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Lung Tumor Image Recognition based on Convolutional Neural Network

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Abstract

Lung tumors are one of the common malignancies. Early detection and treatment are very important for the survival and cure rate of patients. Deep learning-based lung tumor detection uses deep learning models such as convolutional neural network for automatic detection and classification, extracts features from image data, analyzes and processes medical images, and detects early lung tumors to help doctors make more accurate diagnosis and treatment plans. In this research, a lung tumor recognition algorithm based on deep learning is designed by combining Unet network and 3DCNN model, and the recognition accuracy of lung tumors reaches 80.6%. The specificity value reaches 72.2%, which can play a false positive filtering effect.

Keywords

Unet Image Segmentation; 3DCNN Classification; Lung Tumors.

1. Introduction

Lung tumor is one of the most common lung sicknesses. If it is not diagnosed and treated in time, it is easy to cause lung cancer [1]. It is often found in the late stage, which brings great problems to treatment, and high death.Traditional pulmonary imaging screening methods are inefficient and prone to missed diagnosis and misdiagnosis. Over the last few years, the evolution of deep learning technology has made it possible to perform fast and accurate automatic recognition of lung images through computers [2], which provides new ideas and methods for the early diagnosis and screening of lung tumors.

In the field of lung medical image segmentation, Unet network has been used to realize the automatic diagnosis of lung tumors [3]. Foreign scholars have also proposed some new lung tumor recognition methods, such as pulmonary nodule detection method based on neural network [4], lung Cancer Detection Method Based on Deep Learning [5], and CoA Unet [6] and other segmentation methods.

The lung image segmentation and tumor recognition method on the strength of deep learning proposed in this research can segment and detect lung tumors accurately, and filter false positive lung tumors [7].It improves the work efficiency of doctors, reduces the risk of missed diagnosis and misdiagnosis, and eliminates human interference.

2. Data Preprocessing and Augmentation

The data set used in the paper is the open source CT image data set LUNA16 and CSV file [8]. The Medical image data set is stored in the.dcm format and is divided into 654 training sets and 160 testing sets.Among them, the ASCP file contains candidate information added notes to with the location of each candidate tumor in coordinates, the similar category and its scan name.These data will be used to train and test lung tumor detection and models to provide more medical services.

In the process of data preprocessing and improvement, we the pixel values of these medical images [9], ized them to the range of 0 to 1, and finally saved the processed images as png format.

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After that, we perform a series of random translation, left-and-right and up-and-down flipping operations on these CT images to increase the diversity and amount of data to improve the model strength.

The specific process of data preprocessing and augmentation is as follows:

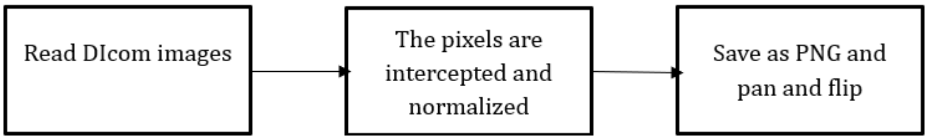
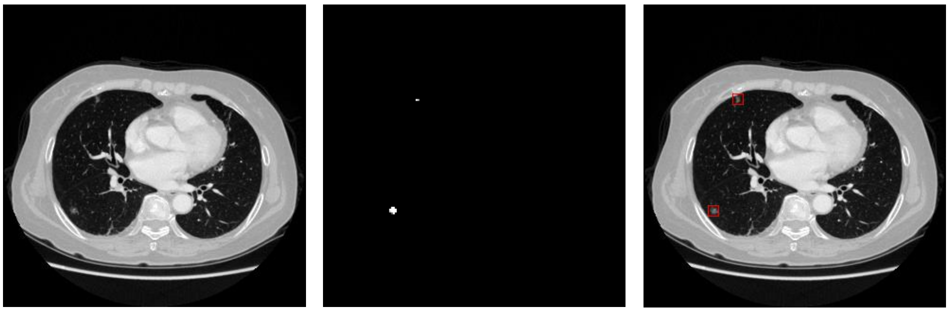


Fig 1. Flowchart of data processing and augmentation

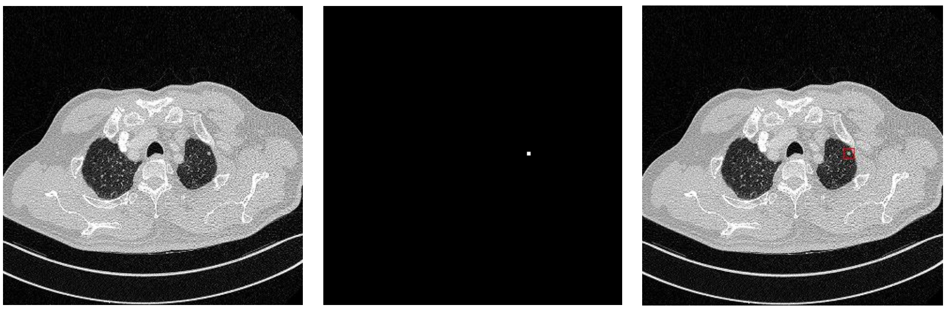
3. Segmentation and Detection of Lung Tumors

The Unet network model is suitable for image segmentation tasks, especially medical image segmentation tasks [10]. Encoder - decoder structure and jump connection mechanism can effectively use high level semantic information and low level detail information to improve the accuracy of segmentation results; In the encoder, a convolution layer with a convolution kernel size of 3×3 is used to extract the feature information of the image and a pooling layer with a size of 2×2 is used to downsample this feature map. In this decoder, a deconvolution layer and an upsampling layer are used to gradually increase the number of features and restore the feature map to the original size.

The Unet network model has a fast training speed and is good for training on a small account of data sets. The effect can be further improved by image improvement and other methods [11]. We use data augmentation to increase the number of samples in the training set, we use image improvement methods such as flipping, rotation, scaling, and translation to reduce the risk of overfitting.Besides, to avoid problems such as disappearance or explosion in the training process, ReLU function and batch ization are also used [12].



(a) Original image (b)Segmentation result (c)Detection results



(e)Original image (f)Segmentation result (g)Detection results

Fig 2. Lung CT image segmentation and detection

The Dice coefficient is used to evaluate the segmentation effect of this model [13], which measures the similarity between the predicted results and the true results. By minimizing Dice loss, the model

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can be optimized to improve the accuracy of segmentation results [14]. The Dice Loss formula is as follows:

$$L_{dice} = 1 - \frac{2|X \cap Y|}{|X| + |Y|} \tag{1}$$

4. False Positive Tumor Filtering with 3DCNN

Convolutional layer, pooling layer, fully connected layer, and activation function layer made up the 3DCNN network. Image height, image width, and image channel are its three dimensions [15].

3DCNN stacks many consecutive frames into a cube, and uses 3D convolution kernels to extract features. The three-dimensional convolution kernel can move along three directions in the cube, so as to obtain the image information better. The (having height, width, and depth) convolution kernel can move along three directions in the cube, to get the image information better. In the 3D-CNN structure, each feature map in the convolutional layer is connected with multiple in-a-row frames in the previous layer to earn information [16].

The 3D convolution is defined as follows:

$$h^l(c_l, x, y) = \sigma(b_{c_l}^l + \sum_{c_l-1} \sum_{u,v,w} w^l(c_l, c_l - 1, u, v, w) h^{l-1}(c_i x - u, y - v, z - w)) \tag{2}$$

In the above formula, x,y,z represent image information, $b_{c_l}^l$ is the paranoid term, w^l denotes the convolution kernel, σ is the activation function so that the neural network has nonlinear characteristics, h^{l-1} is the 3D image information at layer l-1 [17].

Two crucial layers in the 3DCNN network model are the full connection layer and the 3D Max pooling layer, which can further extract image features, shrink the size of the feature matrix, and ultimately produce classification results. The fully connected layer may reduce the dimension of the feature matrix to one dimension for classification, while the 3D Max pooling layer can extract picture features for downsampling.

On false positive tumors, the filtering effect of the model was assessed for accuracy, precision, specificity, and sensitivity:

Table 1. Model Evaluation Effect

TP	FP	TN	FN
2645	673	1748	381
Accuracy	Precision	Sensitivity	Specificity
80.6%	79.7%	87.4%	72.2%

The specificity value was 0.722, which effectively prevented false detection and had a positive filtering effect on false positive tumors. The model was less likely to miss, as indicated by the sensitivity value of 0.874.

5. Conclusion

Deep learning technology provides new ideas and methods for the early diagnosis and screening of lung cancer. In practical applications, we can apply the trained Unet network model to the segmentation of lung CT images to realize the automatic segmentation of lung tumors and improve the diagnostic efficiency and accuracy of doctors. For the authenticity of lung tumors, 3DCNN is used to filter false positives, which can play an auxiliary role in the further diagnosis of medical staff.

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