Segmentation of lung computed tomography images based on SegNet in the diagnosis of lung cancer

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Objective: To apply SegNet approach to establish an auxiliary diagnosis model for lung cancer based on lung computed tomography (CT) image scores, and to explore its value in distinguishing benign and malignant lung CT images.

Methods: We selected 240 patients, half of whom were diagnosed as early-stage lung cancer, and half were diagnosed as benign lung nodules. This paper proposes a model based on SegNet technology to segment images, and compares the accuracy, sensitivity, specificity, and total image segmentation time, and overlap rate of DeepLab v3, VGG 19, and manual image segmentation for lung cancer.

Results: The overlap rate of the SegNet model is 95.11%, and the overlap rate closest to manual segmentation is 95.26%. The overlap rate of DeepLab v3 and VGG 19 is much lower than that of manual segmentation. The SegNet model has a sensitivity of 98.33%, a specificity of 86.67%, an accuracy of 92.50%, and a total segmentation time of 30.42 s, which is shorter than manual segmentation.

Conclusion: Based on SegNet recognition technology, it can effectively improve the diagnostic sensitivity of early lung cancer, and assist physicians to screen early lung cancer more effectively and quickly, which is worthy of clinical promotion.

1. Introduction

The incidence and mortality of lung cancer rank first among all malignant tumors, and the incidence is increasing year by year (Siegel et al., 2019; Wu et al., 2021). The 5-year survival rate of patients with advanced lung cancer is only 18%, even for advanced patients, the 5-year survival rate is less than 8%; the 5-year survival rate of early lung cancer after treatment can reach more than 90% (Zheng et al., 2020).

However, patients with early-stage lung cancer usually have no symptoms and are difficult to detect. Therefore, improving the cure rate of lung cancer patients and improving the prognosis depend on early diagnosis and early treatment. An effective way to advance the diagnostic port of lung cancer is early screening (De Koning et al., 2020).

Chest computed tomography (CT) scans have high-density resolution (Grydeland, 2011; Hedblom, 2013; Pu et al., 2012), which can overcome the shortcomings of traditional X-ray two-dimensional (Awad et al., 2012; Sun et al., 2015) plane overlap, similar tissue absorption, and low contrast. It is considered to be one of the most mature and effective imaging techniques for early lung cancer screening. In CT images, early lung cancer is mainly manifested as pulmonary nodules. How to accurately judge the benign and malignant pulmonary nodules in a noninvasive way is the current research difficulty and hot spot (Loverdos et al., 2019).

Due to the general popularity of thin-slice CT, very small lung nodules can be found by screening. At the same time, due to the increase in the number of scanning layers, radiologists are faced with huge amounts of data and images, not only time-consuming and laborious, low work efficiency, but also easy to cause misdiagnosis or missed diagnosis (Kai & Zhao et al., 2020; Macaulay et al., 1990); therefore, traditional manual segmentation is no longer meet clinical needs.

The continuous development of genomics, metabolomics, and imaging omics has provided big data support for precision medicine for cancer patients, but it also brought huge challenges to oncologists’ data analysis. Convolutional neural network (CNN) can process high-dimensional data in large quantities (Johnson et al., 2020; Long et al., 2021; Luo et al., 2020; Rabbani et al., 2018). In terms of image recognition, CNN can automatically identify and dynamically monitor target lesions, assisting clinicians to obtain more accurate imaging evaluations. Improved work efficiency and reduced
work load have important value in tumor diagnosis, recurrence detection, and individualized diagnosis and treatment (Ehteshami Bejnordi et al., 2017; Kallbn et al., 2016; Song et al., 2014; Srivastava et al., 2018). Although CNN has achieved fruitful results in the field of tumor-assisted diagnosis, it still faces many challenges in clinical practice, such as data accessibility, model robustness and generalization, and result interpretability. This paper mainly discusses the application progress of CNN in the field of lung cancer diagnosis in terms of CNN basic principles, frontier progress, challenges, and future prospects.

This paper proposes a model based on SegNet (Ajay et al., 2018; Armato et al., 2017; Kourou et al., 2014; Lung, 2019; Mittal et al., 2018) for the diagnosis of lung CT, in order to improve the accuracy of the diagnosis of lung cancer and lung nodules, and at the same time, shorten the time to segment the medical image.

2. Methodology

2.1. Structure of this paper

Figure 1 shows the structure of this paper. The 120 patients diagnosed with early lung cancer by pathological examination and 120 patients with benign lung nodules in the same period were identified by SegNet and artificially, and then the diagnosis effect was compared.

2.2. General information

A total of 120 patients with early-stage lung cancer diagnosed by pathological examination were selected in this hospital from August 2018 to August 2020, and 120 patients with benign lung nodules were selected as the research object during the same period. The gender distribution and age distribution of patients with early lung cancer and patients with benign lung nodules are shown in Table 1.

2.3. Basic principles of CNN

CNN includes deep belief network (DBN) (Chilakala & Kishore, 2020; Madhavan & Gopakumar, 2020; Zhao et al., 2020), convolution neural net-works (CNN) (Hirakawa et al., 1997; Moitra et al., 2019), recurrent neural network (RNN) (Lei et al., 2019; Wang et al., 2019; Yan et al., 2019), etc. CNN can directly process unstructured data including images, sounds, and

![Figure 1. The overall structure of the paper.](image-url)
Table 1. Gender and age distribution of patients with early-stage lung cancer and patients with benign lung nodules.

| Category                        | Male | Female | Age distribution |
|---------------------------------|------|--------|------------------|
| Patients with early lung cancer | 71   | 49     | 47.5 ± 2.4       |
| Patients with benign lung nodules | 42   | 78     | 42.1 ± 2.1       |

language, and has advantages in clinical image classification, medical history text analysis, and tumor diagnosis.

This paper proposes a SegNet approach to segment the film, and compares the segmentation effect of Deeplab v3 and VGG 19 networks.

2.3.1. SegNet

Badrinarayanan et al. (Badrinarayanan et al., 2015) proposed the SegNet network structure to solve the problem of image semantic segmentation in the field of autonomous driving and intelligent robots. The novelty of SegNet is the way the decoder samples its low-resolution input feature maps. Specifically, the decoder uses the pooling index calculated in the maximum pooling step of the corresponding encoder to perform non-linear upsampling. This eliminates the need to learn up samples. The up-sampled feature maps are sparse and then convolved with trainable filters to produce dense feature maps. The network structure of SegNet is shown in Figure 2.

2.3.2. Deeplab v3

Deeplab v1 (Chen et al., 2014) uses VGGNet as the basic network, uses the pre-trained model of VGGNet and fine-tunes it. Deeplab v2 (Chen et al., 2018) addresses the problem of image resolution reduction in the feature extraction process and uses deconvolution for upsampling. The network uses dilated convolution and linear interpolation methods. On the basis of Deeplab v2, by adopting global average pooling, the method of ASPP (Atrous Spatial Pyramid Pooling) is improved in the spatial dimension, and Deeplab v3 (Chen & Schroff et al., 2017) structure is proposed. Compared with the previous two versions, Deeplab v3 has achieved better results. The network structure of Deeplab v3 is shown in Figure 3.

2.3.3. VGG 19

Simonyan et al. (Simonyank & Zisserman, 2014) proposed the VGGNet network structure and mainly studied the relationship between depth and performance in convolutional neural networks. According to current standards, this network is not very deep, but when VGGNet was proposed, it had twice the number of layers than the commonly used network at that time, which proved that on the basis of feasible training, the deeper the network, the better the performance. The network structure of VGG 19 is shown in Figure 4.

2.4. Equipment

We used 16-row CT from GE to scan 240 selected patients. The patient was placed in a supine position, scanning the lung tip at a costophrenic angle.

2.4.1. Manual examination and segmentation

In this paper, six senior physicians with more than 5 years of experience were selected to use 6-ITK-SNAP medical image processing software to manually mark and manually segment chest CT films.

2.4.2. SegNet approach

Based on deep learning technology, the SegNet system automatically learns the recognition and classification of lung cancer nodules and segmentation of CT images, and constructs the optimal model for SegNet recognition technology segmentation.

In this paper, 240 patients’ CT images were collected to form 10,000 image data sets, of which 7,400 samples were used for the training set and 2,600 samples were used for the training set.

2.5. Observation indicators

2.5.1. Split image

The evaluation parameters include the overlap area and overlap rate between the SegNet model and the malignant lesion area segmented by the pathologist and the gold standard. The calculation of the overlap rate is as in Equation 1.

\[ or = \frac{2 \times oa}{da + gs} \times 100\% \]  \hspace{1cm} (1)

In Equation 1, or represents the overlap ratio, oa represents the overlap area, da represents the divided area, and gs represents the gold standard area.
2.5.2. Performance Comparison

We compare the sensitivity, specificity, accuracy, and total segmentation time of CNN and manual segmentation for early lung cancer.

The formulations of Sensitivity (Sen), Specificity (Spe), and Accuracy (Acc) are as Equations 2–4.

\[
Sen = \frac{TP}{TP + FN} \quad (2)
\]

\[
Spe = \frac{TN}{TN + FP} \quad (3)
\]

\[
Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)
\]

In Equation 2–4, TP means true positive, FP means false positive, TN means true negative, and FN means false negative.

2.6. Statistical processing

We used SPSS 20.0 software for statistical analysis. The measurement data are expressed as \(x \pm s\), the overlap area and overlap rate are compared by independent sample t test, the diagnosis time is compared by paired sample t test, and the area of malignant lesions segmented by SegNet, Deeplab v3, VGG 19 pathologist and gold standard is compared by one-way analysis of variance; The count data are expressed as the number of cases and percentages, and the comparison of sensitivity, specificity, and accuracy uses McNemar test. The inspection level \(\alpha\) is 0.05.
3. Results

3.1. Segmentation of lung CT images

Figure 5 shows the CT images for manual segmentation, CNN-based segmentation, and gold standard. Red is the manual segmentation (gold standard), yellow is the segmentation result based on SegNet, purple is the segmentation result based on Deeplab v3, and green is the segmentation result based on VGG 19. The white boxes are cancerous sites and nodules.

It can be seen from Figure 5 that SegNet model and the artificial segmentation result are closest to the gold standard and almost overlap, but the segmentation results of based on Deeplab v3 and based on VGG 19 are obviously larger.

3.2. Overlap rate

Table 2 shows the comparison of overlap area and segmentation area between manual image segmentation and CNN recognition technology. It can be seen from Table 2 that the area of the gold standard malignant lesion area in the malignant lesion image, the area of the malignant lesion area segmented by the doctor is, the area of the malignant lesion area segmented by the SegNet model, the difference between the three is statistically significant; the results of the pairwise comparison show that there is no statistically significant difference between the standard and the area of malignant lesions segmented by the pathologist; in addition, the overlap area of the SegNet model is not statistically different from that of the pathologist.

By calculating the overlap rate of manual image segmentation and AI model, the overlap rate of SegNet-based model is 95.11%, the overlap rate of SegNet-based model is 80.24%, and the overlap rate of SegNet-based model is 81.22%. The overlap rate of manual image segmentation is 95.26%, and SegNet model is the closest to manual image segmentation.

3.3. Performance comparison

The diagnosis results of SegNet approach for early lung cancer and benign nodules are shown in Table 3. The sensitivity is 98.33%, the specificity is 86.67%, and the accuracy is 92.50%.

The diagnosis results of Deeplab v3 approach for early lung cancer and benign nodules are shown in Table 4. The sensitivity is 78.33%, the specificity is 82.50%, and the accuracy is 80.41%.

The diagnosis results of VGG 19 approach for early lung cancer and benign nodules are shown in Table 5. The sensitivity is 75.00%, the specificity is 84.17%, and the accuracy is 79.58%.

The sensitivity, specificity, and accuracy of manual segmentation of early lung cancer are shown in Table 6. The sensitivity of manual segmentation for early lung cancer is 80.83%, the specificity is 91.67%, and the accuracy is 86.25%.

The accuracy of lung CT recognition based on SegNet is much higher than that of Deeplab v3, VGG 19, and manual image segmentation. The time for CNN to recognize lung cancer is much shorter than manual. SegNet only needs 30.42 s. The performance comparison of the four methods is shown in Figure 6.

![Figure 5. CT image of manual segmentation and CNN segmentation.](image)

**Table 2.** Comparison of overlap area and segmentation area between manual image reading and SegNet recognition technology.

| Model          | Early lung cancer | Benign lung nodules |
|----------------|-------------------|---------------------|
|                | Gold standard     | Overlap area        | Divided area | Gold standard | Overlap area | Divided area |
| Manual reading | 214,691.59        | 212,578.47          | 211,117.23 | 199,556.75   | 189,567.24   | 198,247.98   |
| SegNet         | 214,122.34        | 213,447.22          |              | 187,445.27   | 197,884.53   |
| Deeplab v3     | 206,453.87        | 217,648.57          |              | 186,247.12   | 200,124.22   |
| VGG 19         | 208,644.15        | 218,114.43          |              | 188,344.27   | 201,241.33   |
| Table 3. Diagnosis results of early lung cancer and benign nodules with SegNet approach. |
|---------------------------------|---------|---------|------|
| SegNet                          | Positive| Negative| Total|
| Early lung cancer               | 118     | 2       | 120  |
| Benign lung nodules             | 16      | 104     | 120  |
| Total                           | 134     | 106     | 240  |

| Table 4. Diagnosis results of early lung cancer and benign nodules with Deeplab approach. |
|---------------------------------|---------|---------|------|
| Deeplab v3                      | Positive| Negative| Total|
| Early lung cancer               | 94      | 26      | 120  |
| Benign lung nodules             | 21      | 99      | 120  |
| Total                           | 115     | 125     | 240  |

4. Discussion

Although SegNet has achieved certain results in the field of assisted tumor diagnosis, it still faces many challenges in the transformation of clinical practice (Simonyank & Zisserman, 2014). The main challenges can be summarized in the following three aspects.

First, the biggest challenge is the availability of data. SegNet is a mathematical science. Reliable SegNet models require a large amount of high-quality training data. However, many hospitals or research institutions are difficult to achieve data sharing due to research confidentiality or patient privacy protection.

Second, model robustness and generalization will affect the recognition results. Robustness refers to the anti-interference ability of the model. Generalization refers to the predictive ability of the model on untrained data, that is, the accuracy of the model obtained from hospital A’s prediction in hospital B. The robustness and generalization of the model are mainly limited by the consistency of the data itself and the subjectivity of data label annotation. Different photographing equipment, lighting conditions, and individual differences will affect the consistency of image data, and different testing instruments and testing reagents will also have a greater impact on clinical data.

Third, the results are interpretable. SegNet is usually considered a ‘black box’ because its internal decision-making process is obscured by thousands of training parameters. In practice, the weights and characteristics of SegNet algorithms are usually unexplainable. Therefore, it is difficult for clinicians to fully grasp the working process and specific influencing factors of the model. With the development of multi-center research and the opening of public database platforms, the accessibility of big data will be further promoted; the development of multiple visualization tools will also provide more references for the interpretation of SegNet results.

5. Conclusion

This paper sets up a controlled experiment to perform CNN-based and manual image segmentation on the chest CT of patients. The experiment shows that SegNet and the artificial segmentation result are closest to the gold standard and almost overlap, but the segmentation results based on Deeplab v3 and based on VGG 19 are obviously larger.

Figure 6. Comparison of sensitivity, specificity, accuracy and total reading time of the four approaches.
The sensitivity of SegNet model to recognize early lung cancer is 98.33% higher than manual segmentation, the specificity of 86.67 is significantly lower than manual segmentation, the accuracy is 92.50% higher than manual segmentation, and the total segmentation time of 30.42 s is significantly shorter than manual segmentation sheet. SegNet approach can effectively improve the diagnostic sensitivity of early lung cancer and is worthy of clinical promotion.

Disclosure statement

No potential conflict of interest was reported by the author(s).

6. Ethical compliance

There is no ethics approval required for this paper.

7. Conflicts of Interest

The authors declare no conflicts of interest.

Highlights

- A segmentation model for lung CT image based on SegNet is proposed.
- Overlap rates of SegNet, DeepLab v3, VGG 19, and manual segmentation are compared.
- The accuracy of SegNet is 92.50%, and the reading time is only 30.42s.
- SegNet accelerates the recognition speed of early lung cancer and benign lung nodules.
- SegNet’s lung CT segmentation image is closest to the gold standard.

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