Computer Methods and Programs in Biomedicine 200 (2021) 105897

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

Coronary angiography image segmentation based on PSPNet

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ARTICLE INFO

Article history:
Received 13 September 2020
Accepted 30 November 2020

Keywords:
Coronary angiography images
blood vessel segmentation
deep learning
multi-scale convolutional neural network
transfer learning

ABSTRACT

Purpose: Coronary artery disease (CAD) is known to have high prevalence, high disability and mortality. The incidence and mortality of cardiovascular disease are also gradually increasing worldwide. Therefore, our paper proposes to use a more efficient image processing method to extract accurate vascular structures from vascular images by combining computer vision and deep learning.

Method: Our proposed segmentation of coronary angiography images based on PSPNet network was compared with FCN, and analyzed and discussed the experimental results using three evaluation indicators of precision, recall and Fl-score. Aiming at the complex and changeable structure of coronary angiography images and over-fitting or parameter structure destruction, we implemented the parallel multi-scale convolutional neural network model using PSPNet, using small sample transfer learning that limits parameter learning method.

Results: The accuracy of our technique proposed in this paper is 0.957. The accuracy of PSPNet is 26.75% higher than the traditional algorithm and 4.59% higher than U-Net. The average segmentation accuracy of the PSPNet model using transfer learning on the test set increased from 0.926 to 0.936, the sensitivity increased from 0.846 to 0.865, and the specificity increased from 0.921 to 0.949. The segmentation effect in this paper is closest to the segmentation result of the human expert, and is smoother than that of U-Net segmentation.

Conclusion: The PSPNet network reduces manual interaction in diagnosis, reduces dependence on medical personnel, improves the efficiency of disease diagnosis, and provides auxiliary strategies for subsequent medical diagnosis systems based on cardiac coronary angiography.

1. Introduction

Coronary artery disease (CAD) has a high incidence and high fatality rate, and is one of the most important causes of death worldwide [1-3]. The pathophysiological basis of CAD is atherosclerotic lesions in coronary arteries, which will cause vascular stenosis or blockage. The primary way of early diagnosis of coronary heart disease is the detection and quantification of coronary artery stenosis.

With the constant understanding of diseases and advancement of imaging technology, these have led to the continuous emergence of new diagnostic methods. Coronary angiography (CAG) is regarded as the gold standard in clinical treatment [4]. This is a non-invasive method of examining coronary arteries. It does not require an arterial catheter, but allows the contrast fluid to flow through the heart by intravenous injection, and complete the heart scans [5]. X-ray angiography has a powerful fluoroscopic ability to examine the structure of coronary arteries, and is the most commonly used technology from in the clinical diagnosis of CAD. This diagnosis and treatment method has opened another door for people to understand CAD. It can clearly and intuitively display the detailed images of the coronary arteries, allowing doctors and patients to observe that the coronary arteries have vascular wall calcification and stenosis problems, which make the diagnosis of coronary heart disease more intuitive and scientific.

CAG image blood vessel segmentation is of great significance in the assessing of the degree of vascular disease, assisting doctors in diagnosis and treatment, and reconstruction of the three-dimensional structure of blood vessels [6-8]. A good segmentation result can save the doctor's manual segmentation time and help the doctor correctly diagnose the condition. The segmented blood vessels can be used for further research, such as blood flow velocity, degree of vascular stenosis, etc., to lay the foundation for subsequent vascular dynamics research and three-dimensional reconstruction.

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https://doi.org/10.1016/j.cmpb.2020.105897

Convolutional neural network (CNN), relying on weight sharing, automatic feature extraction and computer performance improvement, has achieved remarkable results [9]. The medical community has also noticed the great success of deep learning methods and hopes to apply these technologies to different tasks in medical image processing.

The use of deep learning technology to segment coronary vessels has three advantages. The first point is that it can automatically extract features [10]. In the past, meaningful or task-related parts were mainly identified by human experts. Based on their understanding of these images, these features can be carried out by non-experts in the field, using machine learning techniques. Now, deep learning has incorporated feature engineering steps into the scope of learning steps. In other words, there is no need to manually extract features. If necessary, deep learning only needs a small amount of pre-processed data, and then new features can be discovered in a self-learning manner.

The second point is that deep learning technology has good versatility [11]. Because of the difference in imaging environment and the level of radiologists, even the same patient will have different CAG images [12]. The traditional method uses the features designed by experts, who may have a good effect on a certain kind of image, but it is not universal. Deep learning technology uses a large number of high-quality labeled samples for training. This method can be applied to various types of contrast images.

The third point is that deep learning can improve efficiency and detection accuracy [13]. Coronary vascular images will inevitably introduce various noises during the imaging process, and the contrast agent will be unevenly distributed in the blood vessels due to various reasons. The vascular bifurcation will cause the traditional methods to be slow in the segmentation process. The accuracy is low and a lot of labor time is wasted. Deep learning technology relies on powerful feature extraction and classification. This enables deep learning technology to be more efficient and detection accuracy than traditional methods.

2. Methodology

2.1. Target segmentation based on traditional algorithms

Currently, traditional image segmentation comprises threshold-based segmentation, region-based segmentation, edge-based segmentation, and specific theories-based segmentation. With the progress of research, segmentation algorithms are divided into pixel-based classification, threshold segmentation, edge detection, color image segmentation, depth image segmentation, and fuzzy set-based methods.

2.1.1. Threshold segmentation

Threshold segmentation is a region-based image segmentation algorithm. The idea is to use the feature f(x, y) to calculate one or more specific thresholds, and compare the feature value of each pixel with the threshold, and then divide each pixel into its corresponding appropriate category based on the comparison result, which is shown in Equation 1.

$$\mathrm{g(x,y)} = \begin{cases} 1, f(x,y) \geq T \\ 0, f(x,y) \leq T \end{cases} \tag{1}$$

The actual image target and background may not necessarily be distributed in the two characteristic value ranges, the Equation (1) can be transformed into Equation 2.

$$\mathrm{g(x,y)} = \begin{cases} 1, \mathrm{T}_1 \leq f(\mathrm{x,y}) \leq \mathrm{T}_2 \\ \quad 0, else \end{cases} \tag{2}$$

Commonly used feature values can be the grayscale or color feature values of the original image, or the features obtained from the original grayscale or color value transformation [14]. The threshold segmentation method is actually a process of assuming a criterion function and then using it to find the optimal threshold solution. The frequently used threshold selection methods include the maximum inter-class variance method, the maximum entropy automatic threshold method, and the gray histogram method.

At present, image threshold segmentation is also used in many fields, for example, in medical applications, blood cell image segmentation, as well as image segmentation in magnetic resonance have also used threshold segmentation algorithms.

2.1.2. Region segmentation

Region-based segmentation methods comprise region growth and split and merge. The region growing algorithm artificially divides the image into n similar regions, and then gradually connects and merges the adjacent regions according to a judgment criterion. The region splitting algorithm is just the opposite. There is no process of artificially dividing regions. First, the input image is made a complete region, then it starts to split, and finally the similar regions are merged. These two algorithms are serial algorithms, that is, the process of segmentation is multiple steps in sequence, and the subsequent operations are based on the results of the previous step and then continue.

Based on the region segmentation algorithm, it is divided into seed region growth and Region growing algorithm [15]. Seed region growth algorithm groups similar pixels to form regions. First find a seed pixel for each region that needs to be segmented as the starting point for growth, and then merge the pixels in the neighborhood around the seed pixel that have the same or similar properties as the seed into the seed where the pixel is located. The Region growing algorithm inherited the idea of the seed region growth algorithm. It uses the Celular Automaton (CA) as the segmentation frame to transform the category information into the state of the cell. According to features such as location and color, the location is adjacent to the color. Similar pixels change and evolve to the same category.

2.2. Image segmentation using convolution neural network

In the field of computer vision, the most basic work is image segmentation, which is to divide similar parts of the picture into continuous area blocks, such as the roughness, contrast, direction, and compactness of the image block, to assist in image segmentation and enhance the effect. In simple terms, semantic segmentation is to classify pixels on the picture given a picture. Early researchers used decision trees and deep learning methods, which are CNNs (fully connected layer type). In recent years, the network for semantic segmentation is basically based on FCN [16]. Other network structures for semantic segmentation include Dilated Convolutions, PSPNet [17], Deeplab VI [18], Deeplab V2 [19], Deeplab V3 [20] and so on.

Next, this paper will introduce in detail the multi-scale CNN proposed for the problem that the artery is a thin tubular structure in the coronary vascular image, which has relatively low contrast and artifacts, is difficult to accurately segment and effectively annotate the scarcity of samples. Usually when using a deep CNN model, the segmented object is a cropped coronary vascular image patch. Different from the past, this paper uses two different scales of patches for segmentation, one is obtained by cropping the original image; the other is obtained by cropping the original image after downsampling, so that global features can be used to provide local features reference to make pixel segmentation more accurate. The result of segmentation is whether the patch is a probability map of a blood vessel, and then all the probability maps are spliced together to obtain a complete coronary blood vessel segmentation image.

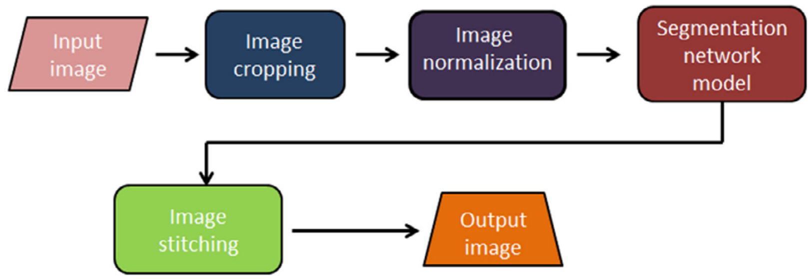

Fig. 1. Multi-scale CNN segmentation flowchart

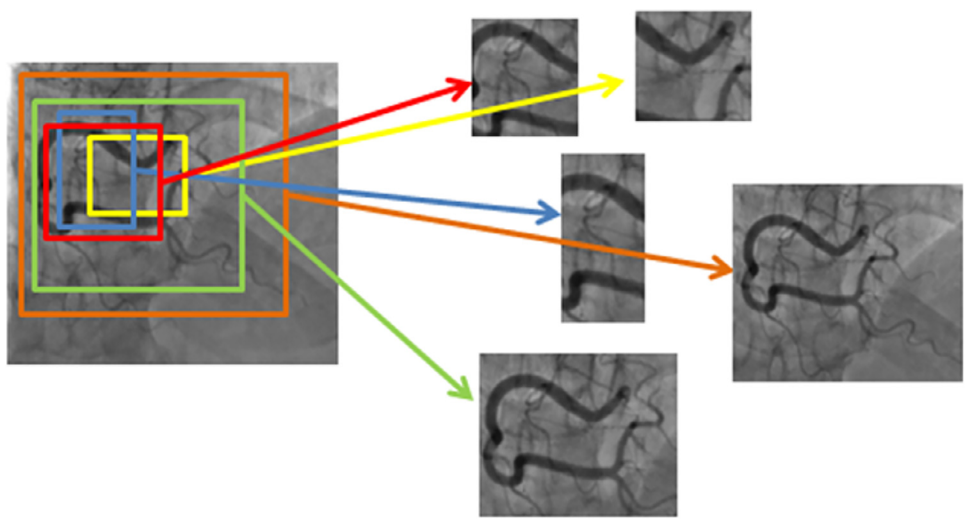

Fig. 2. Schematic diagram of multi-scale image

The entire coronary artery segmentation method is shown in Fig. 1. Fig. 2 is a schematic diagram of the multi-scale image that can be seen. The core part is the construction of the segmentation network model. In this paper, the segmentation model obtained by multi-scale CNN and improved loss function has achieved good results in coronary artery segmentation.

2.3. PSPNet network

2.3.1. Introducing the PSPNet network

Using an image block around the pixel as the input of the CNN network for training and prediction is the characteristic of traditional CNN-based segmentation methods. This method has several disadvantages. First, it requires a lot of storage space; second, the segmentation time is long, but the segmentation accuracy is not high; third, the size of the pixel block often affects the size of the sensing area. FCN overcomes the above shortcomings by recovering the category to which each pixel belongs from the abstract features.

Although FCN realizes the classification of each pixel, it does not fully consider the relationship between pixels. Ignore the spatial regularization step used in the usual pixel classification-based segmentation method, which makes the network lack of spatial consistency.

In the 2016 ImageNet scene segmentation challenge, Zhao et al. proposed Pyramid Scene Parsing Network (PSPNet) [17]. The scene proposed in the paper is accurate. The knowledge graph relies on the prior information of the scene context, and the main problem of the FCN model is the lack of appropriate strategies to use the category clues in the global scene.

2.3.2. PSPNet network structure

Pre-training in PSPNet uses a combination of ResNet and Dikted Network. First, feature extraction is performed on the input data, and the size of the extracted feature map is one-eighth of the original input image. Then input the feature map into the pyramid pooling module, and finally cascade to get the feature surface, and then learn and adjust the parameters by calculating the loss and back propagation algorithm. Compared with Global Pooling, this structure is better for obtaining multi-size global information. Comparing with the calculation, the FCN network will not increase a lot. The Global Pyramid Poling model and the FCN feature extraction model can be trained and optimized at the same time.

The network structure of CAG image segmentation using PSPNet can be presented using Fig. 3. Firstly, the data of CAG is labeled: it is divided into two steps: rough labeling and fine labeling, and then classification and training test are carried out according to the division of body positions in medicine. Then, the annotated image is processed into a grayscale image and input into the Cafe frame. After the image is combined with convolution pooling in the network, Feature Map is extracted, and then it is put into the pyramid pooling layer. The pyramid pooling layer will convolve the feature maps in different sizes, then cascade and integrate the output, and then go through other convolutions and Dropout operations, and finally use the Softmax classifier to classify the pixels, and achieve the final prediction, and complete the segmentation experiment.

2.4. U-Net

2.4.1. Development of U-Net

Long et al. [21] implemented fully connected neural network, referred to as FCN. FCN is a neural network architecture, which realizes object detection by combining low-level appearance infor-

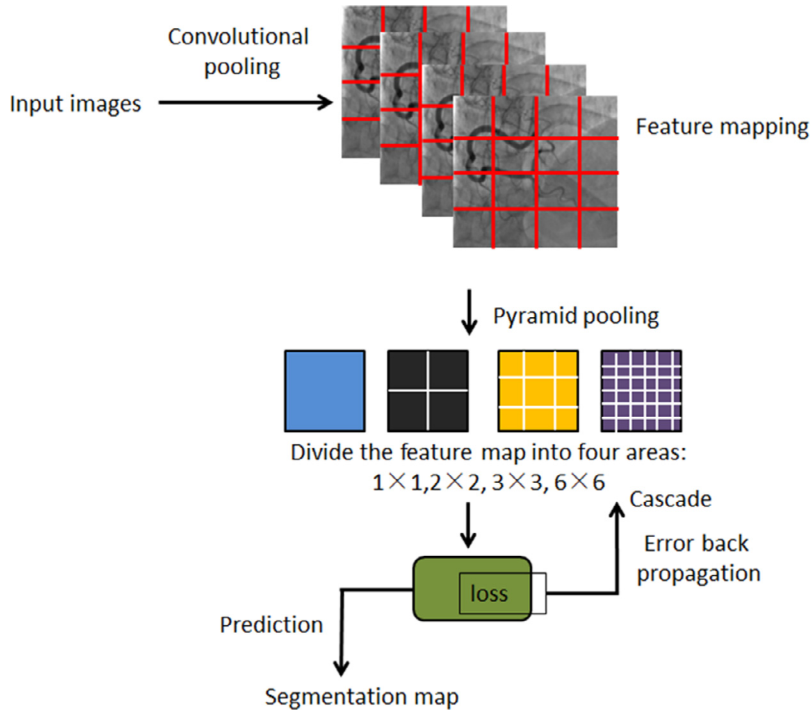

Fig. 3. CAG image segmentation based on PSPNet

mation with high-level semantic information. In 2017, Kim et al. [19] suggested a multi-stage FCN segmentation method to solve the problem of the rough segmentation boundary of skin lesions, in which multiple FCNs learn complementary visual features. According to the period of skin lesions, the early FCN learns rough appearance and positioning information, while the later FCN learns the subtle features of the lesion boundary. They also introduced a new parallel integration method that combines the supplementary information from each segmentation stage to obtain the final segmentation result with accurately positioned lesion boundaries.

In 2018, Nie et al. [22] presented a method for segmenting phase brain images using multiple fully convolutional networks (mFCNs). They used T1-weighted images, T2-weighted images, and FA modal images instead of simply combining the original Three-modal data feature map. The deep architecture they adopted can effectively fuse advanced information from the three images. In this method, the author trained a network model for each mode to effectively use information from multiple image forms.

A relatively new CNN architecture called U-Net convolutional network [23] is dedicated to biomedical image analysis. This network was originally proposed to solve the cell segmentation task. Essentially, U-Net is a technology that combines CNNs and data enhancement technology to increase the amount of medical data. On the basis of U-Net, Lien Kamp et al. [24] introduced the 3D U-Net in 2016. Unlike ordinary images that are two-dimensional data, many types of medical images are 3D. The adjacent image slices display almost the same information, which makes it very difficult and inefficient to label the sample data. And 3D U-Net directly inputs 3D images, and uses 3D convolution, 3D pooling and other operations accordingly, which can output 3D probability maps. This method only needs some labeled two-dimensional slices, making its application range very wide.

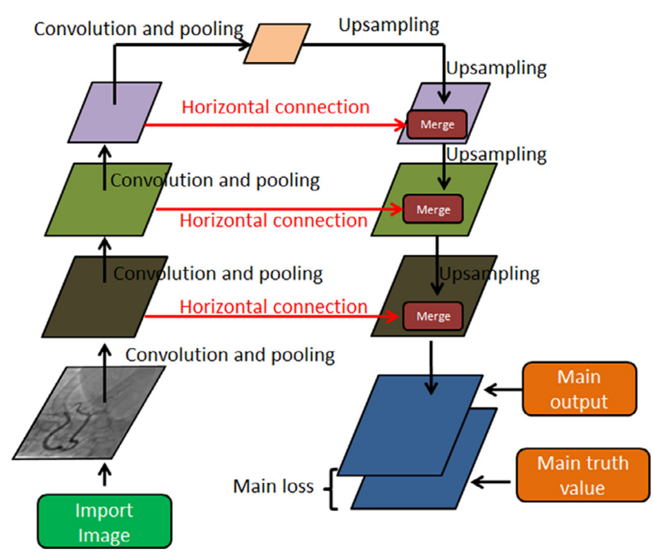

Fig. 4. U-Net's network structure

2.4.2. U-Net network structure

Fig. 4 presents the framework pertaining to U-Net. Compared with other natural images, U-Net performs better on medical images. This is also related to the characteristics of the medical image itself. First, the medical image has a single content and a relatively fixed form. The U-Net's U-shaped structure and layer jump connection make it possible to better extract high-level semantic information and preserve low-level structural features. Secondly, the volume of data in medical images is relatively small, and the parameters of the U-Net model are less than other deep learning models, but the effect is almost the same. Finally, medical images need more universal models than other images. Medical image formats are diverse, and U-Net can input images of any size. After improvements, it can also input three-dimensional images, which has good versatility.

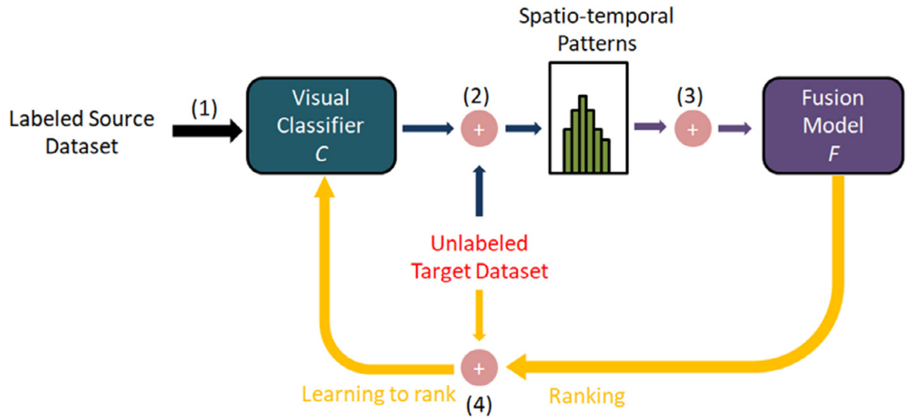

Fig. 5. Schematic diagram of transfer learning

2.5. Transfer learning technique

Machine learning technologies including deep learning have made brilliant achievements in many fields including classification, regression and clustering. However, these methods all assume that excellent results can be obtained only when the training and testing data have the same feature space and the same distribution. As sample data distribution changes, algorithms need to add additional training data and then start training from scratch. In many real-world application scenarios, the cost of this method is high, not to mention that many tasks cannot collect the data required for retraining. These tasks are in great need of methods that can reduce recollection of data and training data. In this case, knowledge transfer or transfer learning between application domains is of practical significance. Schematic diagram of transfer learning as Fig. 5.

2.6. Evaluation criteria for experimental results

For the task of vessel segmentation in CAG images, samples are divided into two categories: vascular and non-vascular. By comparing the results of segmentation with the manual segmentation results of experts, four situations can be obtained, namely: blood vessel pixels are predicted to be blood vessels, which is called true positive (TP); blood vessel pixels are predicted to be non-vessels This is expressed as false negative (FN); non-vascular pixels predicted to be non-vascular are called true negatives (TN); non-vascular pixels predicted to be blood vessels are called false positives (FP).

We often use three criteria to compare the performance of the proposed method with other state-of-the-art methods: sensitivity (Sen), specificity (Spe) and accuracy (Acc). The calculation method is shown by the following Equations (3), (4), and (5).

$$Sen = \frac{TP}{TP + FN} \tag{3}$$

$$Spe = \frac{TN}{TN + FP} \tag{4}$$

$$Acc = \frac{TP + TN}{TP + TN + FN + TN} \tag{5}$$

3. Results

3.1. Data set

3.1.1. Data source

We will perform segmentation tasks and experiments on coronary angiography images. At present, the available coronary angiography image data is collected. This study established a database derived from real patient cases. We collected CAG images of 109 patients from the Fuwai Central China Cardiovascular Hospital.

3.1.2. Data preprocessing

During subsequent training, the network can only accept grayscale images as input, so we convert the blood vessel RGB value to a grayscale value from 0 to N-1 according to the importance of the blood vessel, where N is the type of blood vessel in each position. Considering that some blood vessels have similar functions, they are converted to the same gray value.

3.1.3. Establishment of data set

We prepared the CAG data set as follows. First, we introduced the source of the original data, desensitization processing, data selection and classification, and classified it according to medical common sense according to different lesions and different positions; and then designed according to needs the labeling tool was implemented, and the data was roughly labeled and fine labeled. Part of the process of fine labeling of some angiographic images was introduced. Eventually, we have a series of CAG images, which are labelled using a serial number. Finely annotated images are divided into test set and experimental set with a ratio of 2:1.

3.2. Segmentation experiment results

To obtain intuitively the effectiveness of the method of using the deep learning model to segment coronary arteries proposed in this paper, we tested the 10 images of the test set and gave their human expert results as a reference standard. Fig. 6(A) shows two CAG images with different blood vessel directions selected in this paper (noted as CAG image serial number 1-5). The coronary artery in the left picture is smaller and has more background noise than the coronary artery in the right picture. Figure (B) is the result of the human expert. Figure (C) is the segmentation result of U-Net. Figure (D) is the segmentation result of the PSPNet network. As an illustration of our experimental results, we only show the segmentation of CAG images based on serial numbers 1-5.

Fig. 6 shows that the segmentation result based on the PSPNet network is closer to the result of the human expert segmentation. Compared with U-Net network, the algorithm segmentation edge of this paper is smoother.

3.3. Performance comparison

In order to explore whether the segmentation result of the deep neural network is better than the segmentation result of the traditional algorithm, the traditional algorithm takes the Threshold

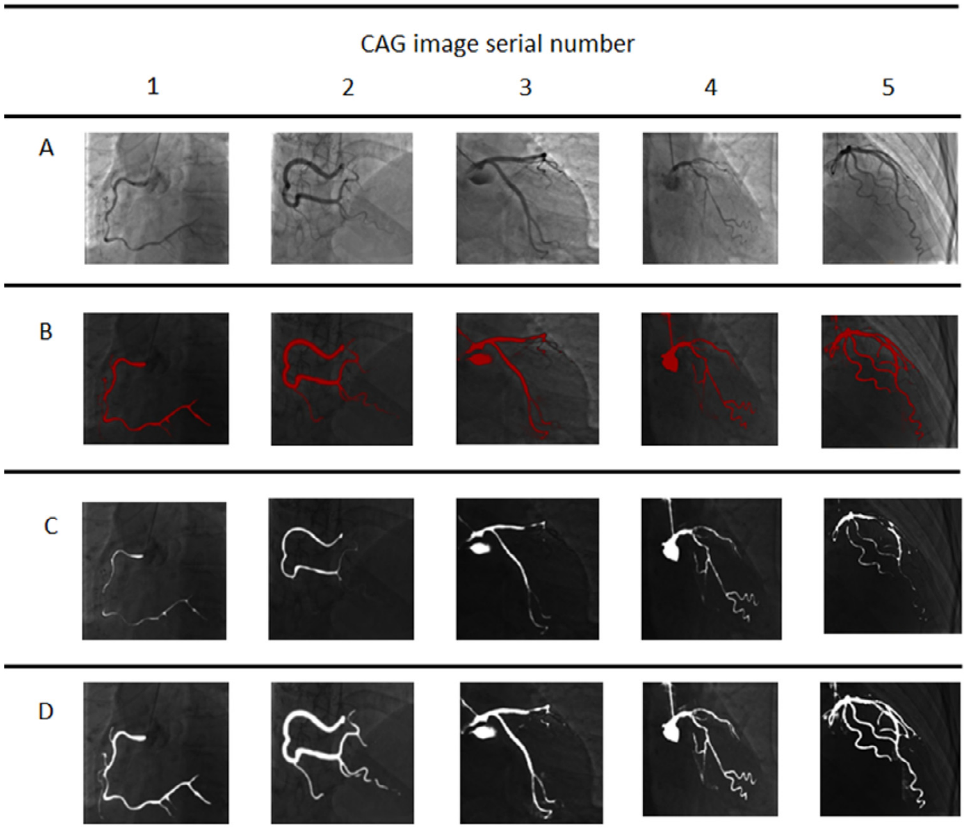

Fig. 6. Experimental results of segmentation results based on two image serial numbers A) Original image; B) Human experts segmentation result; C) U-Net method segmentation result; D) PSPNet network segmentation result

Table 1
Comparison of segmentation performance of three algorithms

Algorithm	Sen	Spe	Acc
Threshold segmentation	0.758	0.830	0.802
Region growing	0.769	0.786	0.755
U-Net	0.911	0.906	0.915
PSPNet	0.947	0.951	0.957

segmentation and Region growing algorithm as an example, and compares it with U-Net and PSPNet. The comparison results are as follows.

Table 1 shows that the segmentation accuracy based on the deep neural network is much higher than that of the traditional algorithm, and the CAG images based on the PSPNet network are higher than U-Net in Sen, Spe, and Acc. The accuracy of PSPNet is at least 10% higher than the traditional algorithms, and 4.59% higher than U-Net.

3.4. Results of transfer learning experiments

Table 1 shows that the segmentation accuracy, and based on the PSPNet network is the highest. On the basis of PSPNet, the accuracy change when using the transfer learning model is tested.

Fig. 7 is a comparison of model performance before and after using transfer learning. It can be seen that after using transfer learning, the accuracy, specificity, and sensitivity of the model proposed in this paper have been improved in coronary artery segmentation. Among them, the average segmentation accuracy on the test set increased from 0.926 to 0.936, the sensitivity increased from 0.846 to 0.865, and the specificity increased from 0.921 to 0.949. This shows that the transfer learning strategy in this paper can improve the model performance.

4. Discussion

At present, deep learning has achieved good diagnostic accuracy comparable to clinical experts and medical doctors in the field of medical imaging. However, in general, there are still many challenges in applying deep learning to the field of medical image processing.

First, there is still a gap between the segmentation accuracy and the current best method. Although deep learning has proven its great success in other fields, it has just entered the field of coronary artery segmentation, and many methods still use the same methods when processing ordinary images. However, the traditional methods have made many improvements to the various segmentation difficulties of CAG images, and there are many targeted and effective techniques. But even so, the accuracy gap between the two is not that big, which shows that deep learning has great potential and can be further studied and explored.

Second, there is a serious imbalance in the number of samples in the model training process. The current mainstream classification algorithms include support vector machines (SVM), neural networks, etc., all of which assume that the samples are in a balanced state and aim for high overall accuracy. However, there is a serious sample imbalance in coronary vascular images, and sometimes the ratio of positive and negative samples is very different. For example, the number of vascular pixels in an image is only one-fifth or less of the number of non-vascular pixels. Each pixel is a training sample, and the final total number of positive and negative samples differs from 103 to 104 [25]. Such a severe

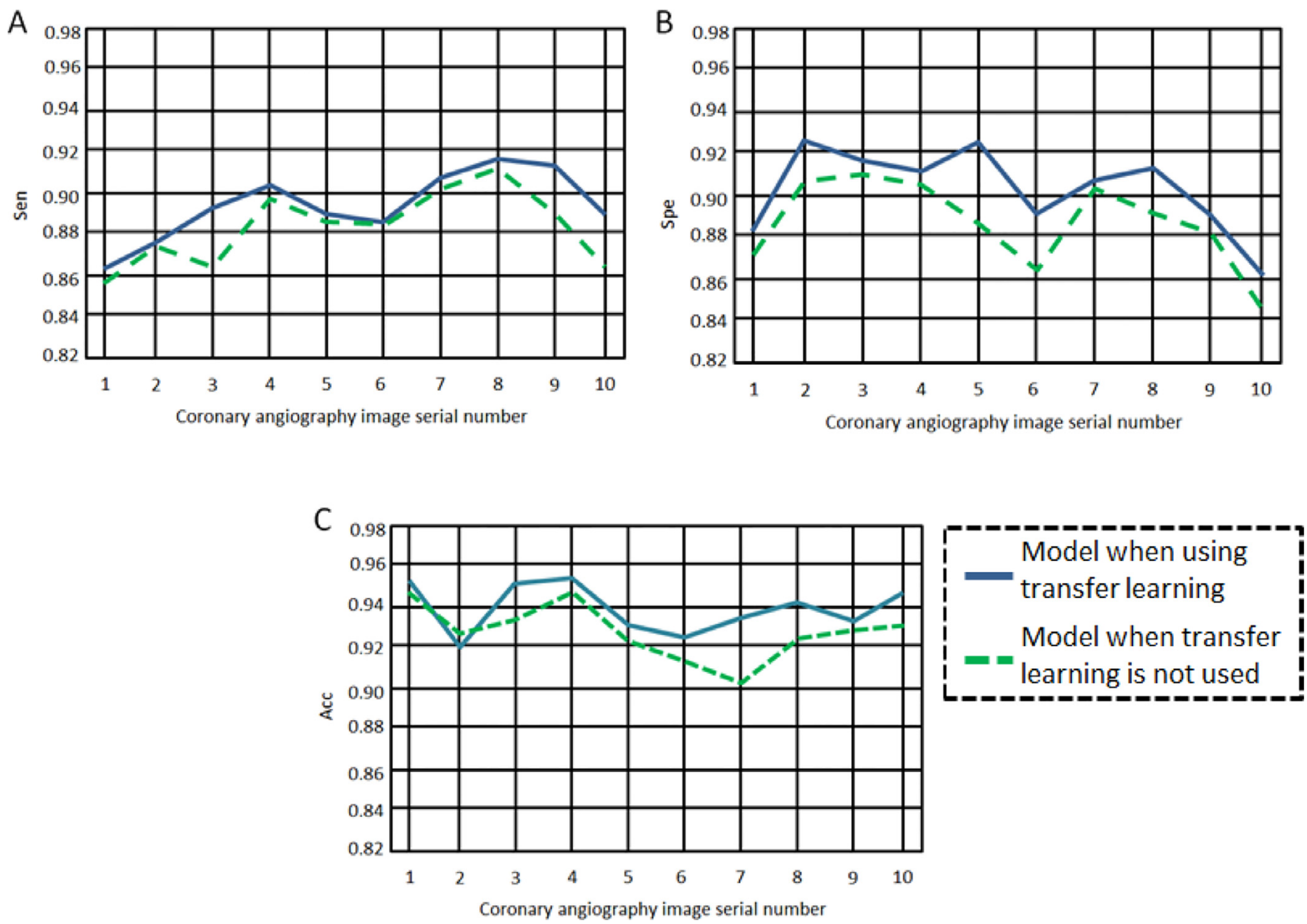

Fig. 7. The improvement of model performance by transfer learning based on A) accuracy; B) sensitivity; C) specificity

situation may lead to model degradation and unable to complete normal classification tasks.

Finally, the sample labeling quality is low and the quantity is small. In this case, the trained model is likely to have overfitting or poor robustness. Just as the computer vision field achieves breakthrough improvements by training tens of millions of natural image data, deep learning models also need a large, public medical image data set in order to find more general features, reduce training time, and improve training performance [26,27]. However, the establishment of such a medical image data set requires high time and economic costs, and the workload is huge.

The segmentation of CAG images is an important practice and innovation of computer vision in the medical field. CAG is also widely used clinically because of its safety and accuracy, and is considered the gold standard for the diagnosis of coronary heart disease [26,28,29]. In the future, image segmentation based on CAG can not only assist doctors in the diagnosis and treatment of clinical diseases, but also become a prerequisite for the quantitative description of vascular diseases, and it can also establish a foundation for the development of three-dimensional reconstruction of cardiac blood vessels [30,31]. Therefore, the experiments in this paper are of great significance to the accurate segmentation of CAG images.

5. Conclusion

Based on the coronary vascular imaging, the artery is a thin tubular structure, which has relatively low contrast and artifacts, and is difficult to accurately segment and effectively annotate the scarcity of samples. A PSPNet-based multi-scale CNN model is proposed. This algorithm first down-sample the pre-processed image to obtain images of multiple scales, and sends them to the CNN. The features of different scales are selected and fused in the fully connected layer, and finally the features are used to segment the CAG images.

It has been confirmed that the coronary angiography image segmentation technology based on PSPNet has higher segmentation accuracy than the traditional Region growing algorithm and U-Net. In order to further improve the segmentation accuracy, we propose migration learning. We use transfer learning technology to solve the problem of limited training data when using deep neural networks to segment coronary vessels. Usually transfer learning is to train in the source domain to obtain the model, and then train to update the model in the target domain. However, because the target domain has less data, the trained model parameters will be destroyed after fine-tuning, resulting in overfitting. Therefore, our paper improves the strategy of using transfer learning for small samples, and makes the newly trained model parameters close to the source domain model by adding regular terms. Finally, after using transfer learning, the accuracy, specificity and sensitivity of the model proposed in this paper in coronary artery segmentation are improved.

Note that this paper compares traditional image segmentation methods and methods using deep learning. The accuracy of deep learning is much higher than that of traditional ones, and our proposed PSPNet-based CAG image segmentation accuracy is the highest.

Declaration of Competing Interest

No.

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