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GENERATIVE ADVERSARIAL NETWORK FOR MEDICAL IMAGE SEGMENTATION

In this paper, a U-Net medical image segmentation method based on generative adversarial networks is proposed. This method is used to solve the problem of performance degradation of modeling algorithms due to insufficient training samples in medical image segmentation.

I. INTRODUCTION

Medical image segmentation is an important field, improving the accuracy of medical image segmentation has always been a hot research topic, but one of the biggest challenges in the field of medical imaging is to learn generalizable feature patterns from small datasets or a limited number of annotated samples. In medical imaging tasks, deep learning-based methods require a large number of training samples with annotations to support inference, which is difficult to achieve in medical image analysis. To solve these problems, this paper designs a u-net medical image segmentation method based on generative adversarial networks.

II. DIFFICULTIES AND CHALLENGES

To solve the problem of limited dataset size, various data enhancement techniques have been used to enhance the training data for medical image segmentation. Common techniques include geometric transformations such as rotation, noise injection and so on. These data enhancement methods have been widely used to augment training sets, thereby improving model performance in a variety of computer vision tasks. While these techniques still suffer from some potential drawbacks such as loss of information, or presence of noise. All of these issues can adversely affect the model's ability to accurately segment medical images.

III. METHOD IMPROVEMENT AND DESCRIPTION

Generative Adversarial Network (GAN) and is consisting of \mathbf{a} generator а discriminator[1]. Figure 1 shows the structure of the model of u-net medical image segmentation method based on generative adversarial network.In this architecture, real medical images are fed into the GAN and the generator of the GAN takes random noise vectors as input and generates synthetic samples that are similar to the real medical images. On the other hand, the discriminator receives both the samples generated by the generator and the input real medical image. The discriminator's task

is to distinguish these samples and accurately categorize them as real samples or generated samples. and the parameters of both networks are updated through a back-propagation algorithm that utilizes feedback signals from the discriminator. This iterative training process continues until the samples generated by the generator are sufficiently realistic. The generates synthetic samples are then fed into the U-Net network for training as additional training samples. This approach reduces the dependence on a large amount of labeled data and enables the training of effective segmentation models even with limited data.

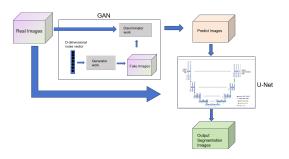


Рис. 1 – The structure of the GAN-based U-Net method

IV. CONCLUSION

Inadequate medical image labeling is a major obstacle in the field of medical image segmentation, the paper designed a new method based on Generative Adversarial Networks , which can improve the quality of segmentation results, generate realistic segmentation results, reduce the dependence on the annotated data, and improve the robustness and generalization ability of the model. The method has a wide range of application prospects and research value in the field of medical image segmentation.

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