Segmentation of Pneumothorax Disease based on Deep Learning

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Keywords: Pneumothorax Segmentation, Residual Module, Attention Mechanism.

Abstract: Pneumothorax is a common acute pulmonary disease. At present, chest X-ray is an important diagnostic method of pneumothorax. The image of pneumothorax has the characteristics of uneven distribution, great changes in the shape and size of lesions, and no obvious characteristics, which makes it difficult for doctors to make early diagnosis. At the same time, the traditional image algorithm is not good for the extraction of pneumothorax lesions. To solve the above problems, a deep learning based extraction method for pneumothorax lesions was proposed. The feature extraction module is constructed by combining the bottleneck module and improved coordatt attention mechanism, so that the neural network can fully capture image features, which effectively solves the problem of inaccurate segmentation and extraction due to the large variation of pneumothorax and the lack of obvious features. Experimental results showed that, on SIIM-ACR Pneumothorax data set, the Dice index, Accuracy, Recall and Iou reached 85.67%, 92.42%, 87.25% and 81.37%, which proved that compared with other image semantic segmentation methods, Segmentation and extraction of pneumothorax region results are more accurate.

1 INTRODUCTION

Pneumothorax is a common acute lung disease (Gilday 2021), which is fatal. The rapid diagnosis and treatment of pneumothorax diseases can help to ensure the safety of patients' lives and have practical significance. At this stage, the main diagnostic method for pneumothorax is the doctor's X-ray chest radiograph. Compared with CT and NMR, X-ray is inexpensive and has obvious advantages. At present, the ratio of doctors to patients in China is seriously imbalanced. Doctors need to diagnose a large number of chest X-rays every day. The results of artificial pneumothorax detection are easily affected by factors such as doctors' experience and level, and are likely to be missed or misdiagnosed. The failure of radiologists to detect pneumothorax early is one of the main causes of death from pneumothorax disease (Suthar 2016). Therefore, the Computer-Aided-Diagnosis (CAD) system (Chen 2021) should be used in the automatic detection of clinical X-ray pneumothorax to help doctors improve the efficiency and accuracy of diagnosis and reduce missed diagnosis.

In recent years, with the continuous development of computer technology, convolutional neural network models represented by LeNet5(Lecun 1998), VGG16(Simonyan 2014) and GoogLenet (Szegedy 2015) have been used in the field of computer vision and medicine. It has achieved success in the image field, and the recognition effect has been greatly improved compared with traditional methods. In 2012, Hinton and Krizhevsky used ReLU as the network activation function, and successfully proposed Local Response Normalization (LRN), and AlexNet(Wang 2020), and used the Dropout layer for the first time to deactivate some neurons and avoid The model is over-fitting; Kaiming He released the ResNet(He 2015) neural network based on the residual module in 2015, which effectively solved the problem that the gradient disappears when the neural network reaches a certain depth. In the field of image segmentation, Ronneberger (Ronneberger 2015) et al. proposed a U-Net network for medical image segmentation tasks based on the FCN architecture. It improved FCN and improved the expansion path a lot. Multi-channel convolution and similar feature pyramid networks the structure is combined, and U-Net can also achieve good results in training and testing with a small amount of data sets, making a great contribution to medical image segmentation. In terms of pneumothorax segmentation, Wang (Wang 2020) et al. proposed a CheXLocNet convolutional neural network based on Mask R-CNN for

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pneumothorax segmentation. The dice coefficient of the test set on the SIIM-ACR Pneumothorax dataset is 82%.

In order to solve the problem of uneven distribution of pneumothorax image data, large changes in the shape and size of the lesions, unobvious features, and inaccurate segmentation of small lesions, this paper proposes a pneumothorax segmentation method based on residual module and attention mechanism. This method adjusts the U-Net network structure and uses the bottleneck residual module to effectively extract the features of the pneumothorax image and perform the semantic segmentation of the pneumothorax region. At the same time, the improved CoordAtt module is embedded in the network to make full use of the detailed information of the pneumothorax image to further enhance the effect of pneumothorax segmentation.

2 METHOD

This article is to realize the pathological segmentation of pneumothorax disease. Taking into account the uneven number of positive and negative samples in the pneumothorax data set, pneumothorax images have problems such as unclear boundaries, large changes in shape and size, the final selection is widely used in medical images and is used in small data. The U-Net network with good performance on the set is used as the basic network. The classic U-Net network is a fully convolutional network segmentation model. The first half of the network is a feature extraction module, and the second half is an upsampling module. This structure is also called an encoder-decoder structure.

In this chapter, we will introduce the structure of the improved U-net in detail and explain how the network is improved. The improved structure is shown in Figure 1.

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In this chapter, we will introduce the structure of the improved U-net in detail and explain how the network is improved. The improved structure is shown in Figure 1

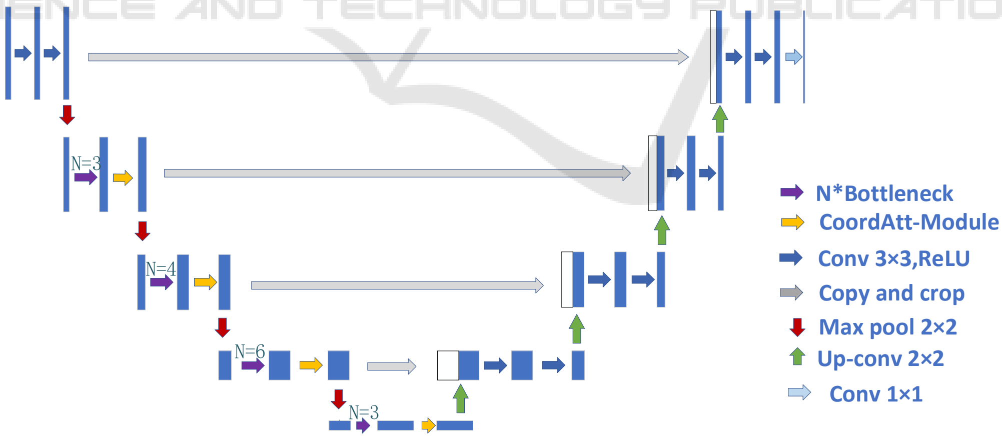

Figure 1: Improved U-Net structure.

The pneumothorax segmentation model proposed in this paper is based on the residual module and improved attention mechanism. While continuing the symmetric structure and jump connection of U-Net, the bottleneck residual module is embedded to optimize the segmentation details, and the CoordAtt module is added to improve the useless features, perform compression. A total of 5 layers of symmetrical structure from top to bottom. The encoder of the first layer contains two 3x3 convolution kernels, and the encoders of the second to fifth layers contain 3, 4, 6, and 3 bottleneck residual modules, except for the first layer. Outside of the first layer, after each layer of encoder completes the convolution calculation, it is accompanied by an improved CA module to fully learn the edge and texture features of the pneumothorax and improve the network segmentation performance.

2.1 Bottleneck Residual Module

The U-Net basic network model selected in this study lost the detailed information in the pneumothorax image during the encoding-decoding process, resulting in a decrease in the accuracy of pneumothorax segmentation. He et al. (He 2015) proposed a residual connection module in 2015, as shown in Figure 2.

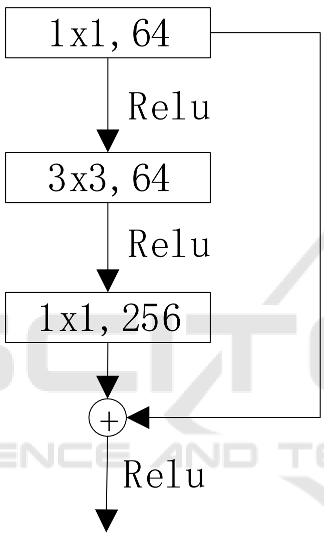

Figure 2: ResNet structure drawing.

The ResNet module contains two paths, one path directly adds the input image information to the bottom layer of the module, and the other path that contains the feature extraction function is added together to form a residual short-circuit connection. Adding Resnet's residual structure to U-Net's network model can effectively alleviate the loss of details caused by encoding-decoding, thereby directly improving accuracy.

2.2 Improved Coordatt Attention Mechanism

The attention mechanism is derived from the research of human vision and is widely used in various fields of deep learning (Krizhevsky 2012, such as image processing, speech recognition, and natural language processing. The attention mechanism helps the convolutional neural network to extract and recognize objects from complex images by assigning different weights to different channels of the feature map, and suppress invalid feature information. In 2021, Hou (Hou 202) et al. proposed CA (CoordAtt), which embeds location information into channel attention to help neural networks extract features more efficiently at a lower cost.

CA uses two 1D global pooling operations to generate two separate feature perceptions for the input features along the vertical and horizontal directions respectively. Then the two feature maps with embedded specific direction information are respectively encoded into two attention maps, and finally both attention maps are applied to the input feature maps through multiplication. However, CA only performs global average pooling in the calculation, and does not pay attention to the detailed texture information. At the same time, in the process of feature weighting, the original feature information cannot be fully utilized. Therefore, this paper improves the CA attention mechanism. Based on the original CA, a residual network is added, and the input features are globally averaged pooled and maximum pooled, so that it can make fuller use of the original features. And detailed information, the structure is shown in Figure 3.

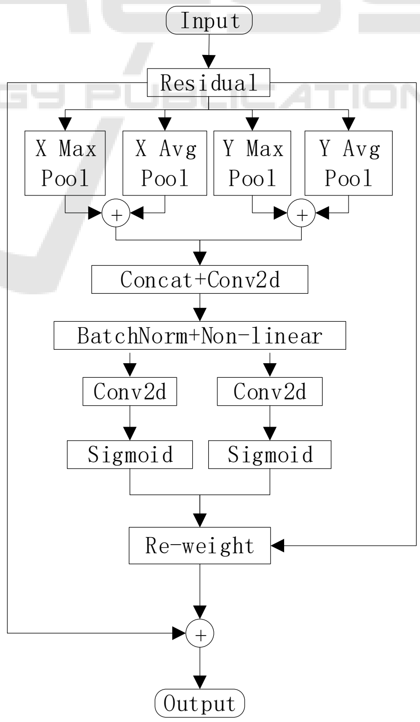

Figure 3: Improved CoordAtt Attention Mechanism.

3 EXPERIMENTS

3.1 Data Set and Data Enhancement

The SIIM-ACR Pneumothorax dataset used in this experiment is provided by Society for Imaging Informatics in Medicine (SIIM) and American College of Radiology (ACR), and is open sourced on the Kaggle platform. The data set contains 12089 Digital Imaging and Communication sin Medicine (DICOM) files, and the annotations are in RLE encoding format.

Figure 4: Pneumothorax data set.

3.1.1 Data Set Preprocessing

The experiment first converts the DICOM file into a 512x512 PNG format image, and converts the RLE encoding format label to a 512x512 label image. Then, in the original data set, pictures with pneumothorax accounted for only about 28%, and the number of positive and negative samples was seriously unbalanced, which would have a greater impact on the convergence speed and effect of the model. Therefore, in training, a sliding sampling strategy is adopted for the data. Specifically, in the early stage of model training, a 2:1 large positive and negative sample ratio is used to randomly sample the data to make the model converge faster. In the middle and late stages, a 1:1 sampling ratio is adopted to make the model more robust.

3.1.2 Image Enhancement

Since there are fewer pneumothorax pictures in the data set, there is insufficient data for the network model to learn, which makes the model easy to overfit during the training process. Therefore, this article performs data enhancement operations before model training, adopts the methods of flipping, random contrast, random gamma, random brightness, random elastic transformation, random grid distortion, and visual distortion, and performs data expansion work to improve the positive sample data. The image enhancement effect diagram is shown in Figure 5.

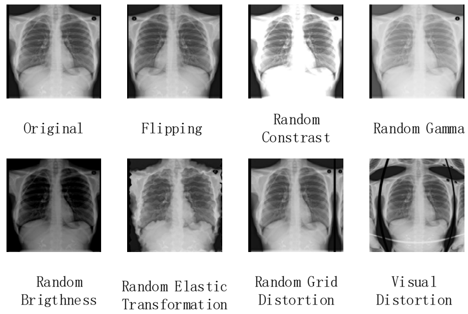

Figure 5: Data enhanced rendering.

3.2 Experimental Details

3.2.1 Experimental Environment

The hardware environment is NVIDIA 1080TI graphics card, 11G running memory, Intel(R) Core (TM) i7-7700K processor. The software environment is Windows 10 system, Python 3.6, Pytorch 1.1 development environment.

3.2.2 Experimental Parameters

The optimizer in training uses the Adam optimizer. The Adam optimizer has the advantages of fast calculation and low memory footprint, and can optimize the model while using a small amount of computing resources. The learning rate adopts the CosineAnnealingLR curve that comes with pytorch. The learning rate change is shown in Figure 6.

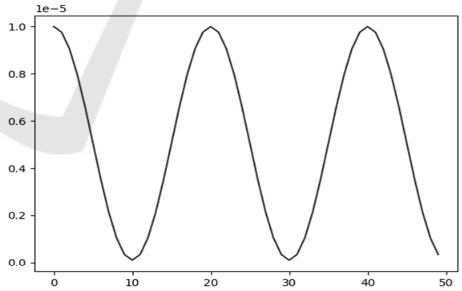

Figure 6: CosineAnnealingLR curve.

3.3 Experimental Results

3.3.1 Comparison of Segmentation Performance of Pneumothorax

After the training is completed, evaluate the segmentation performance of the algorithm on the SIIM-ACR Pneumothorax test set. The comparison experiment results are shown in Table 1.

Table 1: Experimental results of different models.

Model	Dice	Precision	Recall	Iou
U-Net	82.36	89.56	84.51	78.85
CheXLoc Net	82.82	90.36	84.78	79.17
Albunet	83.25	91.41	86.58	79.92
Ours	**85.67**	**92.42**	**87.25**	**81.37**

The Dice, Precision, Recall, and Iou of the algorithm proposed in this paper on the test set are 85.67%, 92.42%, 87.25% and 81.37%, respectively. It can be seen that the ICA-ResUnet proposed in this paper is compared with the series of medical image segmentation previously proposed. Network performance has been greatly improved. Compared with the original U-Net algorithm, it has increased by 3.31%, 2.86%, 2.74% and 2.52% respectively.

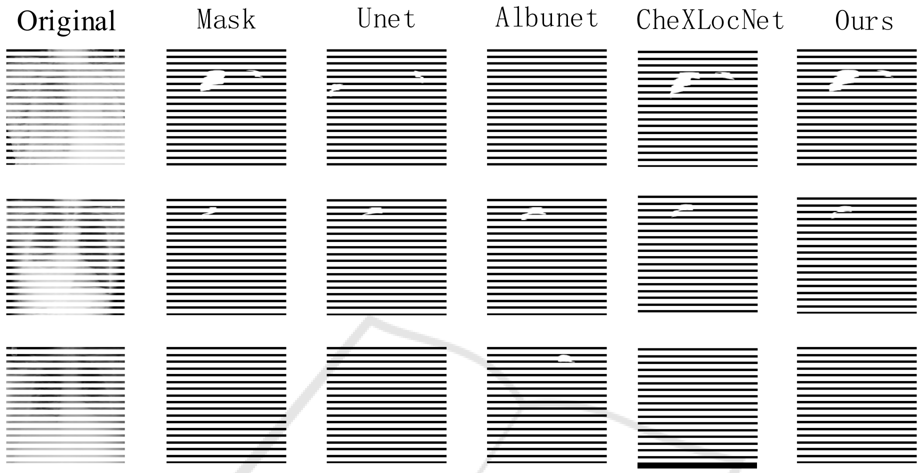

Figure 7: Comparison of segmentation results.

The visualization of the segmentation results of the four networks is shown in Figure 7. The first column in the figure is the chest X-ray picture of the input model, the second column is the real label of the pneumothorax contour marked by medical experts, and the last column is the result of the pneumothorax segmentation in this article. Observing the first and third lines, the unimproved U-Net network is more likely to be affected by the inconspicuous features of the pneumothorax due to insufficient feature utilization, and there are cases of missed detection and wrong detection. Albunet (Shvets 2018) and CheXLocNet have better segmentation effects on large-area pneumothorax, and the segmented shape and edge are relatively close to the real label. But by observing the first row, there are also small-scale misdetections.

In contrast, the network model proposed in this paper can effectively segment the pneumothorax lesions and predict the contour of the pneumothorax more accurately. Due to the small number of pneumothorax images and the small area of the lesion relative to the background area, it is difficult for the deep learning model to extract features and feature learning. The network uses the residual module and attention mechanism to learn in the U-Net network, strengthens the network's ability to extract pneumothorax features, and is more suitable for medical image segmentation tasks.

In summary, compared with other segmentation algorithms, the segmentation effect of the pneumothorax segmentation method proposed in this paper has been significantly improved. It can fully extract features and use detailed information. It can be used in the segmentation of pneumothorax with small area, low image quality, and blurred boundaries. The process is more robust.

4 CONCLUSIONS

X-ray image segmentation of pneumothorax is a key step to achieve accurate display, diagnosis, early treatment and surgical planning of pneumothorax diseases. This paper proposes a new X-ray pneumothorax segmentation method. The neural network model combines the bottleneck module and the Improved CoordAtt Attention Model. Compared with other medical image segmentation networks, the feature extraction ability is greatly improved, so that the network can effectively detect pneumothorax lesions area. It performs well in the experiment of the SIIM-ACR Pneumothorax data set. The above method has a certain generalization, not only suitable for pneumothorax segmentation, but also has reference value for other medical image segmentation research.

The next step of research will continue to optimize the network structure while focusing on trying other data enhancement methods and the choice of loss function.

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