Journal of Image Processing Theory and Applications (2023)
Clausius Scientific Press, Canada
DOI: 10.23977/jipta.2023.060106
ISSN 2560-6239 Vol. 6 Num. 1

Research of Carotid Plaque Segmentation and Classification in MRI Images Based on Artificial Intelligence

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Keywords: Atherosclerosis, carotid artery plaque, machine learning, deep learning

Abstract: Atherosclerosis (AS) is one of the important factors leading to acute cardiovascular and cerebrovascular diseases. Carotid plaque (CP) is formed in the process of carotid atherosclerosis. Accurate identification and classification of carotid plaque by medical imaging is of great significance for the prevention and treatment of acute cardiovascular diseases. Currently commonly used methods of carotid plaque examination include ultrasound (US), digital subtraction angiography (DSA), computed tomography angiography (CTA), and magnetic resonance imaging (MRI). With the rapid development of computer graphics processing hardware, the application of artificial intelligence (AI) in medical image processing is becoming more and more mature. This paper reviews recent studies on the detection, segmentation and classification of carotid plaques in MRI based on machine learning and deep learning models, and summarizes and looks into the current challenges and research trends in this field.

1. Preface

Cardiovascular disease is one of the main causes of human death[1], which has become a major public health problem in the world. One of the important diseases is called peripheral arterial disease. Its main cause is atherosclerosis (Atherosclerosis, AS). Atherosclerosis is the process of plaque formation, and carotid atherosclerosis is closely related to transient ischemic attack and ischemic stroke[2,3]. There are many theories about the pathogenesis of AS. At present, "inflammation theory" gradually occupies the mainstream position. Most researchers think that AS is a chronic inflammatory disease formed by the interaction of environment and gene [4]. At present, there are the following medical imaging methods used in the diagnosis of carotid plaques: ultrasound (Ultrasound, US) imaging, computerized tomography angiography (Computed Tomography Angiography, CTA), magnetic resonance imaging (Magnetic Resonance Imaging, MRI) and digital subtraction angiography (Digital Subtraction Angiography, DSA) [5,6]. The comparison of advantages and disadvantages is shown in Table 1.

Table 1: Comparison of imaging methods for carotid plaque examination.

Imaging modality	Advantage	Disadvantage	Purpose
US	Noninvasive, fast imaging No radiation, low cost	Low resolution, imaging quality depends on the operator, unable to further analyze plaque composition	Measurement of carotid artery lumen stenosis, evaluable hemodynamics and other related information
CTA	Non-invasive, fast scanning speed, high spatial resolution of the image	Radiation, need for injection of contrast agent, nephrotoxic reactions are prohibited	Measure the degree of carotid artery stenosis, measure plaque thickness, detect plaque morphology and composition
MRI	Noninvasive, multi-sequence imaging, high soft tissue resolution	Slow imaging speed, disabled when metal implantation is in body	Detect plaque composition, measure plaque composition volume and area
DSA	Gold standard for measuring the degree of carotid lumen stenosis	Invasive, need to inject contrast agent	To carry out intimal resection and stent implantation.

2. Application of Artificial Intelligence in the Study of Carotid Plaques

For small plaques in images, doctors may easily ignore the existence of plaques because of visual fatigue caused by long-term work, resulting in missed diagnosis or misdiagnosis[7]. Different working experience and professionalism of each doctor may lead to different boundary outline and segmentation accuracy of plaques. From the clinical point of view, plaque classification is of great significance for stroke risk assessment, while the accuracy of plaque classification depends on the qualitative and quantitative analysis of plaque components. It is necessary to consider the degree of stenosis of carotid artery lumen synthetically. Only by human naked eye observation cannot draw accurate diagnostic conclusions from medical images.

With the rise and development of artificial intelligence technology, people have applied this technology to the field of medical imaging and made important progress [8]. Compared with the previous traditional image segmentation methods, the image segmentation technology based on machine learning and depth learning model greatly improves the efficiency and accuracy of clinical diagnosis[9]. In recent years, many scholars have achieved good results in the field of carotid plaque classification and cardiovascular and cerebrovascular disease risk prediction based on US imaging by using machine learning and deep learning methods[10-15]. This paper will focus on the AI-based method to segment and classify carotid plaques in MRI.

Li et al.[13]proposed automatic segmentation of carotid artery MR images based on U-Net neural network model under four sequences: T1 weighted, T2 weighted, TOF and 3D magnetization preparatory gradient echo (Magnetization Prepared Rapid Acquisition Gradient Echo, MPRAGE). In order to ensure that U-Net network adapts to multimodal image input, fine tuning technique is used in image processing[14]. The final experimental results showed that the specificity, sensitivity and Dice coefficient were more than 0.85. The results of intra-group correlation coefficient and Bland-Altman analysis showed that the results of U-Net segmentation were highly consistent with those of manual segmentation. At the same time, the authors also pointed out that the U-Net model was used to segment the carotid artery wall. Low quality MR images with artifacts and low SNR will lead to poor image segmentation results. Multimodal MR images need manual registration before they are input to the model for prediction, and the generalization ability of the model needs to be further strengthened.

Xu et al.[15] proposed a depth learning model VWISegNet based on convolution neural network (Convolutional Neural Network, CNN), which is used to extract and segment the features of carotid artery wall in MR images. The segmentation accuracy and segmentation speed are greatly improved compared with artificial segmentation, and the segmentation effect of vascular wall segmentation is better than that of traditional U-Net, Attention U-Net and Inception U-Net models. However, the limitation of this research is that it is necessary to reconstruct the three-dimensional image into two-dimensional image, and the image contains only one artery, and the dataset is also trained and tested based on the same protocol image, which leads to the generalization ability of the model needs to be improved.

Table 2: The application of machine learning algorithm in MRI image segmentation of carotid artery and its plaque has been reported in some literatures.

Literature	Number of images	Segmentation target	Segmentation algorithm	Optimal performance
Xu et al. [15] (2022)	124	Carotid artery wall	VWISegNet	The DSC of the inner and outer walls are respectively 0.938, 0.860
Li Jifan, et al.[13] (2019)	658	Carotid artery wall	U-Net	Dice,SN,SP are respectively 0.858, 0.878, 0.986
Zhang et al.[16] (2019)	68	Fat-rich / necrotic nucleus	RF	SN, SP, YI are respectively 0.91, 0.89, 0.79
		Intra-plaque bleeding		SN, SP, YI are respectively 0.81, 0.87, 0.77
		calcification		SN, SP, YI are respectively 0.83, 0.93
Dong et al.[17] (2017)	1098	Fiber tissue	ResNet-101	PWCA,Recall are respectively 0.951, 0.973
		calcification		PWCA, Recall are respectively 0.704, 0.492
		Fat-rich / necrotic		PWCA, Recall are respectively 0.576, 0.474
		Intra-plaque bleeding		PWCA, Recall are respectively 0.729, 0.622
Engelen et al.[21] (2015)	41	Fiber tissue	ABH+TL	SN is 0.96
		Lipid tissue		SN is 0.14
		calcification		SN is 0.37
		Intra-plaque bleeding		SN is 0.68

Notes: Sn= Sensitivity; Sp= Specificity; DSC= Dice Similarity Coefficient; YI=Youden's Index; PWCA=Pixel-Wise Classification Accuracy; ABH = Adaptive Histogram Binning; TL= Transfer Learning.

Zhang et al.[16] proposed to identify and analyze the four plaque components of LRNC,IPH, Calcification (CA) and Fibrous Tissue (FT) in synchronous non-contrast angiography of single SNAP sequence and MRI of plaque bleeding. Naive Bayes, NB, Support Vector Machine, SVM, Random Forest, RF and Gradient Boosting Decision Tree were used at the same time. GBDT) and artificial neural network (Artificial Neural Network, ANN) models segment plaque components and evaluate the segmentation results. Finally, it is proved that RF model has the best segmentation effect in the sequence imaging.

Dong et al. [17] also constructed three improved CNN models: Google Net[18], VGG-16 [19] and ResNet-101 [20] for carotid plaque recognition and segmentation. 20 per cent of 1098 images were randomly selected as test sets and 80 per cent as training networks. From the classification results of pixel level accuracy, it can be seen that the ResNet-101 model achieves the best result with the highest classification accuracy of 0.933, especially the recognition accuracy of fiber tissue reaches 0.951.

Engelen et al.[21] proposed two methods to segment the carotid plaque components of multicenter MRI. Firstly, the ABH (Adaptive Histogram Binning) method is used to normalize the piecewise linear features, which can widely normalize the images of different data centers, and then a migration learning classifier with sample weighting is used to make up for the shortcomings of adaptive histogram in dealing with the nonlinear changes of feature distribution in feature space. Finally, when the comments of dataset images are few, the segmentation accuracy of carotid plaque components in multicenter MRI can be improved, and the accuracy of plaque segmentation in MRI of the same center is the same. This method can promote the application of automated image analysis in large-scale multicenter MRI research and clinical practice.

As mentioned above, machine learning algorithm and depth learning algorithm have been widely used in carotid artery and plaque segmentation in MRI images, and good results have been achieved. Their respective research methods have different optimal performance, as shown in Table 2.

3. Summary

3.1 Data Sources and Quality Issues

The carotid plaque data set based on MRI is few and difficult to obtain. Because the marking of carotid plaques is time-consuming and labor-consuming, it needs experienced senior experts to operate, so the professional requirements of marking doctors are high, and because of ethical issues such as patient privacy, there is a lack of standardized data sharing mechanism between research institutions and medical institutions, resulting in the lack of publicly available MRI database of carotid plaques in China, so it is even more difficult to obtain tagged data sets. Many references have pointed out that the shortage of data sets used in the experiment may affect the experimental results, and affect the robustness and generalization ability of the AI model. Due to the lack of data sets, machine learning methods are mostly used in the carotid plaque classification model, and there is a lack of carotid plaque segmentation or classification model based on depth learning method.

3.2 Joint Application of Multimodal Image

At present, most of the studies of carotid plaques are limited to one imaging method, and only a small number of literatures have fusion studies on multicenter or multi-sequence MRI. Although DSA is the gold standard for measuring the degree of carotid artery stenosis, doctors will determine whether patients need surgical treatment according to the measured results, but more and more studies have shown that patients with vulnerable plaques with low degree of carotid artery stenosis are also at risk of causing acute cardiovascular and cerebrovascular diseases. Therefore, the joint study of multimodal imaging methods, such as US, CTA images or two or three kinds of MRI in the same patient, makes full use of the advantages of each imaging mode to comprehensively evaluate the risk degree of carotid plaques, which may further improve the accuracy of plaque classification, so as to provide doctors with more accurate diagnosis and treatment decisions.

Acknowledgments

Funding: This work has been supported by the National Key R&D Program of China with Grant No.2019YFC0118805.

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