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Deep Learning-Driven Advances in Lung Tumor Segmentation and Diagnosis

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Abstract: Lung tumors, one of the most prevalent respiratory conditions, pose a significant health risk when left undiagnosed and untreated, often progressing to lung cancer with high mortality rates. Traditional imaging screening methods suffer from inefficiencies and frequent diagnostic errors, emphasizing the urgent need for innovative solutions. This study explores the transformative potential of deep learning in enhancing lung tumor diagnosis. By employing the Unet network for CT image segmentation and integrating 3DCNN to filter false positives, the proposed methodology achieves precise lung tumor recognition while minimizing human interference. The findings demonstrate improved diagnostic efficiency and accuracy, providing a robust framework for aiding medical professionals in early detection and reducing diagnostic errors.

Keywords: Unet Image Segmentation; 3DCNN Classification; Lung Tumors.

1. Introduction

Lung tumors are among the most prevalent lung diseases and, if not diagnosed and treated promptly, can develop into lung cancer [1]. This progression is often discovered only in advanced stages, posing significant challenges to treatment and resulting in high mortality rates. Traditional pulmonary imaging screening methods are characterized by inefficiencies and a high likelihood of missed diagnoses or misdiagnoses, further exacerbating the burden on both patients and medical professionals. Over recent years, the rapid evolution of deep learning technology has revolutionized the field of medical imaging, enabling fast, accurate, and automated recognition of lung images through computer-aided techniques [2]. These advancements provide novel approaches and methodologies for the early diagnosis and screening of lung tumors.

In the domain of lung medical image segmentation, the U-Net network has proven to be a reliable tool for automating the diagnosis of lung tumors [3]. Researchers worldwide have introduced various innovative lung tumor recognition methods, including a pulmonary nodule detection method based on neural networks [4], a lung cancer detection method leveraging deep learning [5], and advanced segmentation techniques such as CoA U-Net [6]. These approaches represent significant progress in the application of artificial intelligence to medical diagnostics.

The lung image segmentation and tumor recognition methodology proposed in this research builds upon the strengths of deep learning frameworks. Specifically, it is designed to accurately segment and detect lung tumors while effectively filtering out false positives [7]. This dual capability not only enhances the efficiency and accuracy of medical diagnostics but also minimizes the likelihood of human error. By reducing missed diagnoses and misdiagnoses, this approach significantly improves the workflow for medical professionals, enabling them to focus on critical cases. Furthermore, it eliminates potential human interference, ensuring consistency and reliability in diagnostic outcomes. As a result, this research contributes to advancing lung cancer prevention and treatment strategies, ultimately improving patient care and outcomes.

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.

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:

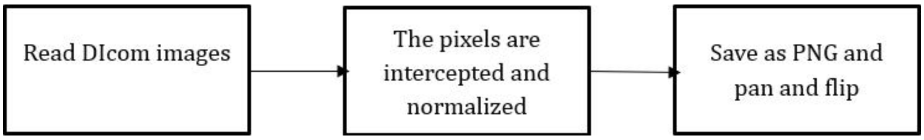
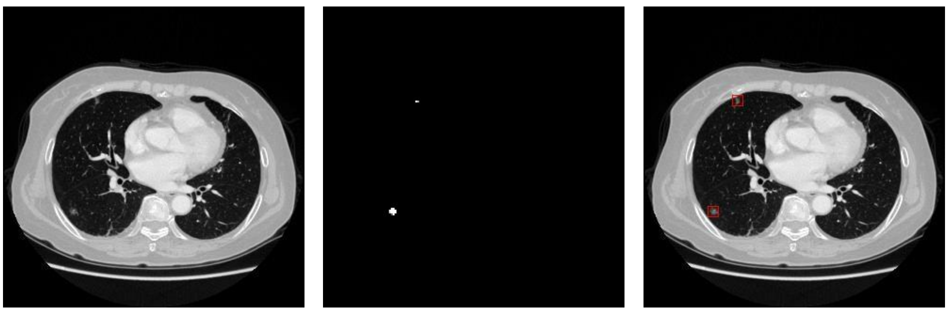


Fig 1. Flowchart of data processing and augmentation

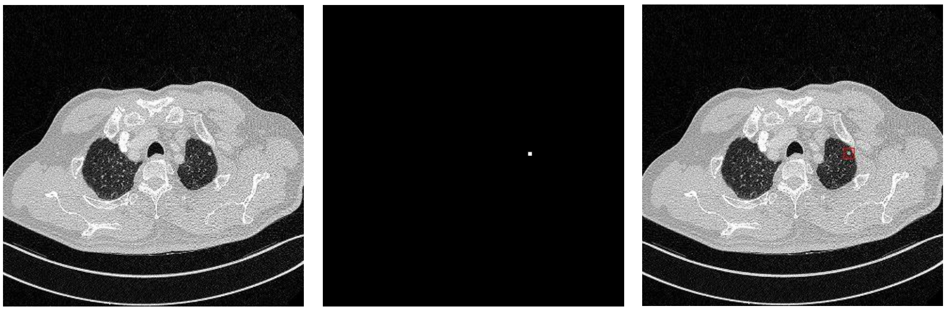
3. Segmentation and Detection of Lung Tumors

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

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

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:

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

In the above formula, x,y,z represent image information, r^{x}_{Y} 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 offers innovative ideas and methodologies for the early diagnosis and screening of lung cancer, significantly advancing the field of medical imaging. In practical applications, the trained U-Net network model can be effectively utilized for the segmentation of lung CT images, enabling the automatic delineation of lung tumors. This not only improves diagnostic efficiency but also enhances the accuracy of clinical assessments conducted by medical professionals. Additionally, to ensure the authenticity and reliability of detected lung tumors, the use of 3D Convolutional Neural Networks (3DCNN) provides robust filtering of false positives. This complementary approach serves as a critical auxiliary tool, assisting medical staff in making more precise and informed diagnostic decisions, ultimately contributing to better patient outcomes.

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