Orthopedic Image Segmentation and Recognition Based on Deep Neural Networks

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Abstract: In the field of medicine, especially orthopedics, accurate diagnosis is crucial. However, due to the uneven distribution of medical resources and the continuous growth of patient numbers, the diagnostic efficiency of hospitals has been significantly affected, and the problems of misdiagnosis and missed diagnosis are becoming increasingly prominent. To address these issues, this study explores a deep neural network-based orthopedic image segmentation and recognition model, aiming to improve the accuracy and efficiency of diagnosis. Firstly, we use U-Net neural network for segmentation training of orthopedic images in order to extract detailed features from the images.
Keywords**:** deep neural network, U-Net, ResNet50, transfer learning

1. Introduction

The development of medical imaging technology plays an important role in clinical diagnosis and medical research. With the passage of time, people have continuously invented new medical imaging technologies, such as X-rays, ultrasound (Ultrasound), computed tomography (CT), magnetic resonance imaging (MRI), positron emission computed tomography (PECT), and so on. Every technological innovation has made significant contributions to the enrichment of observation capabilities and means in clinical treatment and life science research. These imaging technologies play a crucial role in improving medical methods, enhancing medical standards, and other aspects.[1]

2. Relevant theoretical foundations

2.1 Convolutional Neural Networks

Convolutional Neural Network (CNN) is a special type of deep neural network that is specifically used to process data with network structures, such as images and videos. The design inspiration of CNN comes from the understanding and imitation of the biological visual cortex, and its main feature is to achieve efficient processing and feature extraction of input data through local parameter sharing. Compared to other deep learning models, CNN has advantages such as fewer parameters and lower computational complexity, making it widely used in computer vision, text data analysis and classification.[2]

2.2 U-Net Network

The U-Net network model is a classic convolutional neural network structure published in 2015. Its design inspiration comes from the Fully Convolutional Network (FCN) in semantic segmentation tasks, which is a variant of FCN. Its name comes from the fact that its network structure is extremely similar to the letter "U" and is named U-Net neural network, as shown in Figure 1. The original intention of proposing U-Net was to solve problems in biomedical images in the future, but due to its good performance, it has also been widely applied in other fields of semantic segmentation, such as satellite image segmentation, industrial defect detection, etc.

One major difference between U-Net and FCN is that U-Net introduces skip connections and oversampling, which allows the network to retain more spatial information while performing feature extraction. Therefore, it has good performance in image segmentation tasks. From other structures, both U-Net and FCN adopt an Encoder Decoder structure, which is simple but effective.

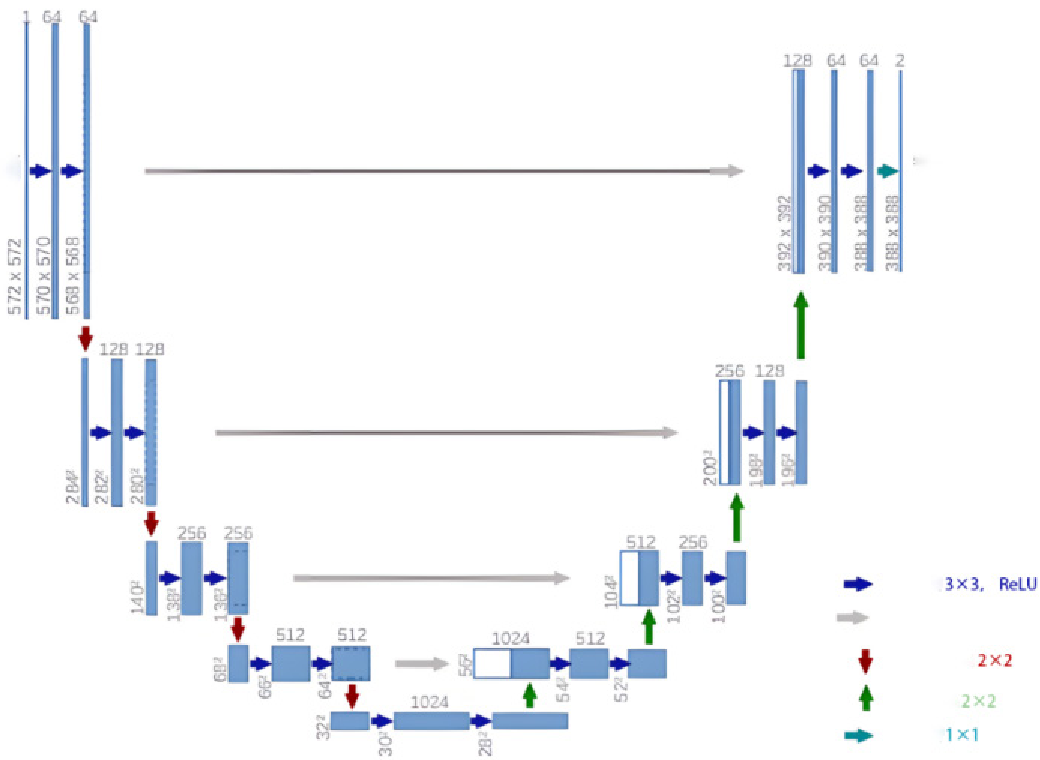

Figure 1. Schematic diagram of U-Net network structure

3. Training of orthopedic image segmentation model based on improved U-Net

In the field of medical image segmentation, U-Net is widely used and has excellent performance in semantic segmentation tasks. However, despite its significant success in segmentation tasks, the performance of the original U-Net shows significant shortcomings in binary segmentation problems, especially in pixel level classification of fine structures in medical images. [3]The possible reason for this performance decline is partly attributed to the original intention of U-Net design, which was mainly aimed at semantic segmentation rather than binary segmentation. In binary segmentation problems, the shortcomings of U-Net mainly lie in its tendency to classify pixels with similar features into the same category, while ignoring subtle differences, especially in situations where the target boundary is blurred or there is grayscale transition between the target and the background. Therefore, in handling binary segmentation tasks that require precise boundary partitioning, U-Net often cannot meet the requirements of high accuracy and robustness.

In response to this situation, this article chooses to improve the loss function in the U-Net model training network by changing it to a binary cross entropy loss function.

Binary Cross Entropy Loss (BCE Loss) is a commonly used loss function in binary classification problems. In deep learning, especially in binary classification tasks, we usually need to measure the difference between the predicted values of the model and the true labels, so introducing a loss function for model training is a very important means.

The mathematical expression for the binary cross entropy loss function is shown in equation (3-1):

$$L = \{l_1, l_2, l_3, \ldots l_n\} \tag{3-1}$$

$$-y\log\hat{y} - (1-y)\log\left(1-\hat{y}\right) \tag{3-2}$$

$l_n = -w_n\left[y_n \log\hat{y}_n + (1-y_n)\log\left(1-\hat{y}_n\right)\right]$, Here "L "represents the value of the loss function, "n" represents batch size, "w_n" Representing weights,"y_n" the true value in the true value vector represents, " $\hat{y}_n$ "the predicted value in the predicted value vector.

Since the final output image is a binary image, we define the form of binary cross entropy as: The mathematical expression is shown in equation (3-2), the interval where the output value is located is [0,1].

The advantage of BCE loss is that it is more intuitive and easy to calculate in binary classification problems. It has a lower loss when the model predicts close to the true label, and a higher penalty for obvious model prediction errors. This can help the model quickly correct errors. During the training process, the model parameters are adjusted by minimizing the BCE loss, which enables the model to better understand the training data and improve the accuracy of binary classification tasks.[4]

4. ResNet50 based transfer model for orthopedic image recognition

Due to the different functions of various parts of the human body and the significant anatomical differences between them, the treatment of each part in medicine is also subdivided into various specialized departments. In general, what we refer to as orthopedics is also subdivided into upper limb orthopedics and lower limb orthopedics. Due to the significant differences in bone morphology and their respective characteristics, in order to treat orthopedics more efficiently and accurately, we should also classify and recognize orthopedic images. Due to the fact that orthopedic images often come from different imaging devices, and the imaging quality is also easily affected by the imaging equipment and surrounding environment.[5] Usually, manually identifying image types requires significant time and labor costs, which greatly reduces the efficiency of image classification. With the rapid development of deep neural networks and large-scale updates of hardware equipment in recent years, the use of deep neural networks for orthopedic image recognition has become possible.

5. Conclusion

The focus of this project is on the role of deep neural networks in orthopedic image processing, which includes training segmentation models based on U-Net network structure and transfer learning for medical image recognition based on ResNet50. By freezing the underlying feature extractor structure of the model during the retraining process, the extracted feature parameters from the pre trained model at the lower level will not be updated, while fine-tuning the top-level or some grassroots parameters to adapt to the task objectives. In data testing, its accuracy exceeded 99% and the loss continued to stabilize, indicating that the model has reached a state of regional convergence.

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