RESEARCH ON LUNG TUMOR IMAGE SEGMENTATION ALGORITHM BASED ON U-NET

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Abstract

Aiming at the problem of complex and variable tumor regions and fuzzy boundaries in lung CT images, an improved U-Net network is proposed by introducing the attention mechanism and optimizing the loss function. Training is performed on a clinical multimodal medical dataset to verify the effectiveness of the algorithm.

Keywords: U-Net, Lung tumor, Image segmentation algorithm.

Introduction

In the process of lung cancer diagnosis, accurate segmentation of lung tumor images is the basis for evaluating key information such as tumor size, morphology and location [1]. In recent years, with the rapid development of deep learning technology, the convolutional neural network (CNN), especially the U-Net architecture, has shown great potential in the field of medical image segmentation [2].We focus on the application effect of U-Net model in lung tumour image segmentation, aiming to improve the segmentation accuracy through model optimization and innovation, and provide technical support for accurate diagnosis of lung cancer. Through in-depth research and experimental validation, it is expected to contribute new ideas and methods to the field of lung tumour image segmentation, and promote the further development of lung cancer early diagnosis and treatment technology.

Based on the classical U-Net architecture, an enhanced deep learning model for lung tumor image segmentation is constructed by introducing the attention mechanism and optimizing the loss function, as shown in Fig. 1. The U-Net is used as the baseline model [3], which consists of two symmetrical parts: the encoder and the decoder. The feature maps of each layer of the encoder are fused with those of the corresponding layer of the decoder through hopping connections, so as to achieve the feature reuse and detail information retention. reuse and detail information retention.

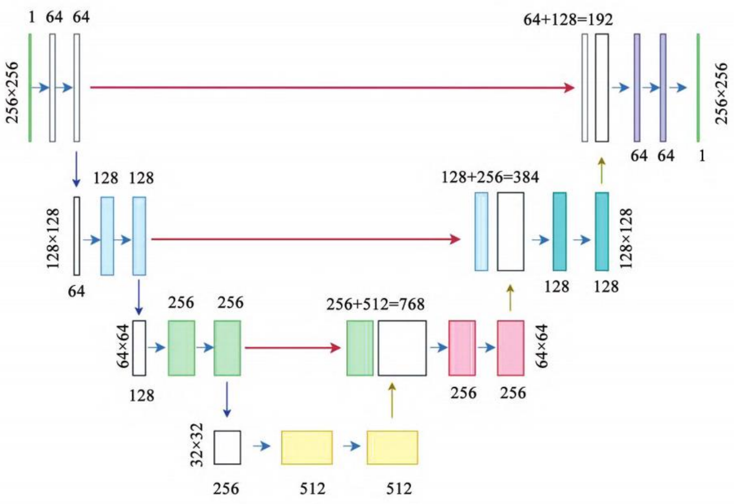

Fig. 1. U-Net model structure

To enhance the accuracy of segmentation, we optimized the model's loss function. Traditional segmentation techniques typically employ Cross-Entropy Loss, which often proves inadequate in addressing class imbalance issues. In the context of lung tumor segmentation, the tumor region constitutes a small portion of the entire image, resulting in a significant imbalance between positive and negative samples. To address this challenge, we utilized a weighted combination of Dice Loss and Cross-Entropy Loss as the final loss function. Dice Loss directly optimizes the overlap between the predicted and true segmentations, demonstrating particular effectiveness in small target segmentation scenarios. By adjusting the weights of these two loss components, we achieved improved segmentation accuracy while ensuring model stability.

$$DiceLoss = 1 - Dice = 1 - \frac{2|X \cap Y|}{|X| + |Y|}$$

Results

The U-net-based lung image segmentation algorithm, which is derived from the COVID-19 dataset, contains the CT scan images of the patient's lungs and the corresponding annotation information, which provides rich imaging information for the diagnosis of lung diseases, treatment planning and efficacy assessment, as shown in Fig. 2.

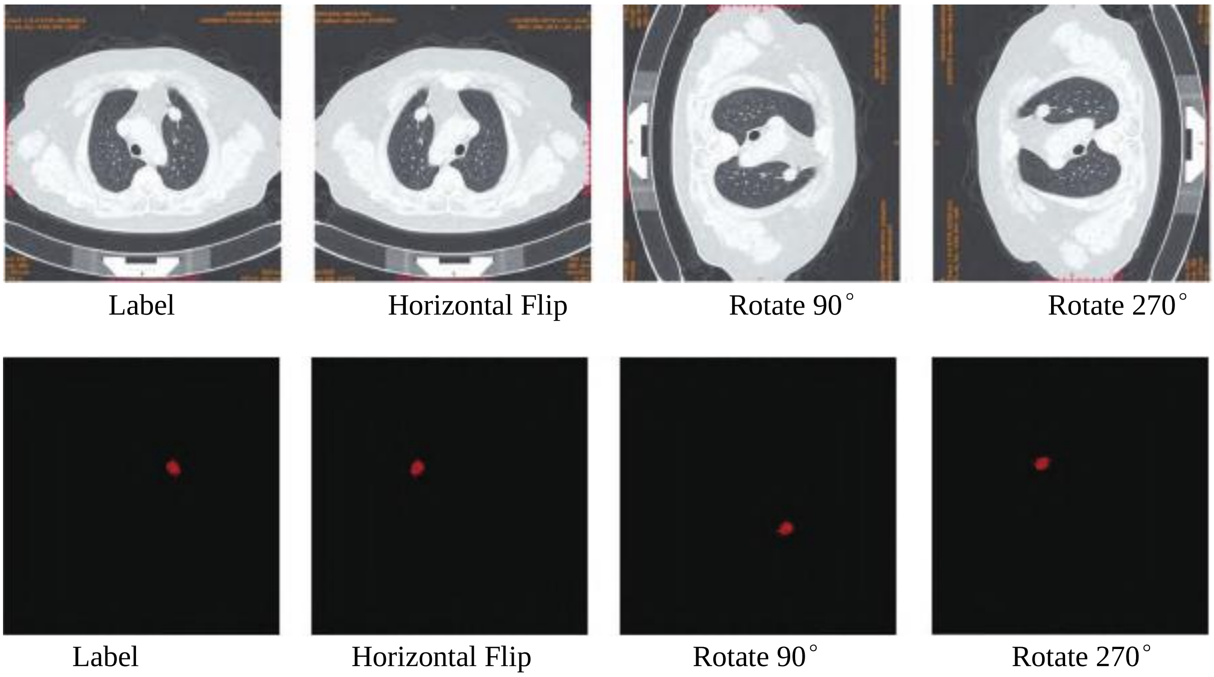

Fig. 2. Date enhancement effect

After successfully introducing the attention mechanism and optimizing the loss function, a comprehensive experimental evaluation of the improved U-Net model is conducted. Through comparative experiments, it is found that the model with the introduction of the attention mechanism outperforms the traditional U-Net model in several evaluation indexes. As shown in Table 1, the Dice coefficient, which is the key index of segmentation accuracy, is found to be better than the traditional U-Net model in several evaluation indexes. The average improvement of the improved model was approximately 5%, indicating a significant improvement in the ability of the model to identify tumour regions. The Jaccard index (also known as the intersection and integration ratio IOU) of the model also achieved an improvement of about 4%, and the PPV and sensitivity of the model in predicting the correct results achieved the optimal values of 0.952 and 0.983, respectively, which further verified its advantage in segmentation accuracy.

Table 1. Comparison of quantitative results of two models on test datasets

Model	Dice	IOU	PPV	Sensitivity
Traditional U-Net model	0.908	0.877	0.886	0.947
Improved U-Net model	0.952	0.918	0.952	0.983

The optimized loss function effectively alleviates the model bias problem caused by data imbalance during the training process. By combining the weighted combination of Dice loss and cross-entropy loss, the improved model focuses more on the fine segmentation of the tumor region while maintaining the ability to learn the overall image features, thus improving the accuracy and robustness of the segmentation results, see Fig. 3. Through the visual analysis and prediction, it can be observed intuitively that the improved model is smoother and more continuous when segmenting the boundary of the tumor, and the cases of erroneous and missed segmentation are reduced. It can be observed that the improved model is smoother and more continuous in segmenting the tumor boundary, reducing mis-segmentation and omission. It shows that the attention mechanism not only enhances the model's attention to the tumor region, but also improves its generalization ability when dealing with complex image structures.

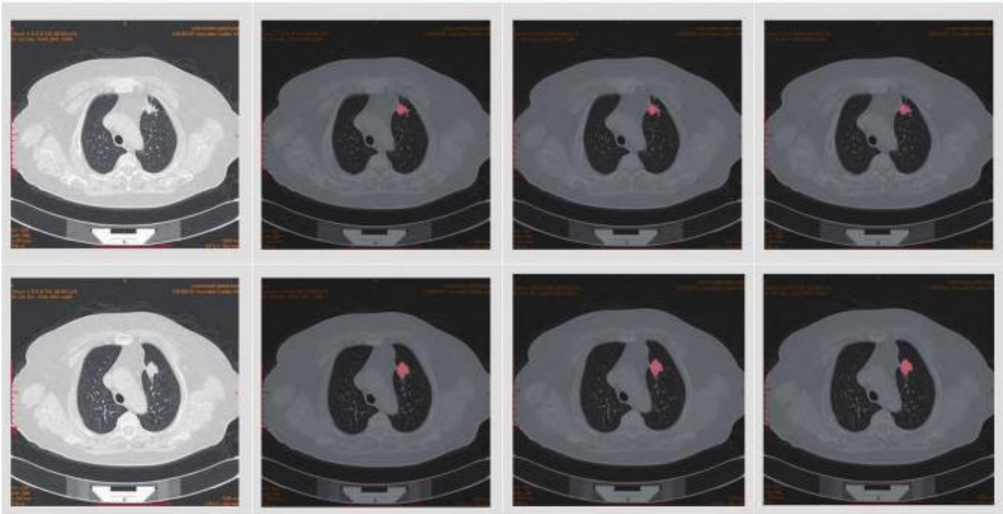

Fig. 3. Segmentation and prediction results of several models

Conclusion

For the lung tumour image segmentation technique, the classical U-Net model is improved by introducing the attention mechanism and optimising the loss function. Experimental results demonstrate that these improvements significantly enhance the segmentation performance of the model, thereby providing robust support for the early diagnosis and treatment of lung tumors. The introduction of the attention mechanism plays a key role in improving the segmentation accuracy of the model.

Min Wang et al [4]. found that the attention mechanism is particularly significant for improving the performance of the model on boundary segmentation. The boundaries in lung tumour images are often fuzzy and irregular, and traditional segmentation methods are prone to mis-segmentation or missed segmentation at the boundaries. With the introduction of the attention mechanism, the model is able to identify and segment the boundary of the tumour more accurately, which is attributed to the fact that the attention mechanism strengthens the features of the tumour region and at the same time suppresses the interference of non-tumour regions, and this enhancement of the ability is of great significance in improving the accuracy of lung tumour diagnosis.

Regarding the optimisation of the loss function, we adopt a weighted combination of Dice loss and cross-entropy loss, which retains the advantages of cross-entropy loss in classification problems and exploits the characteristics of Dice loss in dealing with unbalanced data. The experimental results show that the optimized loss function is more stable during the training process and can guide the model to learn the characteristics of the tumor region more effectively. By adjusting the weights of the two types of losses to find a balance point, the model maintains the overall segmentation performance while paying more attention to the fine segmentation of the tumor region, and this optimization strategy of the loss function not only improves the segmentation accuracy of the model, but also strengthens the model's robustness and generalisation ability.

The improved model shows good performance in dealing with lung tumours of different morphology, size and location, which proves that the model learns the rich expression of tumour features as well as the joint effect of the attention mechanism and the optimized loss function during the training process, and these improvements make the model more adaptable to the complex medical image environment, which provides a reliable guarantee for the practical clinical application [5].

Although some remarkable results have been achieved in this study, there are still some problems that deserve further exploration. For example, how to further optimise the structure and parameter settings of the attention mechanism to further improve the segmentation performance of the model, how to incorporate more advanced knowledge and contextual information to guide the training process of the model, and how to apply the model to a wider range of medical image segmentation tasks.

In this study, by introducing the attention mechanism and optimizing the loss function, we successfully improved the performance of the U-Net model in the lung tumor image segmentation task, which not only improved the segmentation accuracy and robustness of the model, but also provided theoretical support for the early diagnosis and treatment of the related diseases.

References

1. Zhang X., Wang J., Kong H., Wen Y.T., Liu W., Wang B. CT Image Lung Tumor Segmentation Based on Random Walk Algorithm // Journal of Hebei University (Natural Science Edition). – 2019. – 39(03). – P. 311. – URL: xbzrb.hbu.edu.cn/CN/Y2019/V39/I3/311.

2. Zhu Y.J., Han Z., He S.H., Hu X.R., Chen P.D. Remote Sensing Image Tidal Channel Extraction Method Based on Maximum Inter-Class Variance and Mathematical Morphology // Journal of Shanghai Ocean University. – 2017. – 26(01). – pp. 146–153. – [Электронный ресурс]. – URL: aquaticjournal.com/data/article/shhydxxb/preview/pdf/20160701818.pdf (date of access: 19.02.2025).

3. Ronneberger O., Fischer P., Brox T. U-net: Convolutional networks for biomedical image segmentation // Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18. Springer international publishing. – 2015. – P. 234-241. – URL: link.springer.com/chapter/10.1007/978-3-319-24574-4_28.

4. Wang M., Wang P.G., Wang N., Zong X.P. Image Segmentation Algorithm Based on GVF Snake Model // Electronics World. – 2017(14). – P. 11-12. – [Электронный ресурс]. – URL: d.wanfangdata.com.cn/periodical/dzsj201714013 (date of access: 19.02.2025).

5. Liu Y.X., Zhong J.J., Sun Y.X., Peng H.C. Research on Lung Tumor Image Segmentation Based on Deep Learning // Computer Products and Circulation. – 2020(07). – P. 79-80. – [Электронный ресурс]. – URL: d.wanfangdata.com.cn/thesis/Y4151855 (date of access: 19.02.2025).