % on three datasets.

The modified approach achieves significant improvements in segmentation accuracy and efficiency, surpassing some existing methods.

References

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EXPLORING THE ROLE OF LOSS FUNCTIONS IN BIOMEDICAL IMAGE SEGMENTATION

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Annotation. The loss function is an important part of the segmentation method based on deep learning, and the improvement of the loss function can improve the segmentation effect of the network from the root, however, there are few literatures to do specific analysis and summary of various types of loss functions, this paper summaries some commonly used loss functions from the common problems in the current medical image segmentation task.

The loss function has important meanings such as measuring segmentation accuracy, promoting model convergence, improving spatial consistency, and improving the generalisation ability of the model. Following loss functions are commonly used:

1. Cross-entropy loss: this is a loss function commonly used for classification tasks and can also be used for image segmentation at the pixel level, which measures the loss by comparing the difference between the model's predicted segmentation results and the true labels. A number of articles have studied it, [1] have chosen to apply CE Loss in segmentation models. The formula for cross-entropy loss is as follows:

$$L_{CE} = -\Sigma_{i=1}^{C} q_i \, log(p_i).$$

2. Dice loss: it is used to measure the overlap region between the predicted and true values, it works better when in dealing with the category imbalance problem. DSC reflects the segmentation results with the real situation size and localisation consistency, which is more in line with the perceived quality compared to the pixel level evaluation metrics. The Dice Loss formula is as follows:

$$Dice = \frac{2TP}{2TP + FP + FN} \; .$$