

Image Content Segmentation Based on Convolutional Neural Network

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Abstract: In real life, images are widely used in medicine, commercial marketing and other fields. Image recognition technology has developed rapidly and has played a huge role in our daily life and work. So in order to make better use of image technology, this paper intends to delve into image content segmentation in convolutional neural networks. This paper mainly studies the role of convolutional neural networks and image segmentation in specific operations through experimental methods and interactive ratio IoU analysis methods. The experimental data show that in the PASCAL VOC 2015 and IRCAD datasets, the optimal parameters obtained by G-FCN are $\alpha=0.6$, $\beta=0.6$. Therefore, the result of using the improved algorithm is close to the marked result, which can better reflect the details of the image, and the segmentation effect is better.

1. Introduction

A convolutional neural network model is a probability-based statistical method that learns and predicts possible information in a collection of images by modeling sample data. We need to understand image content analysis techniques. It is a technology for processing and detecting object characteristic information, and can describe it and then extract the data to be quantified. It is widely used in many fields and has been well developed.

There are many studies on convolutional neural networks and image segmentation, and many scholars still analyze these two aspects. For example, some scholars have proposed that deep convolutional neural networks have been widely used in many image tasks [1-2]. Some scholars have proposed a method based on convolutional neural network combined with deep learning technology to accurately segment plant images under artificial color cast light [3-4]. Others provide a method and system for lesion image segmentation based on deep convolutional neural network [5-6]. These theoretical studies undoubtedly highlight the important role of convolutional neural

networks in images. Therefore, this paper is valuable for this network and its application in image content segmentation.

This paper studies some techniques involved in the process of image segmentation. After learning and mastering these methods, a simple and easy-to-understand image content segmentation method is proposed. This article introduces the convolutional neural network and applies it to real life.

2. Convolutional Neural Network and Image Segmentation Technology

2.1. Image Segmentation Method

Image segmentation is a key technology for image recognition and analysis in computer vision. Image segmentation is to divide the image into several regions, the pixels between different regions have obvious differences in this characteristic, and then extract the region of interest after a series of operations. The fundamental purpose of image segmentation is to choose an appropriate representation, and then to better identify and understand the image [7-8].

The texture feature extraction method uses a specific method to obtain this spatial characteristic of the image. The gray level co-occurrence matrix (GLCM) can extract energy, entropy, maximum probability, contrast, reciprocal difference moment and correlation. Local Binary Pattern (LBP) is a simple and efficient texture description operator. Wavelet analysis not only integrates its localization characteristics, but also links the window size and frequency changes, and is an effective tool for image and signal transformation [9-10].

Image segmentation is divided into threshold segmentation, region segmentation, edge segmentation and segmentation based on energy functional. The principles and implementation details of these segmentation methods are relatively simple, and the algorithm performance is relatively stable, so they have always been the most basic methods in the field of image segmentation.

The K-Means segmentation algorithm is a relatively simple and fast segmentation algorithm in this class of algorithms. Since there is no need to classify objects, image segmentation technology generally only needs to use the local information of the image. And it does not need to further extract more complex features. The model of the segmentation algorithm is relatively simple. Semantic segmentation not only needs to accurately segment the region where the object is located, but also needs to obtain the object to which the region belongs. Therefore, the semantic segmentation model must have the ability of object classification and image segmentation at the same time. The key update step in a typical mean-field inference algorithm can be simplified as a convolution operation, and the convolution operation has a fast algorithm that can simulate the convolution process to speed up the operation. At the same time, due to the characteristics of the convolution kernel in the frequency domain space, the mean field the convolution operation simplified by the inference algorithm can be further truncated. Various optimization operations reduce the model inference speed from hours to seconds [11-12].

Image segmentation technology is an indispensable process for image information processing, and its applications have spread in various fields. In medicine, image segmentation technology can help doctors accurately determine the location of lesions and provide convenience for the diagnosis and treatment of acute diseases. As shown in Figure 1, it is a common medical image segmentation system.

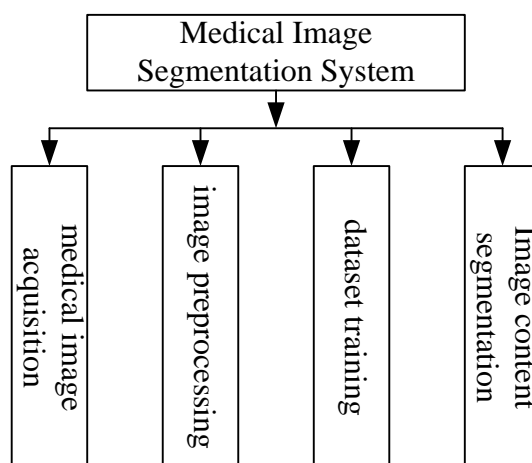


Figure 1. Medical image segmentation system module

The main function of medical image acquisition is to load the medical image to be segmented, and this step needs to be completed under the operation of the user. Image preprocessing completes the unification of image scales in the dataset. The data set training function realizes the full convolutional neural network training of the image data set, and obtains the training model, which provides a template for the subsequent image segmentation. The image segmentation module uses the template obtained after training on the dataset to complete the initial segmentation, and then runs the optimization procedure [13-14] on this basis.

2.2. Convolutional Neural Networks

CNN adopts a structure of alternating local feature extraction layers and feature transformation layers, so the model always retains the recognition ability when objects move or deform. CNN is a multi-layer neural network. The neurons of a convolutional neural network share the same set of weights, which reduces the complexity of the network model [15-16].

Generally speaking, the deeper the CNN layer, the higher the performance, but the higher the hardware requirements, the slower the calculation speed.

Thresholding is a common image segmentation preprocessing technique. It has better segmentation efficiency for images in which the target and background occupy different grayscale regions. Global thresholding refers to using a single gray level as the threshold for the entire image. Therefore, this method is particularly suitable for images with significant differences between target pixels and background pixels. Threshold segmentation only considers the grayscale of the image and is very sensitive to noise. Segmentation methods based on edge detection achieve segmentation of objects by locating their boundary edges [17-18].

Convolutional Neural Networks need to continuously use data for iterative calculations to complete the self-learning process. This learning process requires that the scale of the training sample set is large enough. Convolutional neural networks are supervised learning in machine learning, so we need to prepare a large amount of labeled data in advance, which increases the workload.

The algorithm based on convolutional neural network and fuzzy membership method segmented lung parenchyma texture, and transformed the segmentation task into segmentation task through fuzzy membership probability method. First, we segmented the lung parenchyma through image preprocessing, and retained the texture details of the lung parenchyma to reduce the difficulty of segmentation; then, the lung parenchyma was divided into blocks, and the image blocks were taken

in a sliding manner. When the boundary extension is required, the segmented image block is divided into a training data part and a test data part. Next, the convolutional neural network is trained and the test data is used to classify through the trained network. Finally, the method based on fuzzy membership value is used to achieve texture segmentation, and the segmented image includes the texture part of lung parenchyma and the boundary part of lung parenchyma.

2.3. Medical CT Image Segmentation Based on Convolutional Neural Networks

The process of medical image segmentation is to complete the segmentation of the entire medical image. To evaluate the effect of CT image segmentation, the main accuracy measures used include the following three:

The formula for the Dice coefficient is defined as:

$$Dice = \frac{2|X \cap Y|}{|X| + |Y|} \quad (1)$$

The correct rate formula is defined as:

$$Accuracy = \frac{|X \cap Y|}{|Y|} \quad (2)$$

The recall formula is defined as:

$$Recall = \frac{|X \cap Y|}{|X|} \quad (3)$$

Where X represents the manual segmentation result and Y is the automatic segmentation result of the algorithm.

The difference between the pixel gray values of CT images is relatively large, and the gray value threshold can be used for segmentation to distinguish different regions. Neural network method is an important branch of machine learning by simulating biologically relevant functions under a large amount of data. Convolutional neural networks have been successfully used as supervised networks in the machine learning category.

3. Simulation Experiment

3.1. Experimental Environment

Experimental environment: The experimental platform is the Windows 17.05.6 operating system, the CPU is Intel E6-2650, the memory is 512G, the graphics card is GPU GeForce GTX 1080, and the Caffe platform is used to train the dataset. The simulation experiment is carried out according to the G-FCN algorithm designed above.

3.2. Experimental Data

The dataset is from PASCALVOC 2015, NYUDv4 in the field of computer vision, and the medical dataset is from lung CT scan images in the French International Medical Center database.

In the algorithm, the training part is used to complete the construction of the algorithm network model. During the training process, different values are assigned to the parameters to obtain

different results, and then the test set is used to record and analyse the results of the network model.

3.3. Evaluation Criteria

The evaluation method of the system segmentation results in this paper adopts the interactive ratio IoU analysis method. That is, the intersection of the results segmented by the segmentation model and the results of manual annotation.

The algorithm parameters include the ratio of energy function α , β , the parameters of Gabor filter and the number of clusters of k-means algorithm, the number and depth of random forest decision trees. These parameters can be divided into three groups according to their relationship with each other, α and β are divided into one of them, and these parameters will affect the final segmentation effect from different aspects.

4. Experimental Results

According to the experimental scheme to verify the results of the algorithm, the influence of different parameters on the results should be divided into two stages. The whole result analysis is based on the quantitative analysis of mean IU, and the annotated image is used as a comparison template to prove that the algorithm proposed in this paper can significantly improve the image segmentation effect.

4.1. The Mean IU Value under the Variable of Alpha Proportion

According to the experimental results in this paper, we can find that the PASCAL VOC2015 data have different results in the α value. As shown in Table 1, in the PASCAL VOC 2015 dataset, the mean IU value at $\alpha=0.8$ is 68.3, and the mean IU value at $\alpha=0.6$ is 69.5, which are significantly higher than other values.

Table 1. Experimental mean IU values in different domains under α value variation

| α | PASCAL VOC2015 | NYUDv4 | IRCAD |
|----------|----------------|--------|-------|
| 1 | 67.2 | 35.1 | 70 |
| 0.8 | 68.3 | 35 | 72.1 |
| 0.6 | 69.5 | 35.4 | 73 |
| 0.4 | 68.6 | 35 | 72 |
| 0.2 | 67.7 | 34.1 | 70.9 |

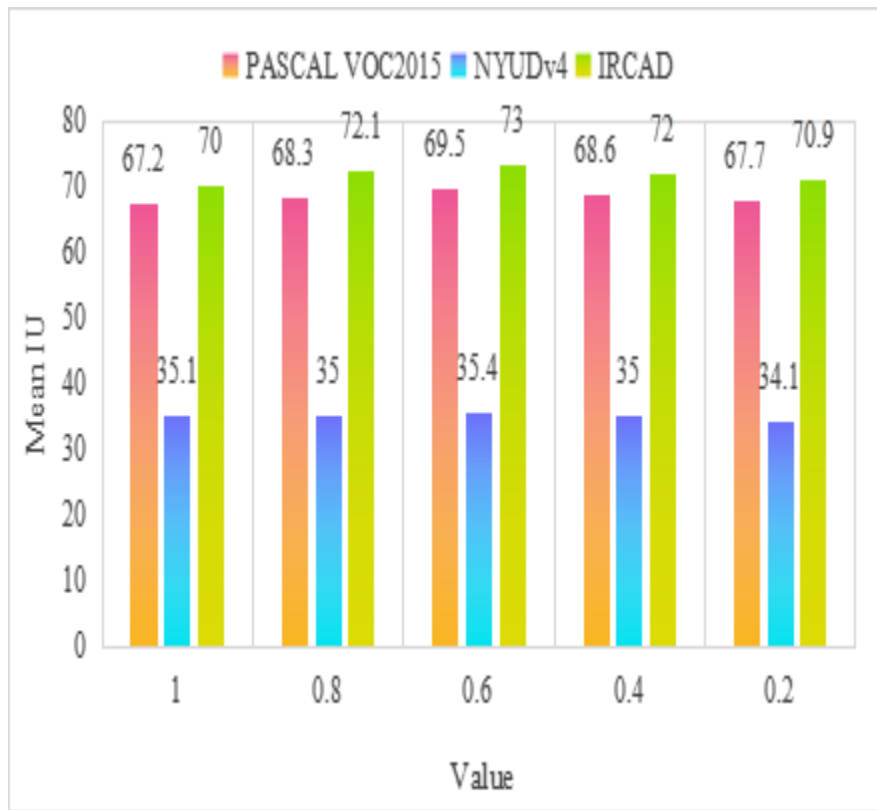


Figure 2. Experimental mean IU values in different domains under α value variation

As shown in Figure 2, we can conclude that in the IRCAD dataset, the mean IU value at $\alpha=0.8$ is 72.1, the mean IU value at $\alpha=0.4$ is 72, and the mean IU value at $\alpha=0.6$ is 73, significantly higher than the other values. So when the ratio is 0.6, segmentation on the dataset IRCAD works best.

4.2. The Mean IU Value under the Variable of Beta ratio

According to the experiments, we can see that in the beta value, the NYUDv4 data have different results. As shown in Table 2, in the NYUDv4 dataset, the mean IU value at $\beta=1$ was 34.2, and the mean IU value at $\beta=0.4$ was 35.4, which were significantly higher than other values.

Table 2. Experimental mean IU values in different domains under β value variation

| β | PASCAL VOC2015 | NYUDv4 | IRCAD |
|---------|----------------|--------|-------|
| 1 | 67.3 | 34.2 | 71 |
| 0.8 | 67.9 | 34.6 | 71.1 |
| 0.6 | 68.5 | 34.4 | 73.1 |
| 0.4 | 68.1 | 35.4 | 72.2 |

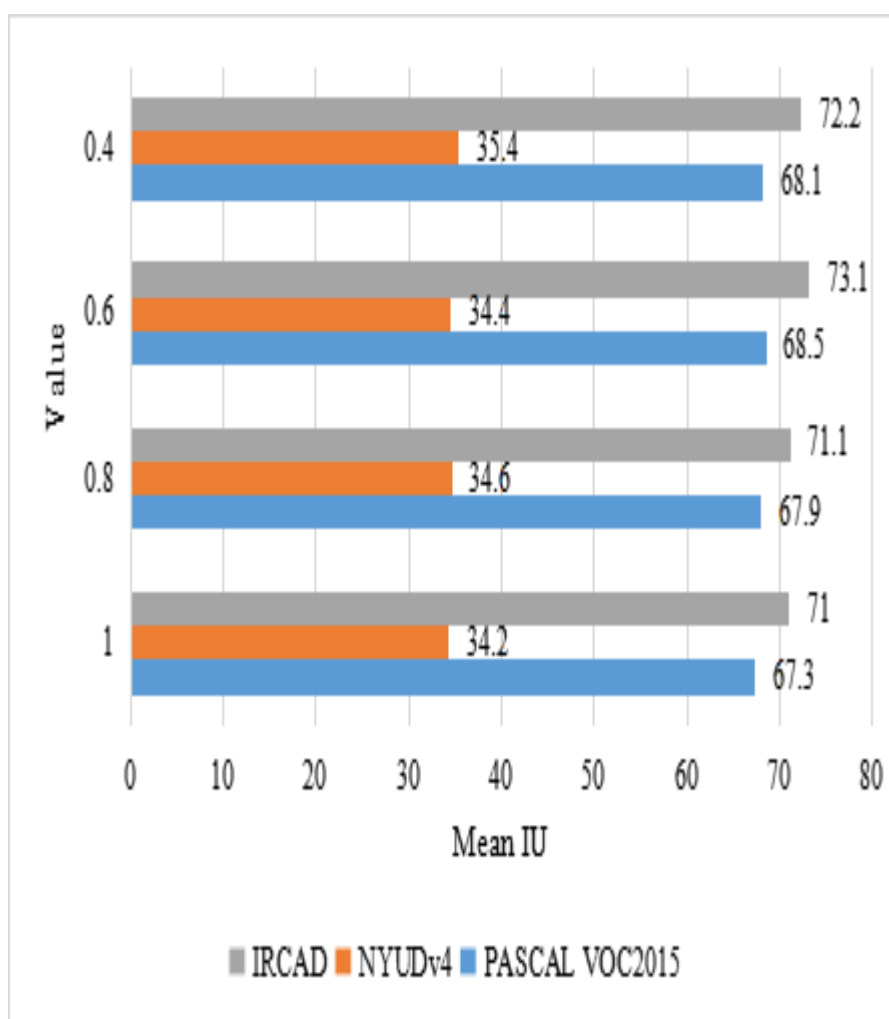


Figure 3. Experimental mean IU values in different domains under β value variation

As shown in Figure 3, we can conclude that in the IRCAD dataset, the mean IU value at $\beta=0.8$ is 71.1, the mean IU value at $\beta=0.4$ is 72.2 and the mean IU value at $\beta=0.6$ is 73.1, significantly higher than the other values. So when the ratio is 0.6, segmentation on the dataset IRCAD works best.

5. Conclusion

With the development of computer technology, image processing has gradually shifted from traditional machine learning methods to two algorithms based on model transfer and manual computing. After combining the convolutional neural network and BPF (based on fuzzy mathematics), by using the gradient descent method, a very good image segmentation effect can be obtained. In the experiments of this paper, it can be found that the calculation results under different parameters can well achieve image segmentation. However, this experiment still has the phenomenon of unstable data. Therefore, further research on the convolutional neural network algorithm is required, and testing with more powerful data resources is required.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

- [1] Madhu, Raman Kumar: A Hybrid Feature Extraction Technique for Content Based Medical Image Retrieval Using Segmentation and Clustering Techniques. *Multim. Tools Appl.* 81(6): 8871-8904 (2022). <https://doi.org/10.1007/s11042-022-11901-8>
- [2] Lakshmana, Sunil Kumar S. Manvi, K. G. Karibasappa: Hybrid Kernel Fuzzy C-means Clustering Segmentation Algorithm for Content Based Medical Image Retrieval Application. *Int. J. Bioinform. Res. Appl.* 17(6): 496-511 (2021). <https://doi.org/10.1504/IJBRA.2021.120534>
- [3] Sneha Kugunavar, C. J. Prabhakar: Content-Based Medical Image Retrieval Using Delaunay Triangulation Segmentation Technique. *J. Inf. Technol. Res.* 14(2): 48-66 (2021). <https://doi.org/10.4018/JITR.2021040103>
- [4] Yashwant Kurmi, Vijayshri Chaurasia: Content-Based Image Retrieval Algorithm for Nuclei Segmentation in Histopathology Images. *Multim. Tools Appl.* 80(2): 3017-3037 (2021). <https://doi.org/10.1007/s11042-020-09797-3>
- [5] Hager Merdassi, Walid Barhoumi, Ezzeddine Zagrouba: Optimisation of Linear Dependence Energy for Object Co-Segmentation in a Set of Images with Heterogeneous Contents. *IET Image Process.* 14(1): 201-210 (2020). <https://doi.org/10.1049/iet-ipr.2018.5176>
- [6] Anastasia Iskhakova, Daniyar Volf, Roman V. Meshcheryakov: Method for Reducing the Feature Space Dimension in Speech Emotion Recognition Using Convolutional Neural Networks. *Autom. Remote. Control.* 83(6): 857-868 (2022). <https://doi.org/10.1134/S0005117922060042>
- [7] Myasar Mundher Adnan, Mohd Shafry Mohd Rahim, Amjad Rehman Khan, Tanzila Saba, Suliman Mohamed Fati, Saeed Ali Bahaj: An Improved Automatic Image Annotation Approach Using Convolutional Neural Network-Slantlet Transform. *IEEE Access* 10: 7520-7532 (2022). <https://doi.org/10.1109/ACCESS.2022.3140861>
- [8] Sonam Aggarwal, Sheifali Gupta, Ramani Kannan, Rakesh Ahuja, Deepali Gupta, Sapna Juneja, Samir Brahim Belhaouari: A Convolutional Neural Network-Based Framework for Classification of Protein Localization Using Confocal Microscopy Images. *IEEE Access* 10: 83591-83611 (2022). <https://doi.org/10.1109/ACCESS.2022.3197189>
- [9] Michael Opoku Agyeman, Andres Felipe Guerrero, Quoc-Tuan Vien: Classification Techniques for Arrhythmia Patterns Using Convolutional Neural Networks and Internet of Things (IoT) Devices. *IEEE Access* 10: 87387-87403 (2022). <https://doi.org/10.1109/ACCESS.2022.3192390>
- [10] Adal A. Alashban, Al-Hanouf Al-Aljmi, Norah F. Alhussainan, Ridha Ouni: Single Convolutional Neural Network With Three Layers Model for Crowd Density Estimation. *IEEE Access* 10: 63823-63833 (2022). <https://doi.org/10.1109/ACCESS.2022.3180738>
- [11] Eoin Brophy, Bryan M. Hennelly, Maarten De Vos, Geraldine B. Boylan, Tomás Ward: Improved Electrode Motion Artefact Denoising in ECG Using Convolutional Neural Networks and a Custom Loss Function. *IEEE Access* 10: 54891-54898 (2022). <https://doi.org/10.1109/ACCESS.2022.3176971>
- [12] Asghar Ali Chandio, Md. Asikuzzaman, Mark R. Pickering, Mehjabeen Leghari: Cursive Text

- Recognition in Natural Scene Images Using Deep Convolutional Recurrent Neural Network. IEEE Access 10: 10062-10078 (2022). <https://doi.org/10.1109/ACCESS.2022.3144844>*
- [13] Suci Dwijayanti, Muhammad Iqbal, Bhakti Yudho Suprpto: *Real-Time Implementation of Face Recognition and Emotion Recognition in a Humanoid Robot Using a Convolutional Neural Network. IEEE Access 10: 89876-89886 (2022). <https://doi.org/10.1109/ACCESS.2022.3200762>*
- [14] Ali Pourramezan Fard, Joe Ferrantelli, Anne-Lise Dupuis, Mohammad H. Mahoor: *Sagittal Cervical Spine Landmark Point Detection in X-Ray Using Deep Convolutional Neural Networks. IEEE Access 10: 59413-59427 (2022). <https://doi.org/10.1109/ACCESS.2022.3180028>*
- [15] Ahmed Y. Hatata, Mohammed Abd-Elnaby, Bishoy E. Sedhom: *Adaptive Protection Scheme for FREEDM Microgrid Based on Convolutional Neural Network and Gorilla Troops Optimization Technique. IEEE Access 10: 55583-55601 (2022). <https://doi.org/10.1109/ACCESS.2022.3177544>*
- [16] Svetlana Illarionova, Dmitrii Shadrin, Vladimir Ignatiev, Sergey Shayakhmetov, Alexey Trekin, Ivan V. Oseledets: *Estimation of the Canopy Height Model From Multispectral Satellite Imagery With Convolutional Neural Networks. IEEE Access 10: 34116-34132 (2022). <https://doi.org/10.1109/ACCESS.2022.3161568>*
- [17] Andac Imak, Adalet Celebi, Kamran Siddique, Muammer Turkoglu, Abdulkadir Sengür, İftekhar Salam: *Dental Caries Detection Using Score-Based Multi-Input Deep Convolutional Neural Network. IEEE Access 10: 18320-18329 (2022). <https://doi.org/10.1109/ACCESS.2022.3150358>*
- [18] Ahmed H. Janabi, Triantafyllos Kanakis, Mark Johnson: *Convolutional Neural Network Based Algorithm for Early Warning Proactive System Security in Software Defined Networks. IEEE Access 10: 14301-14310 (2022). <https://doi.org/10.1109/ACCESS.2022.3148134>*