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Survey paper

A review of deep learning segmentation methods for carotid artery ultrasound images

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ABSTRACT

The carotid artery is a critical blood vessel that supplies blood to the brain, and its health and function are essential for preventing cardiovascular diseases such as stroke. Ultrasound imaging is commonly used to diagnose the carotid artery and monitor its health, but traditional methods have limitations in terms of accuracy and efficiency. In recent years, deep learning segmentation methods have been developed to improve the diagnosis of the carotid artery, which have shown great potential for improving the accuracy and efficiency of cardiovascular diagnosis. In this paper, we aim to review and summarize the recent research on deep learning segmentation methods for the carotid artery ultrasound images. Specifically, we focus on techniques for the segmentation of the intima-media, plaque, and lumen sites, which are important for clinical diagnosis. Through our analysis of the literature, we seek to identify the key trends and challenges in this field, and to provide insights into the opportunities and challenges for future research and development in this area.

1. Introduction

Cardiovascular disease (CVD) is the primary cause of mortality and morbidity worldwide [1]. In 2019, the total number of CVD cases reached a staggering 523 million, as reported in a statistical study [2]. CVD poses a severe threat to global health, with atherosclerosis being one of its most significant factors [3,4]. Atherosclerosis obstructs blood flow within blood vessels, leading to the insufficient blood supply to vital organs [5]. Moreover, stroke ranks as the third most common cause of death [6], and a quarter of all strokes result from atherosclerosis in the carotid arteries [7]. Therefore, it is paramount to study the carotid artery's structure. The carotid artery is typically divided into the left common carotid artery (CCA) and the right, which have similar structures [8]. As depicted in Fig. 1, the right CCA bifurcates into the internal carotid artery (ICA) and the external carotid artery (ECA) [9]. The carotid artery is the primary blood vessel supplying blood to the brain, and the health of the carotid arteries is intrinsically linked to the brain's health [10]. Fig. 1 illustrates the normal and abnormal vascular structure with plaque.

The intima-media, plaque, and lumen all hold significant roles in the diagnosis of the carotid artery [11–13]. Fig. 2 depicts a lateral schematic view of the distribution of the three components in the carotid artery. Generally, there are no plaques in the carotid artery of individuals without any underlying illnesses. However, in the presence of an infection, lipids slowly accumulate within the arterial lining, resulting in the formation of plaques. With time, the plaques grow, and calcification may occur within them, ultimately leading to arteriosclerosis. Additionally, as the plaque volume increases, blood flow may become obstructed, resulting in inadequate blood supply or the rapid formation of blood clots [14]. Thus, the formation of plaques may lead to several complications, such as thrombosis and stroke [15]. Hence, analyzing the structure of the plaque is crucial when dealing with carotid artery plaque development. The intima-media is located between the lumen-intima interface (LII) and the media-adventitia interface [16]. If the intima-media thickness (IMT) increases beyond 0.15 *mm*, it indicates the possibility of plaque formation [17]. Moreover, the intima-media's thickness significantly correlates with CVD [15]. Research suggests that the risk of stroke increases by 1.41 times for every 0.163 *mm* increase in IMT [18]. Furthermore, the thicken-

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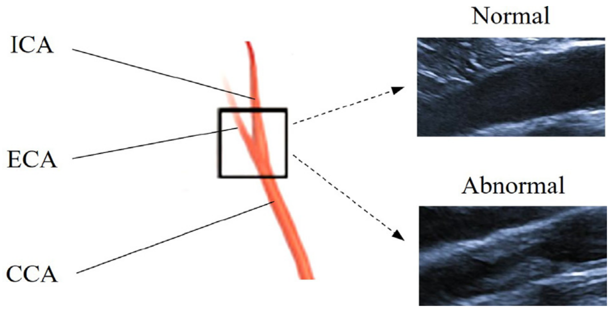


Fig. 1. Schematic diagram of the carotid artery. There are three important structures: common carotid artery (CCA), internal carotid artery (ICA) and external carotid artery (ECA). Normal indicates healthy vascular structure. Abnormal indicates diseased vascular structure.

ing of the intima-media is another indication of plaque development due to lipid accumulation [19]. Thus, detecting the structure of the intima-media is crucial. The lumen structure of the carotid artery most effectively reflects the blood supply of the blood vessel. Lumen affects blood supply and blood pressure [20]. Studies have shown that carotid artery diameter and stroke hold a 26% correlation [21], and vascular diameter is directly linked to CVD, including stroke [22,23]. Accurate segmentation aids doctors in identifying and analyzing the causes of diseases [24], and holds significant research value. In summary, this article primarily focuses on the intima-media, plaque, and lumen of the carotid artery, and reviews segmentation techniques for medical diagnosis.

Various imaging technologies such as digital subtraction angiography (DSA), computed tomography (CT), magnetic resonance angiography (MRA), and ultrasound (US) are currently employed for scanning the carotid artery. Although DSA provides reasonably good image quality and comprehensive information, it has some limitations. It is an expensive procedure, and the inspection time is relatively long. Conversely, CT has a short examination time but involves radiation exposure and requires skilled physicians. MRA may result in the omission of calcified plaques due to its imaging principles and is costly. Among these methods, US is currently the most widely used inspection method for CCA. In the United States, 80% of patients use US imaging as a preoperative reference, and over time, the frequency of US screening may increase as carotid artery atherosclerosis progresses. Using US imaging can reduce the financial burden on patients relatively [25]. Physicians frequently utilize ultrasonography due to its inexpensive, quick, safe, non-invasive, and reliable advantages. This article focuses on studies conducted on carotid artery US images.

Currently, the most typical procedure for carotid artery diagnosis is to scan the patient's carotid artery by a sonographer, select appropriate images and save them during the scanning process. The US images are then analyzed and annotated by another physician. During this procedure, labeling and analyzing images is time-consuming and relies on the subjective consciousness of doctors. To reduce the doctors' burden and improve accuracy, computer-aided diagnosis (CAD) systems have been developed. In order to obtain information about essential structures in the carotid artery, image segmentation techniques are widely used in the automatic analysis of carotid artery US images.

In recent years, researchers have done a lot of research on segmentation technology for medical images [26–29]. Before 2015, machine learning (ML) was the dominant algorithm in the field of medical segmentation. As segmentation techniques have evolved, deep learning (DL) techniques with improved robustness have generated interest among researchers. In comparison to ML-based methods, DL has the advantage of being able to automatically capture features [30]. Constructed by neural networks, DL methods are capable of processing massive amounts of features, making them widely used in image segmentation tasks [31]. Recently, DL has gained popularity in medical image analysis, with algorithms roughly categorized and listed according to their backbones.

U-Net [32] is proven to be effective in dealing with medical image segmentation tasks. An encoder structure is used to extract massive features from the inputted image, as its convolution component can automatically understand the images according to the receptive fields. The other part of the U-Net is a decoder structure that handles the task of up-sampling to recover the processed image. Since the U-Net model was put forward, medical segmentation algorithms based on DL have developed rapidly [33–36]. Latha et al. [37] and Archana et al. [38] have outlined segmentation algorithms for carotid arteries. These reviews mainly provide a good summary of traditional methods.

In traditional methods, segmentation tasks are mainly regarded as classification tasks, with the technical goal of detecting the boundaries of segmented regions. Technical solutions mainly include the Snake algorithm and counter [39–41], Otsu threshold [42], and classification-based methods [43]. These methods are usually more sensitive to gradient changes at edges [44] due to their focus on pixel position, and are heavily influenced by the actual conditions of human tissues. Most research is interested in using contours or snakes for segmentation, but they still have some drawbacks, such as discontinuity and false edges. To reduce these effects, some studies have artificially set default shape structures, such as assuming that arterial structures are straight lines, but this is not always the case and can lead to erroneous estimates in some situations. On the other hand, DL-based methods typically use CNNs to extract image features, which is more conducive to grasping the overall semantic information. In recent years, they have shown significant effectiveness in research. Therefore, this article

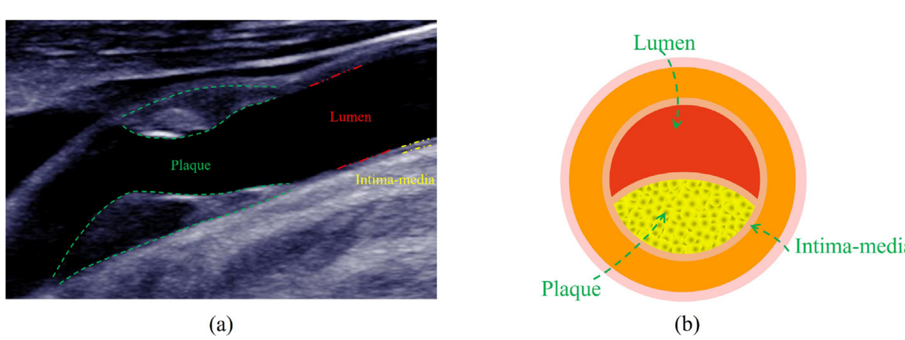


Fig. 2. Diagram of the internal structure of the carotid artery. (a) Longitudinal US image of the carotid artery. Healthy carotid arteries have no plaque structure. (b) Schematic diagram of the transverse section of the carotid artery.

mainly indicates the application of DL in the field of carotid artery segmentation.

In this article, we review currently available DL-based algorithms and models for carotid artery segmentation. All the algorithms and models we collected are carried out separately according to the mentioned three subjects of the carotid artery, including the intima-media, lumen, and plaque. In terms of future research, we combine the characteristics of different parts to analyze and discuss current challenges. At the end of the article, we discuss the common difficulties of carotid artery segmentation and make prospects for these issues.

The structure of this paper is as follows. In the next section, we mainly introduce the general evaluation metrics for segmentation. In Sections 3–5, we present all the collected algorithms and models designed for the segmentation of intima-media, plaques and lumen, respectively. In Section 6, we summarize the challenges for the future development of segmentation techniques, before concluding in Section 7.

In order to make it easier for the reader to read, all abbreviations mentioned in the article are summarized in lexicographical order as shown in the Table 1.

2. Evaluation metrics for the segmentation methods

To evaluate the performance of the model, the authors use a series of evaluation metrics. In this section, we explain these evaluation indicators. By defining, the meaning of each evaluation index could be better understood in the following paragraphs, which can help us to have a clearer understanding of these articles.

Dice similarity coefficient (DSC). The Dice coefficient, also known as the Sørensen–Dice coefficient, is a measure of the overlap between two sets of data. In the context of carotid artery segmentation, it is often used to assess the similarity between the segmentation results produced by a model and the ground truth annotations [45].

$$\mathrm{DSC} = \frac{2|\mathscr{S} \cap \mathscr{G}|}{|\mathscr{S}| + |\mathscr{G}|} \tag{1}$$

Table 1
All the abbreviations mentioned in the review are listed in lexicographical order.

Abbreviation	Description
CAD	computer-aided diagnosis
CCA	common carotid artery
CNN	convolutional neural network
CT	computed tomography
CVD	cardiovascular disease
DL	deep learning
DSA	digital subtraction angiography
DSC	Dice similarity coefficient
ECA	external carotid artery
ECG	electrocardiogram
FCN	fully convolutional network
HD	Hausdorff distance
HDL	hybrid deep learning
ICA	internal carotid artery
IMC	intima-media complex
IMT	intima-media thickness
IoU	intersection of union
JI	Jaccard index
LII	lumen-intima interface
MAD	mean absolute distance
MAI	media-adventitia interface
ML	machine learning
MRA	magnetic resonance angiography
RL	reinforcement learning
RNN	recurrent neural network
ROC	receiver operating characteristic
SDL	solo deep learning
US	ultrasound

where $\mathscr{S}$ represents the segmentation result. $\mathscr{G}$ represents the ground truth annotation. DSC can comprehensively measure the classification effect of foreground and background, so it is currently the most commonly used evaluation indicator in segmentation tasks.

Intersection of union (IoU). IoU represents the overlap rate of $\mathscr{S}$ and $\mathscr{G}$ [46].

$$\mathrm{IoU} = \frac{|\mathscr{S} \cap \mathscr{G}|}{|\mathscr{S} \cup \mathscr{G}|} \tag{2}$$

IoU is also called *Jaccard index* (JI) [47], which is an excellent evaluation index. It intuitively reflects the overlap between the predicted segmentation result and the groundtruth annotations. However, as it is only a statistical indicator and does not reflect the corresponding relationship between pixels, it needs to be further evaluated with the help of other indicators.

Hausdorff distance (HD). HD is a measure of dissimilarity between two point sets [48]. Often used in the field of medical segmentation. HD between point set A and point set B can be represented as follows.

$$\mathscr{H}(A,B) = \max\left\{\check{H}(A,B), \check{H}(B,A)\right\} \tag{3}$$

where $\check{H}$ means directional HD. $\check{H}(A,B)$ is defined as follows

$$\check{H}(A,B) = \max_{x\in A}\left\{\min_{y\in B}\|x,y\|\right\}$$

The main limitation of HD is to measure only the distance between points. Therefore, this metric is important when two boundaries have almost the same number of points. To assess observer differences between different experts, manual measurements were repeated after a period of time.

Mean absolute distance (MAD). MAD is widely used to evaluate the accuracy of measurement systems [49].

$$\mathrm{MAD} = \frac{\sum_{1}^{N}|\hat{y} - y|}{N} \tag{4}$$

where N is the total number of points. $\hat{y}$ means the predicted value and y is the true value. If two boundaries do not have the same number of points, then one of them can be interpolated. This measurement method is particularly suitable when the boundary of the arterial wall is horizontal and does not include the curved part.

Classifiction metrics. Segmentation can be regarded as a binary classification task at the pixel level; that is, each pixel point only belongs to the target object or the background. As a result, popular evaluation metrics used in classification jobs are also employed in segmentation tasks, including *Accuracy* (Acc), *Specificity* (Spe), *Precision* (Pre), *Sensitivity* (Sen) and *F1-Measure* (F1) [50,51].

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

$$\mathrm{Spe} = \frac{TN}{FP + TN} \tag{6}$$

$$\mathrm{Pre} = \frac{TP}{TP + FP} \tag{7}$$

$$\mathrm{Sen} = \frac{TP}{TP + FN} \tag{8}$$

$$\mathrm{F1} = \frac{2\mathrm{Pre} \cdot \mathrm{Sen}}{\mathrm{Pre} + \mathrm{Sen}} \tag{9}$$

The commonly used evaluation indicators in these classification tasks can be used for receiver operating characteristic (ROC) analysis.

Generally speaking, all the above evaluation indicators can be divided into two perspectives. The evaluation of segmentation from the overall perspective is essentially the comparison of the overlapping situation of two regions. Therefore, from this perspective, it mainly includes DSC and IoU, which take the overlapping situation of regions as the research object, and HD and MAD, which take the boundary difference as the research object. In addition, when it comes to the prediction process of segmented areas, it can be found that segmentation is still a classification task in essence—the object of this classification is all the pixels in the image. Therefore, from the perspective of pixel points, evaluation indexes mainly include Acc, Sen, Spe, F1 and other indexes commonly used in classification tasks. Each of the above evaluation indicators is good in its own field. Considering the overall perspective of regional expression information provides a more macroscopic evaluation of segmentation performance. Conversely, the pixel perspective focuses on the individual pixels comprising the segmented regions, providing a finer-grained analysis of the overall results. For instance, when examining the reasons for experimental outcomes, it is necessary not only to consider the overall design architecture but also to conduct a specific analysis of the synergistic interactions among the components of the model. Therefore, in practical use, it is suggested to match each other and learn from each other.

Overall, the choice of evaluation metric depends on the specific goals and requirements of the segmentation task, as well as the specific characteristics of the data being analyzed. It is important to carefully consider these factors when selecting evaluation metrics for carotid artery segmentation. Different evaluation indicators have their own advantages and disadvantages, so a comprehensive consideration is needed to highlight the advantages of the model.

3. Segmentation techniques of intima-media

In this section, we focus on the intima-media of the carotid artery. We briefly discuss the medically relevant knowledge of the intima-media and outline the current challenges based on existing medical clinical applications. Then, we describe the current research status in detail regarding segmentation technology. Finally, an analysis is provided for future research.

3.1. Clinical goals and Challenges

The intima-media part is a vital examination site for CVD. According to the Mannheim consensus [11], it could be inferred that there is a direct relationship between plaque formation and IMT. IMT can be utilized to predict the formation of plaque and is a marker for the early detection of CVD [68]. It is possible to comprehend the lesions caused by atherosclerosis and other diseases by monitoring changes in the intima-media [69]. Early detection and diagnosis can delay the progression of atherosclerosis. Therefore, the intima-media is of influential clinical significance.

As shown in Fig. 3, the intima-media is much thinner in thickness than the diameter of the vessel. Therefore, it is time-consuming to complete the thickness measurement of the intima-media and prone to positioning errors. How to expedite the measurement and avoid positioning error is an intractable challenge for segmentation. In order to relieve the burden on physicians and improve the accuracy of diagnosis, many researchers have recently designed fully automatic or semi-automatic CAD systems to complete the diagnosis of intima-media. The segmentation and measurement of the intima-media are automatically accomplished by algorithms using traditional or DL-based methods.

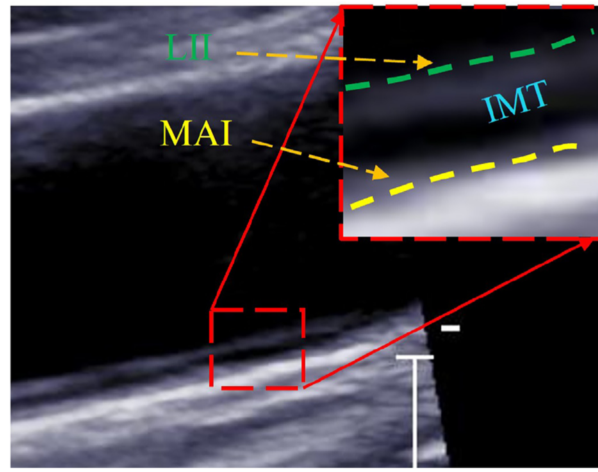


Fig. 3. Detailed structure diagram of the intima-media. The lumen-intima interface (LII), media-adventitia interface (MAI) and intima-media thickness (IMT) are shown in a US image.

Due to the quality of the US images and the characteristics of the intima-media, it is challenging to complete the diagnosis of intima-media. We enumerate a few of the difficulties that exist currently as follows.

1. Artifacts are prone to appear in the process of US imaging. The presence of the artifact generates less grayscale differences between the LII and the lumen. The hardest part is that there is no clear boundary between the media-adventitia interface (MAI) and the adventitia. Therefore, the localization of LII and MAI is a difficult challenge.
2. The intima-media area usually only occupies a small part of the US images. The problem of locating the focus of the intima-media area needs to be solved.
3. The intima-media often appears intermittently in US images. To avoid this situation affecting the results of segmentation or measurement is an essential research direction.
4. Due to different brands of US equipment or parameter settings, the intensity of US images generated by different equipment is different. Therefore, how to successfully segment or measure the intima-media region in images with different intensities is also a significant challenge. In other words, how to design a CAD system with better robustness.

3.2. Methods and Performance

With the emergence of the above importance, more and more researchers have begun to focus on segmentation of the intima-media. In the early days, unsupervised traditional ML algorithms were the main algorithms for measuring IMT, such as SVM [70], random forest [71], clustering [72], active contour [73], boundary detection [56], threshold segmentation [74], gradient calculation [75], and so on. These methods simply abstract the segmentation task as a mathematical problem and compute it using well-established algorithms. Therefore, the requirements for image quality are relatively high, and the robustness is poor. If the contrast of the boundary is slight or artifacts exist in the boundary, the segmentation effect of the traditional ML method will not be up to our satisfaction. DL offers a practical solution to these problems.

Many models designed today for medical images are derived from typical segmentation models, including U-Net [32], fully convolutional network (FCN) [76], DenseNet [77], the encoder-decoder paradigm network, and other segmentation networks. In addition,

Table 2
Most recent/relevant DL-based techniques for **intima-media** segmentation with their main characteristics: investigator(s) and reference, year of publication, the segmentation technique(s) used, whether the workflow is "Semi-Automatic" (SA) or "Fully-Automatic" (FA), the number of images in the dataset(s), the type of data as "Frames" (F) or a "Video" (V), the performance metrics and results, main merits and demerits of the techniques. Notice that "–" means the item is not mentioned in the referenced paper.

Investigator	Year	Segmentation technique(s)	Workflow	Dataset size(s)	Image modality	DSC	Merits and demerits
Shin et al. [52]	2016	CNN	FA	92	V	–	1. Keyframes extraction. 2. Perform not well for border contrast cases.
Biswas et al. [53]	2018	Encoder-Decoder	FA	396	F	–	1. Simultaneous segmentation of area. 2. Boundaries extraction and correction.
Zhou et al. [54]	2019	U-Net	SA	144	F	0.928	1. Preprocessing to enhance edge contrast. 2. Added class weights. 3. Human participation in initialization.
Azzopardi et al. [55]	2020	U-Net	FA	750	F	0.962	1. Intensity normalization. 2. Geometric constraint. 3. Less initial data.
Biswas et al. [56]	2020	Encoder-Decoder	FA	250	F	–	1. Multiple ROIs cropping. 2. Clipping causes missing contextual information.
Qian et al. [57]	2020	SSAE	FA	60	F	–	1. ROI reconstruction. 2. Less initial data.
Vila et al. [58]	2020	DenseNets	FA	331	F	>0.85	1. Single-step localization and segmentation. 2. Morphological operations to smooth.
Zhao et al. [59]	2020	OF-MSRN	FA	202	V	–	1. Simultaneous measurement, segmentation and motion estimation. 2. Multitasking reinforcement. 3. Optical flow prevents artifacts.
Zhou et al. [60]	2020	FCN	FA	1007	F	0.893	1. Pyramid pooling for feature extraction. 2. Attention mechanism. 3. Multi-class continuous maximum flow algorithm.
Xia et al. [61]	2020	MFAU-Net	SA	1024	F	–	1. Spatial and temporal information extraction. 2. Multi-resolution input image.
Lian et al. [62]	2021	RL	FA	4351	F	–	1. Complex model design. 2. Poor robustness.
Al-Mohannadi et al. [63]	2021	Encoder-Decoder	FA	100	F	0.742	1. Multi gradient directioninput. 2. Post-processing morphological methods. 3. Non-original image input.
Lainé et al. [64]	2022	U-Net	SA	2176	F	–	1. Better quality control of the image. 2. Image cropping to enhance the reliability. 3. Additional extra overhead.
Yuan et al. [65]	2022	Encoder-Decoder	FA	1600	F	0.885	1. Dilated convolution and squeeze excitation modules. 2. Spatial attention mechanism. 3. Multi-scale weighted loss function.
Gago et al. [66]	2022	U-Net	FA	172	F	0.969	1. Lightweight design of models. 2. Multi images for generalization improvement.
Huang et al. [67]	2023	NAG-Net	FA	359	F	0.899	1. Integrate multi attention. 2. Transfer learning strategy. 3. Clinical knowledge incorporation.

many researchers design their models or introduce more advanced other technologies. We have summarized these techniques in Table 2.

In 2016, Shin et al. [52] first proposed a fully automatic intima-media segmentation and measurement framework, including the selection of keyframes in the scanning process, the localization of the intima-media region, and the segmentation and measurement, which is still instructive today. With the selected keyframes by analyzing the electrocardiogram (ECG) signal, the intima-media was segmented roughly by a convolutional neural network (CNN) model and then refined by Snakes algorithm [78] to obtain more accurate and acceptable segmentation results. Unfortunately, the segmentation accuracy was not described in detail in the paper. The performance of the model was evaluated by intima-media boundary location error. The error of the manually annotated boundary is less than $0.08\,mm$ while the error achieved by the model is even less than $0.025\,mm$. It could be indicated that the model achieved better results than humans.

In 2018, Biswas et al. [53] proposed a two-stage segmentation network. The original boundaries were generated by an encoder-decoder network, and then the boundary was smoothed by a regression model. Between the VGG16 encoder and the FCN decoder, two skip connection modules were added to prevent the loss of spatial information. The model achieved an IMT error of $0.126 \pm 0.134\,mm$, and more detailed segmentation results were not provided in this paper.

In 2019, Zhou et al. [54] proposed a dynamic CNN for the intima-media segmentation in 3D US images. By enhancing the contrast of the boundary in the images, several anchor points were determined by doctors to generate a rough outline of the boundary. Some regions of interest (ROIs) were generated and one best was filtered out as the input of the improved U-Net to complete the segmentation. In this way, the segmentation difficulty is reduced and the segmentation performance is improved, achieving a DSC of more than 0.928 ± 0.045.

Since 2020, more and more researchers have focused on the design of DL-based model structures in the intima-media. Azzopardi et al. [55] proposed a novel encoder-decoder network for the segmentation of the intima-media. They proposed a new optimization function for geometric shape constraint functions to penalize the results that violated prior medical knowledge. In addition, the authors prevented the initial data from affecting the model results due to different intensities by using the novel fusion of envelope and phase congruency data as the input to the network. The model achieved a DSC of more than 0.910 ± 0.070. Biswas et al. [56] used a CNN classification model to classify image patches and extract useful patches for segmentation. Instead of the whole image, the authors believed that the cropped local patch could better convey the internal information inside the image, which was similar to the idea in [54]. The model achieved an IMT error of $0.126 \pm 0.134\,mm$. In addition, the segmentation method of this model was the same as that in [53], while the segmentation strategy was different. Qian et al. [57] proposed a fully automatic method for segmenting the intima-media. ROIs were captured by a continuous max-flow model. A stacked sparse auto-encoder (SSAE) was introduced to complete the reconstruction of the image to improve the quality of the image and increase the accuracy of the segmentation. The model achieved an MAD of $0.028 \pm 0.016\,mm$. Vila et al. [58] directly utilized multiple DenseNet to segment the image instead of the ROI detection processing, by which more contextual information could be captured. At last, the wrong segmentation results, such as small holes in the segmentation, were removed by morphological operations. The model eventually achieved a DSC of more than 0.85. Zhao et al. [59] proposed an intima-media segmentation model, namely OF-MSRN, for the US videos. Due to the artifacts from radial motion, the authors utilized the optical flow and designed a motion estimation module to assist the segmentation of intima-media. By mining the relationship between frames, an accurate segmentation result was obtained. The model achieved an IoU of 0.893 ± 0.015 on the test dataset. Zhou et al. [60] proposed a voxel-based FCN named Voxel-FCN. The pyramid pooling module was introduced to obtain more spatial and contextual information. The useless features were suppressed and valuable features were enhanced through the attention mechanism. In the end, a multi-class continuous maximum flow algorithm was introduced to optimize the segmentation results smoothly. The model achieved a DSC of more than 0.893 ± 0.068. Xia et al. [61] proposed a multi-scale feature aggregation network named MFAU-Net, which is improved based on the U-Net model. The images with multiple resolutions were fed into the model, and a bi-directional convolutional long short-term memory, namely BConvLSTM, was added to the skip connection part to extract contextual information from a spatiotemporal perspective. Due to more details being saved, the whole model achieved an HD of less than 1.07 ± 0.72. Lian et al. [62] used a combination of DL and reinforcement learning (RL) to segment intima-media. The model utilized a SE-ResNeXT to extract features, which were then input into a deep q-learning network (DQN) model to train with the prior knowledge. After training, the segmentation results were improved by the trained RL model to obtain better segmentation results. The model achieved an MAD of $0.06 \pm 0.04\,mm$.

In 2021, Al-Mohannadi et al. [63] proposed an encoder-decoder structure. The model used two encoders to extract different features and two decoders processed those on the input Sobel gradient orientation image and Prewitt gradient orientation image, respectively. Features were fused by concatenation, and a decoder completes the segmentation. In order to prevent the influence of speckle noise, morphological operations were used to optimize the results. The model achieved an F1 measure of 0.7992.

In 2022, Lainé et al. [64] mainly proposed an overlapping segmentation strategy. With the determined areas in the images to be processed by two marked points, a U-Net was applied to the segmentation of these overlapping patches. In the end, by fusing the results of multiple patches, the boundary could be smoothed to improve the reliability of the segmentation results. This method required human participation, but it was equivalent to performing an image quality evaluation on the image and obtaining the area. It was most conducive to the segmentation of the intima-media from the image for subsequent operations. This method exactly increased the computational complexity while the reliability of the results was improved. The model achieves an MAD less than $0.120\,mm$, which is better than manual measurements. Yuan et al. [65] improved M-Net [45] and proposed the CSM-Net. The authors added a cascaded dilated convolution and squeezed excitation module to enlarge the receptive field and obtain more contextual information. Besides, an attention mechanism was added to enhance valuable information. To avoid the influence of class imbalance, the authors used a weighted loss function. The model achieved a DSC of 0.885 ± 0.067, which was 0.02 higher than the traditional U-Net. Gago et al. [66] designed an end-to-end network structure. The model was based on U-Net and used the EfficientNet [79] to make lightweight improvements to the model to achieve more precision segmentation at a lower computational cost. In addition, the authors proved that predicting multiple parts, such as lumen and IMT, at the same time could improve the segmentation accuracy by using the influence between different types. The final model achieved a DSC of 0.969.

As the field of DL-based model research advances, researchers face challenges in further improving segmentation performance through model structure design. In recent years, some studies have shifted towards a multi-domain knowledge fusion approach, incorporating additional domain background information into the model to better align with practical application scenarios. In 2023, Huang et al. [67] proposed a novel nested attention-guided network that models clinical medical knowledge and utilizes attention to guide the segmentation task. This approach enables the model to concentrate more on the visual focus areas of clinical physicians for the same task. The segmentation results are refined through a simple process, eliminating the need for complex post-processing steps and obtaining finely detailed boundaries directly. Ultimately, the proposed approach achieved an average DSC of 0.899 on LII and MAI segmentation tasks.

3.3. Discussion

Before segmentation processing, many researchers performed some pre-processing on the data. The pre-processing unifies the image quality, enhances the valuable features, and reduces the segmentation difficulty. After compilation, we found several interesting preprocessing methods. The first is to determine the segmented image. The method proposed by Shin et al. [52] to select keyframes based on ECG signal is very representative. After the image was determined, some algorithms did not need to intercept the intima-media region [55,63], but some algorithms needed to detect the ROI in advance [56,52,57,64]. In addition, in order to ensure the quality of the segmented images, image enhancement methods were commonly used [54,55,57]. Zhou et al. [54] made the demarcation line between the intima-media region and the lumen more obvious by enhancing the image contrast. Azzopardi et al. [55] communicated the intensity of the image through the novel fusion of envelope and phase congruency data to prevent the segmentation effect from being reduced due to different image intensities of different devices. Qian et al. [57] used SSAE to reconstruct the intima-media region to improve the quality of the intima-media part. Segmentation region refinement is also a commonly used pre-processing method [56,54,64], mainly to enable the segmentation model to obtain better local segmentation capabilities. Zhou et al. [54] cropped the intima-media region into multiple small patches for segmentation along the contour of the intima-media. Biswas et al. [56] cropped the intima-media region into 16 patches, from which the images of the intima-media border region were selected for segmentation. Lainé et al. [64] improved the reliability of segmentation by cropping the intima-media region into multiple overlapping patches.

Segmentation modules must be deliberately designed. In order to allow the model to obtain more feature information, Al-Mohannadi et al. [63] simultaneously input the Sobel gradient orientation image and the Prewitt gradient orientation image into the model through two encoders. Xia et al. [61] simultaneously input images of multiple resolutions to provide inputs of different scales. In order to ensure to obtain more details in the intima-media features during feature extraction, Biswas et al. [53] added skip connections. Vila et al. [58,60,61] adopted different technical methods, such as pyramid pooling, dilated convolution, and BConvLSTM, to capture more contextual information and spatial information, which can prevent slight discontinuities from affecting the results. In addition, boundary errors are always inevitable in the results of segmentation. To obtain more accurate boundaries, Lian et al. [62] introduced RL to limit and penalize wrong boundaries. Azzopardi et al. [55] designed geometric shape constraint functions to penalize results that did not conform to shape priors. Since the intima-media is relatively small relative to the background, there may be a class imbalance. Yuan et al. [65] assigned different weights to different classes in the loss function. Gago et al. [66] used a lightweight technique to reduce the model size to facilitate clinical application.

After predicting segmentation, there are some wrong segmentation pixels, and the post-processing algorithm plays a vital role at this time. Shin et al. [52] correspond to the original image area according to the segmentation result and use the snake algorithm to refine the boundary. Biswas et al. [53] smoothed the segmented boundaries through regression operations. Vila et al. [58] remove the wrong results, such as small holes and white points in the segmentation results, through the traditional opening and closing operations. Zhou et al. [60] used a multi-class maximum continuous flow algorithm to remove false blobs and smooth the boundaries.

The above literature demonstrates that contemporary algorithms have commenced tackling extant predicaments. Researchers with antecedent knowledge and geometric shape constraints can resolve the boundary issue of LII and MAI [61]. Internal segmentation algorithms or the addition of ROI identification algorithms during pre-processing [54] enables the positioning of intima-media. Conditions such as intima-media discontinuity [59] are prevented from interfering by broadening the receptive field. Data augmentation is utilized to enhance the resilience of CAD. Although the above methods have achieved good results, future research needs to continue to be in-depth. For example, most of the existing algorithms for the intima-media region are aimed at still images, while few are video processing. The videos can better reflect the thickness of the intima-media during the diastole of the carotid artery. Most of the existing processing methods are spliced together by several algorithms. Therefore, the multi-task learning method can be considered to achieve end-to-end detection. In addition, existing methods are too simple to apply prior knowledge. There are many complex situations in actual clinical situations. It should be possible to consider introducing more prior knowledge of doctors into the model. Build better medical expert systems. Therefore, there are still many improvement directions in the future. Researchers need to work harder to overcome these problems.

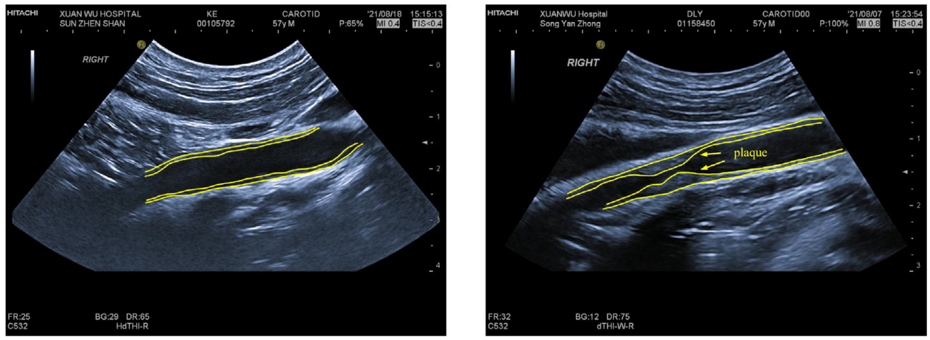
4. Segmentation techniques of plaques

In this section, we focused on the plaques in the carotid arteries. We briefly discussed the importance of plaque segmentation and outlined the current challenges in light of existing medical clinical applications. Finally, we summarized the existing technical solutions and figure out the challenges for future exploration.

4.1. Clinical goals and Challenges

Atherosclerotic plaques in the carotid artery may rupture, leading to cerebrovascular embolism and even a stroke. Retrospective research has shown that the 5-year ipsilateral stroke risk increased with the degree of stenosis [88]. Evidence is accumulating that carotid artery with $\geq 50\%$ stenosis causes around 9–15% of ischemic strokes [89,90], and low-grade stenosis also bears a high risk for ischemic stroke [91–94]. It was reported that in stroke, high-risk patients with asymptomatic ICA stenosis $> 60-70\%$ carotid endarterectomy reduced the risk of stroke from 2 to 1% per year [95]. Only a minority of plaques are unstable and ruptured, resulting in an annual stroke incidence of 1–2% in asymptomatic patients with $> 80\%$ stenosis [96]. Therefore, preliminary operations on patients with high stenosis will result in many preventable and unnecessary surgeries. The plaque segmentation technique can help separate the region of diagnostic interest from the background in medical images and then assess the vulnerability of the plaque based on its textural features.

As shown in Fig. 4, due to the diversity of plaque tissues and US gain instruments, several challenges have hindered the research in



(a) (b)

Fig. 4. The intima-media and plaque in the carotid artery. It can be seen from the US image that (b) the plaque has a thicker structure, but it is similar to (a) the intima-media.

Table 3
Most recent/relevant DL-based techniques for **plaque** segmentation with their main characteristics: investigator(s) and reference, year of publication, the segmentation technique (s) used, whether the workflow is "Semi-Automatic" (SA) or "Fully-Automatic" (FA), the number of images in the dataset(s), the type of data as "Frames" (F) or a "Video" (V), whether the presence of plaque in the images "Yes" (Y) or "Not All" (NA), the performance metrics and results, main merits and demerits of the techniques. Notice that "–" means the item is not mentioned in the referenced paper.

Investigator	Year	Segmentation technique(s)	Workflow	Dataset size(s)	Image modality	Presence of Plaque	DSC	Merits and demerits
Meshram et al. [80]	2020	Dilated U-Net	SA	352	V	Y	0.84	1. Better performance for complex cases. 2. Acceptable performances require sonographer input via a bounding box on plaque.
Xie et al. [81]	2020	cascaded U-Net	SA	500	F	Y	0.69	1. Without any pre-processing or narrowing the ROIs. 2. Segmentation of both the vessel and plaque. 3. Unacceptable performance.
Zhou et al. [82]	2021	Ensemble UNet++	SA	510/683	F	Y	0.886	1. Multiple datasets validation. 2. Acceptable speed. 3. Additional statistical analysis. 4. Small test dataset. 5. Manual cropping the ROIs.
Mi et al. [83]	2021	MBFF-Net	FA	430	F	Y	0.780	1. Outperformed state-of-the-art methods. 2. Physiological characteristics. 3. Precise boundary detection. 4. Complex network structure.
Jain et al. [84]	2021	HDL networks	FA	970	F	Y	0.895	1. Good robustness and scalability. 2. Acceptable speed. 3. Data argumentation. 4. Large memory size. 5. Poor reusability.
Liapi et al. [85]	2022	U-Net	SA	210	V	NA	0.736	1. Designed workflow for CAD system. 2. Intensity-normalized preprocessing. 3. Not well performance.
Jain et al. [86]	2022	HDL networks	FA	970	F	Y	0.868	1. Faster training, small memory size. 2. Multiethnic database. 3. Outperform Autoencoder based model. 4. Only far wall plaque measurement.
Yuan et al. [87]	2022	PA-Net	SA	–	F	NA	0.820	1. Parallel networks. 2. Post-processing segmentation refinement. 3. Too small dataset.

the segmentation of rupture-prone plaque or plaque at the risk of rupture. It includes:

1. The distribution of grayscale intensities is uneven in plaque echolucency [97,98];
2. The shadows exist in the far wall plaque region due to the calcium in the near wall;
3. The plaque area is relatively larger due to the various components of plaque such as calcium, lipids, fibrin, and fibrosis [99,100], especially for high-risk patients;
4. The noises in the plaque region and tissue around obstruct the analysis of the images.

The characterization of plaque tissue types viewed by the naked eye is challenging and offers variability between observers [101]. Consequently, accurate and precise plaque segmentation in US images is imperative for evaluating and following up on the risk of stroke in asymptomatic or symptomatic patients at risk of atherosclerosis, including automated plaque segmentation, quantification, and monitoring over time techniques are required.

Manual segmentation by sonographers is time-consuming and unrepeatable. Several CAD methods have been proposed for the segmentation of plaque in the carotid artery in the last decade [102,103]. These methods mainly adapted (a) geometric feature extraction, line fitting, and pixel classification [104] or (b) scale-space paradigm [105]. These conventional methods are challenging since most of those processes have grayscale intensity in local or global frameworks.

DL-based technology, especially CNN, offers unique advantages in image feature extraction. In the section, we have presented the most widely used DL-based techniques for the segmentation of plaques in US images, which are summarized in Table 3.

4.2. Methods and Performance

The researchers are exploring the effects of U-Net in the field of plaque segmentation. Many researchers have token improvements based on U-Net to explore the unique feature of US images better. Meshram et al. [80] developed an automatic and semi-automatic approach for plaque segmentation in carotid US images. They introduced the dilated U-Net [106] architecture that can stride the image data in dilated convolution to enlarge the receptive field and compared it with standard U-Net architecture. Their model achieved a DSC of 0.55 on the automatic approach and 0.84 on the semi-automatic approach. Eventually, the significance of the bounding box in improving the performance of the segmentation of plaque is indicated. Zhou et al. [82] proposed an ensemble algorithm to obtain the total plaque area in carotid US images automatically. They modified the original U-Net architecture and designed an ensemble UNet++ architecture consisting of eight individual UNet++ [107] networks with different backbones and slight architectures in encode layers. The model achieved a DSC of 0.833–0.857 and 0.886 on two large datasets with GT masks from different institutions. In addition, they compared the segmentation results with the manual segmentation results using statistical analysis methods to verify the feasibility of a clinical application. Aside from the basic U-net that was used as a baseline, Xie et al. [81] investigated two extensions: a cascaded model with two networks and a dual decoder network with separate decoders for vessel and plaque, which achieved an improvement of 68.8% compared to basic U-Net. However, due to raw US images without any pre-processing or narrowing of the ROIs, the segmentation is missing part of the vessel that contains the plaque, which severely affects the plaque segmentation accuracy.

Prior knowledge can add a new perspective to the bland image features. Inspired by the prior knowledge that carotid plaques generally grow in carotid artery walls, in 2021, Mi et al. [83] designed MBFF-Net with three branches to extract plaque features of multiple scales and different contexts and exploit the physiological characteristics of carotid artery walls as the prior knowledge. Compared to the most advanced methods, MBFF-Net achieved a DSC of 0.780 and an IoU of 0.702 on the challenging carotid longitudinal section US images. Due to the designed feature fusion module, the results obtained were more convincing and improved the interpretability of the model.

In 2022, Yuan et al. [87] proposed an automatic CNN, namely PV-Net, for plaque segmentation in carotid US images using a small dataset. The whole network consists of a parallel network with three independent scale decoders that are used to enlarge receptive fields and a SENet [108] to rectify channel features. The multiple enlarged receptive fields improved segmentation performance and achieved a DSC of 0.820, an IoU of 0.701, and an Acc of 0.969. This approach of introducing attention between different feature layers deserves to be further investigated and extended.

In real image diagnosis scenarios, the diversity of lesion features presented in US images and the complexity of data sources themselves pose challenges to the learning ability of DL models. Hybrid deep learning (HDL) has shown a more effective solution than solo deep learning (SDL) [109]. Jain et al. [84] introduced an HDL-based model into carotid plaque segmentation and designed the Seg-

Table 4
Most recent/relevant DL-based techniques for **lumen** segmentation with their main characteristics: investigator(s) and reference, year of publication, the segmentation technique (s) used, whether the workflow is "Semi-Automatic" (SA) or "Fully-Automatic" (FA), the number of images in the dataset(s), the type of data as "Frames" (F) or a "Video" (V), the performance metrics and results, main merits and demerits of the techniques. Notice that "–" means the item is not mentioned in the referenced paper.

Investigator	Year	Segmentation technique(s)	Workflow	Dataset size (s)	Image modality	DSC	Merits and demerits
Yang et al. [113]	2018	IVUS-Net	SA	109	F	–	1. 3D features are ultilized flexibly.
Catarina et al. [114]	2018	FCN	SA	–	F	–	1. Well done on the task of CCA. 2. Ignored the influence of the deformation.
Xie et al. [115]	2020	U-Net	SA	2156	F	0.943	1. Acceptable result. 2. Part of carotid artery listed independently. 3. Both transverse and longitudinal images. 4. Few validation parameters.
Zhou et al. [60]	2020	Voxel-FCN	SA	1007	F	0.932	1. Great Timing control. 2. Limitation on the performance. 3. Limitation on segmenting ICA. 4. 3D features.
Tan et al. [116]	2020	lightweight coarse-to-fine network	SA	–	F	0.854	1. Great Timing control. 2. Application on subsequent work. 3. Performance Limitation.
Azzopardi et al. [55]	2020	U-Net	SA	750	F	0.925	1. Weighted generalised Dice Loss. 2. Geometric constraints. 3. Multi means of acquiring images. 4. Limited dataset.
Joerik et al. [117]	2021	compact U-Net	SA	18000	F	–	1. Validation on multiple datasets. 2. Able to get results that can be applied to follow-up work.
Zhang et al. [118]	2021	NVNet	SA	2439	F	0.776	1. Faster training, small memory size. 2. Multiethnic database.
Park et al. [119]	2022	USUNet	SA	–	F	0.94	1. Further applications are performed. 2. Acceptable result. 3. Synthetic images. 4. Few validation parameters.
Lian et al. [62]	2021	RL	SA	4351	F	–	1. Fully consideration of disease influence. 2. Influenced by the spackle in the images.
Yuan et al. [65]	2022	Encoder-Decoder	FA	100/1600	F	0.941	1. Fully consideration of the vascular structure. 2. Outperformed state-of-the-art methods. 3. ROI pre-processing is not necessary. 4. Not accurate for recognizing IMC.

UNet model. In 2022, Jain et al. [86] proposed three novel HDL segmentation designs of UNet, namely, Inception-UNet, Fractal-UNet, and Squeeze-UNet, using parallel convolutions that are automated, fast, have fewer training parameters, and require small memory sizes. The proposed Squeeze-UNet was the best-performing model under the HDL model category, with a DSC of 0.96 and a seven times reduction in model size. Above all, this approach is only a compromise and does not consider how to better extract the characteristics of the plaques in US images in terms of network structure.

Based on prior research, Liapi et al. [85] presented a CAD system for the automated segmentation of the plaque in carotid US images and the extraction of a refined set of ultrasonic features to characterize plaques in carotid US images and videos robustly. Though it is still unclear whether the performance can be improved when there is no human intervention, the study provides a relatively well-established workflow.

4.3. Discussion

Unlike the lumen and intima-media which have relatively fixed morphological structures, plaques in US images may have a more diverse appearance and shape depending on their location in the carotid artery. This variability challenges the generalizability of the model, which is the reason why some DL models [84,86] are established with a mixture of multiple simple networks. Of course, current schemes cannot solve the problem of generic feature extraction of plaques well. Currently, attention mechanisms are widely used in the field of medical image segmentation and classification [110–112]. By adding mask attention weights to the extracted features of CNN, the characterization ability of features can be enhanced, such as the spatial attention that can provide a priori knowledge of location information to guide the localization of ROIs and the channel attention that can fuse semantic information of different feature layers to guide scene analysis. A specially designed attention module for plaque segmentation can explore the common features of plaques to achieve accurate recognition for various plaques. In addition, it also enhances the interpretability of the model.

Considering the excellent performance of U-Net in medical image segmentation tasks, most current research still adopts it or its variants as the basic network structure [81]. Meshram et al. [80] used dilated U-Net, while Zhou et al. [82] used UNet++, which is essentially based on U-Net and its variants for improving the model structure. Additionally, to address the diversity of plaque features and locations, some studies have introduced prior attention information to guide the segmentation location. The fusion of multi-scale information provides the model with a larger receptive field [83], while the introduction of spatial attention fully utilizes location information [87]. Scientific research has gradually focused on exploring and utilizing other available information. On the other hand, Jain et al. [86] have proposed another solution for improving model performance from the perspective of model training methods.

Generally speaking, to ensure the effectiveness of the model in medical scenarios, it is inevitable to involve human intervention. This mainly includes the selection of candidate boxes and data annotation. Some studies have attempted to use fully automatic segmentation models, but they often fail to handle complex situations. This poses a challenge to the robustness of the model and also highlights the need for further standardization and unification of annotated datasets. Currently, most studies still only use their own collected and annotated data, which cannot achieve effective comparisons, and this remains one of the challenges faced in the field.

The presence of echolucency in the tubular lumen and intima during imaging can create noise in the image and interfere with the identification of plaques. This requires a suitable denoising method during preprocessing. At the same time, the components of plaques are various, and areas of varying brightness and darkness exist in the US images, which offers challenges to the detection area of the plaque. However, most current studies only take image cropping and intensity normalization during preprocessing and ignore the noise. Future research should focus more on better extraction of texture features from the intima-media complex (IMC) and the atherosclerotic carotid plaque.

5. Segmentation techniques of lumen

In this section, we primarily discussed the segmentation methods for the lumen of the carotid artery. We outlined the current goals and challenges based on existing clinical applications. Finally, we summarized the existing technical solutions and pointed out the challenges faced by future explorations.

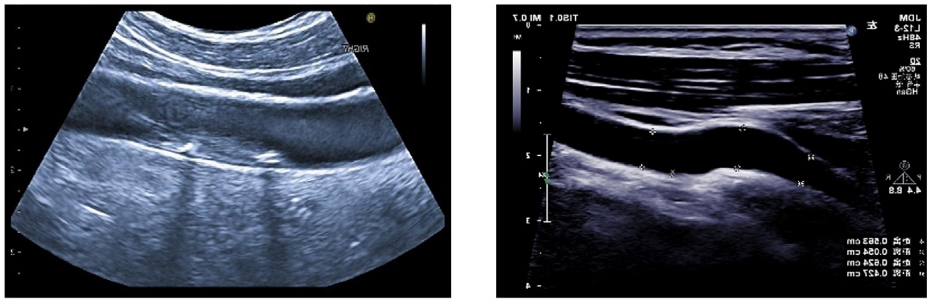
5.1. Clinical goals and Challenges

The present need to diagnose whether a patient is suffering from CVD has prompted using non-invasive methods to capture carotid artery images, extracting the necessary features for diagnosis [120]. By accurately segmenting the lumen's edge, the vessel's thickness can be calculated with less error [121,122]. Therefore, precise lumen segmentation aids in the diagnosis of carotid disease [38]. Furthermore, as depicted in Fig. 5, the velocity of blood flow in the carotid artery, combined with the interaction of the vessel wall, can show near-wall blood flow. Calculating the thickness and the near-wall blood flow can determine blood pressure, providing valuable information for diagnosing CVD [123].

Over the past decade, reconstruction of the carotid artery has been a focal point of research [124–126]. Since B-mode US images may contain speckles and are acquired with non-uniformity due to doctors' use of different scanning trajectories, the reconstruction process is highly prone to errors. Thus, improving the precision of lumen segmentation is essential for reconstructing the carotid artery [127], which can benefit medical researchers studying the structure of a patient's carotid artery [128].

Here we summarize some challenges as follows.

1. Unclear areas in US images. Although US images are brilliant in analyzing the carotid artery, there are still limitations to the quality of the images. According to the particularity of the ultrasonic imaging, spackles are randomly distributed in the lumen area [129]. Therefore, the method to maximize the elimination of the unclear parts is necessary to be studied. Moreover, US images will have different qualifications as the devices are different in imaging effects [130]. There are difficulties in understanding the semantic information in different images equally.
2. Similarity between the lumen and the intima-media in the images. Boundary segmentation has been complex in this task due to the unknown thickness of the lumen. The presence of plaques can also complicate matters in patients suffering from CVD [39]. Texture features showing the difference between the lumen and another participant of the artery should be studied.
3. Deformation caused by diseases. The lumen is elliptical when normal and healthy [131]. Researchers have applied geometry to the algorithm by exploring datasets consisting of healthy carotid arteries. However, as the disease can narrow the lumen, the



(a) (b)

Fig. 5. Different carotid artery B-mode US images show the difference between (a) narrow carotid artery and (b) normal carotid artery, attention that they are not paired.

structure may not always be elliptical [132]. Thus, it is essential to consider deformation to broaden the algorithm's application range.

4. The computation time. The time should be reduced as much as possible to improve the efficiency of the clinical system. The calculation time of the algorithm should be short [133]. The number of parameters and the structures of the network should be studied.

Compared to the segmentation of smaller areas such as the intima-media and plaque, which requires attention to integrity, the lumen area is larger, and the morphology of the lumen in the image plays a significant role in diagnosis. Thus, it is crucial to consider whether the segmentation area is consistent with prior medical knowledge. This relatively unique requirement has presented a challenge to researchers, who have made several attempts at lumen segmentation.

5.2. Methods and Performance

Before the widespread use of DL-based techniques for carotid artery segmentation, researchers employed traditional ML methods to address related problems. Some studies have revealed that while segmentation results using ML can fulfill medical requirements, there is still room for improvement. We have summarized those DL-based studies in Table 4.

U-Net is the first to be mentioned, which has shown unique advantages in the segmentation of medical images. In 2020, Xie et al. [115] employed a dataset comprising 2156 2D B-mode CCA US images, ECA US images, and ICA US images to train their models. To avoid overfitting, they performed 10-fold cross-validation on their data. Results indicated that the algorithm based on U-Net was effective, as it could achieve a DSC of 0.943. Carl et al. [134] transformed 2D B-mode US images based on original B-mode datasets using a series of rotations, translations, and skewing operations. U-Net was found to be effective in handling the task of segmenting transformed US images, with a DSC score of 0.925 ± 0.049.

In 2021, Joerik et al. [117] tested the effect of Compact U-Net, Dense U-Net, and Residual U-Net as it performed on the task of lumen segmentation. Compared to the standard U-Net structure, Compact U-Net has only one connection in each building block, and Dense U-Net-connected networks have interconnections after each convolution. Meanwhile, the Standard U-Net block has been replaced by a Residual block in the Residual U-Net. Dice loss, IoU loss, Precession loss, and Recall loss were used as validation loss in this work. Zhang et al. [118] solved the problem of segmenting longitudinal and transverse B-mode US images with the same algorithm by adding an improved full-scale connection and changing the connection between different layers in the U-Net structure. Max-pooling was added to the feature map obtained by the first and the second layer. Meanwhile, the feature map obtained by the third layer was obtained without additional operation. The feature map obtained by the fourth layer is used for up-sampling to get the decoded result. Dice loss and IoU loss were used to validate the effectiveness of the produced algorithm. The algorithm gets a DSC of 0.776 and an IoU score of 0.641, higher than FCN and U-Net.

In 2022, Yuan et al. [65] were inspired by M-Net [135], which is inspired by the U-Net. Cascaded multi-dilation convolutions [136] were proposed on the last layer of the encoder to capture more receptive fields for various contextual discrimination features in a cascade style. Triple spatial attention module (TSAM) as a self-attention [137] after the skip fusion of each decoder layer, which merges three types of spatial constraint mechanisms for position attention to fulfill precise semantic segmentation. One hundred US images were collected from patients with the normal carotid artery, thickened intima-media in the carotid artery, and plaques in the carotid artery, to make the algorithm more adaptable to all kinds of patients. Dice loss, Precision loss, recall loss, and F1 loss are used to build the validation formula. Results showed that the DSC was 0.941 ± 0.024, which proved that the algorithm could be universally applicable to patients. Park et al. [119] used US images and synthetic images to expand the amount of the data. The proposed USU network performed a DSC of 0.94 for the synthetic test images and 0.90 for US images. The segmentation result was applied as a pre-result to measure the blood flow.

Apart from the U-Net, other CNN-based algorithms have been applied to deal with lumen segmentation tasks. In 2018, Catarina et al. [114]used a deep CNN network to judge whether the selected pixel was a part of the vessel wall. CNN is only used as a classifier in this work without semantic prior, which is widely studied by researchers in the latter works. J. Yang et al. [113] used an open-source dataset: the ivus US dataset [138], which contains 109 images to train their FCN-based algorithm. Multi-branch was adopted to the algorithm, as a "refining branch" combined with convolutional layers was involved. The algorithm reached an HD score of 0.26. In 2020, Zhou et al. [60] used FCN to build the backbone of the algorithm. The prior knowledge of the voxel was applied to the algorithm to increase the accuracy. An attention mechanism was applied to the decoder module, which made the decoder focus on salient features dynamically, as using dynamic features can benefit the segmentation of the lumen. Results proved that the algorithm could reach a DSC of 0.932 ± 0.030. Moreover, since the amount of parameters is much smaller than U-Net, the computation time can be shortened to 0.82s per every testing image. Tan et al. [116] combined the multi-branch module and FCN. Dilated convolution was used to build the convolution layers. Results proved that the accuracy and the calculation time cost are both satisfactory. In 2020, Jiang et al. [139] used 3D transverse US images to build the dataset. The triple Dice loss was proposed to construct the loss function, which made the algorithm not require manual ROI identification or interactive initialization for CCA segmentation. The result showed that the algorithm could get a satisfactory result without outlining the ROI area.

RL [140] has been suggested to procure the optimal solution to issues that can be explicated through a Markov model. However, as the complexity of the query rises, the dimension of the state space and the action space must necessarily expand, thereby rendering the transfer function's generation significantly more intricate. Hence, since neural networks specialize in accommodating complex fitting equations, DL-based paradigms have been incorporated into RL to construct the q-function. Consequently, the deployment of a DQN has been posited as a prospective solution to tackle intricate assignments, such as image segmentation [134]. In 2021, Lian et al. [62] introduced an algorithm to manage segmentation tasks on a dataset of 4351 US images based on DQN. To gauge the efficacy of their approach, they employed the mean-absolute-error as a validation function. The outcomes of their investigation have demonstrated that deep RL-based algorithms can lead to satisfactory results regarding image segmentation.

5.3. Discussion

Lumen segmentation based on DL methods has proved to be a success according to accuracy. Moreover, the validation function proposed by the researchers could evaluate the algorithm from multiple perspectives. The main contribution of the above algorithms and models can be attributed to the different aspects.

In order to attain primacy, contextual information is deemed to be the preeminent factor that warrants consideration. Due to the relatively uniform shape and spatial characteristics of the lumen, it has been found in recent years that the improvement of the model structure has essentially reached the bottleneck of regional segmentation, thereby making it arduous to achieve a further breakthrough. Therefore, researchers have gradually shifted their research focus to extracting high-level semantic features and embedding various internal attention. Using the encoder-decoder mechanism will make the model more sensitive to the ROI. Local features will make a certain loss in the down-sampling operation. Zhang et al. [118] used full-scale to overcome the shortcomings. Zhou et al. [60] used multi-level features to capture more information.

Furthermore, some studies have focused on the issues of practical application in medical settings. The first issue to be mentioned is physician intervention. Due to the significant physiological examination significance of lumen segmentation, most studies [113–115,60,116] currently adopt semi-automated means to ensure the segmentation effect. Yuan et al. [87] took a novel approach by attempting to use a fully automated method for segmentation, taking into full consideration the vascular structure information. Although good results were achieved, the accuracy of IMC segmentation was not adequate. Secondly, the inherent diversity of vascular structure and the complexity of tissue information in vascular images collected under the influence of disease on patients' physiological systems present a more significant challenge to the segmentation model. It is crucial to take into account the impact of diseases. Additionally, as demonstrated by [141], the effect of the disease on patients has been studied, with the results clearly indicating that it cannot be disregarded. Subsequent algorithms have all utilized images of patients with varying degrees of lumen stenosis. Some studies have proposed utilizing feedback mechanisms. As demonstrated in [60,119], feedback from applications can aid in improving the segmentation effect of several algorithms. The segmentation of the lumen can be advantageous in detecting blood flow velocity, and the calculated velocity can indicate the accuracy of the segmentation results. Lian et al. [62] were the first to attempt utilizing RL for this purpose. Additionally, certain studies have considered the issue of time constraints. Tan et al. [116] have made a remarkable effort to reduce computation costs and time through a lightweight network. However, this has resulted in a reduction in the accuracy of the segmentation. However, this has reduced the accuracy of segmentation, which could potentially be resolved by employing a DL structure.

However, several medical needs must be considered to apply the algorithm to medical practice. The features of the vascular lumen in images of various definitions should be studied, and similar parts should be used in the algorithms in future works. The other concern is the calculation costs. Since the popular U-Net has a large number of parameters, which can be up to 31 M in total, most algorithms cannot get an instant result. Therefore, lightweight networks need to be researched in future works to meet clinical use needs containing both time and accuracy.

6. Future research challenges and directions

Above, we summarized the DL-based algorithms and models designed by current researchers for the segmentation tasks of carotid intima-media, plaque and lumen. We marvel at the rapid development of DL technology and the convenience it brings to people's daily life, but at the same time, we also notice many challenges still facing the development of technology. Here we summarize these challenges as follows.

Datasets. In this article, we discussed many methods. But we cannot make a direct comparison for the following reasons. (a) The datasets used are different. The datasets vary in size. The quality of the datasets varies. (b) The parts of the segmentation are different. For example, it is also the segmentation of blood vessel parts, some are the interior of the segmented lumen, and some are the boundaries of the segmented blood vessels. Therefore, we found that there is currently a lack of a high-quality standardized open-source dataset to have a unified evaluation of the model. With open-source datasets, researchers can make good comparisons to highlight the superiority of their models. Therefore, a mature dataset may be needed in the future.

Quality evaluation. Before performing algorithm evaluation, it is best to have a quality evaluation module to screen images. We believe that the quality evaluation module is necessary. Because even a doctor doesn't diagnose all the images, it doesn't make sense to segment a poor-quality image and then compute the result. In addition, using images of poor quality to train the model will affect the training effect of the model, mislead the model, and be detrimental to the optimization of the model. Therefore, we suppose that the quality evaluation module may also be necessary.

Interpretable. There are many existing medical DL-based models, and there are many good results. An important reason why DL-based models are not widely used in clinical practice is the uninterpretability of the models. DL is like a black box. We have a hard time understanding how it works. So, some unpredictable errors will result. If the segmentation process of the model can be explained, there is a clear logic like a doctor. Then the application of DL-based models may be much wider than now.

Medical Prior Knowledge. In our previous review, there have been examples of researchers using prior knowledge to optimize models. There are two main methods. One is to directly segment the results after segmentation and correct the results that do not meet the medical knowledge [58]. The other is to add prior knowledge to the model and penalize wrong segmentation [62]. The application of existing medical priors is relatively simple. There is still a lot of room for development in the future.

Calculating Costs. Costs are an important consideration in the promotion of any technology or product. Many existing DL algorithms are improved based on U-Net. The parameters of the model are relatively large, which is not conducive to clinical application. The existing lightweight technology is relatively mature [66]. For example, in 2017, Google proposed depthwise separable convolution [142] as a new convolution strategy that expands the receptive field and facilitates the integration of contextual information. Additionally, it reduces the number of parameters in convolution operations, providing an effective lightweight approach for DL-based models primarily based on CNNs. This technique has been widely adopted in various applications [143]. Therefore, the integration of DL-based models with lightweight technologies can be considered in the future. The future is also a good development direction.

Although the above problems need to be further solved, there is no denying that it still needs a long period of research and breakthrough in the future. In order to achieve your goals early, here are some suggestions that are currently feasible.

Develop algorithms that can handle the complexity and variability of the carotid artery. One key challenge in the field of carotid artery segmentation is the complexity and variability of the artery. In order to improve the performance of DL-based algorithms, it will be important to develop approaches that can handle this complexity and variability effectively. This could include the use of multi-task learning, ensembles of models, or other techniques that can improve the generalizability and robustness of the algorithms.

Invest in the development of high-quality datasets. Another key challenge in the field of carotid artery segmentation is the limited availability of high-quality ground truth data. Due to the lack of standardized data sets with annotations, some researches [144] have to adopt special methods such as semi-supervision to complete the segmentation task, which hinders the technological breakthrough. In order to develop and evaluate DL algorithms effectively, it will be important to invest in the development of large datasets of annotated images. This could involve collaborating with clinicians and researchers to collect and annotate a diverse range of images, or developing strategies for synthesizing or augmenting existing data.

Explore the use of different DL architectures and techniques. Another potential direction for future development is to explore the use of different deep-learning architectures and techniques for carotid artery segmentation. This could include the use of CNNs, recurrent neural networks (RNNs), or other architectures that have shown promise in other applications. Additionally, it could involve the use of transfer learning, semi-supervised learning, or other techniques that can improve the performance of the algorithms. It is worth noting that, given the unique nature of medical images, an increasing number of studies have focused on the extraction and fusion of different medical features [145–147]. How to cleverly utilize available medical features to guide segmentation tasks is also a question that needs to be considered in the future.

Overall, challenges and opportunities coexist side by side for future development in the field of DL-based segmentation algorithms for the carotid artery. By addressing the challenges and exploring new techniques and approaches, researchers and practitioners can continue to make progress in this important area.

7. Conclusions

The intima-media, plaque, and lumen sites are important for the clinical diagnosis of CVD. In this paper, we reviewed the literature on DL-based segmentation methods for carotid artery US images in the past six years. We identified a range of techniques that have been developed for the segmentation of the intima-media, plaque, and lumen sites, and discussed the clinical implications of these techniques for improving the accuracy and efficiency of CVD diagnosis. Our analysis reveals a number of important trends and challenges in this field, and suggests that future research should focus on US image quality evaluation, model interpretability, prior medical knowledge, and model computational consumption. In addition, different parts of the carotid artery have individual characteristics. We need to design different models according to the individual characteristics and challenges of each, and make full use of the lightweight skills of the model to better apply to the real medical scenario. With the development of technology and the efforts of researchers, we believe that models with higher reliability, better accuracy, and more conducive to clinical application and popularization will be specially designed. DL segmentation technology will bring great changes to the field of carotid artery clinical diagnosis.

CRediT authorship contribution statement

Qinghua Huang: Conceptualization, Supervision, Validation, Resources. **Haozhe Tian:** Visualization, Writing - original draft, Writing - review & editing. **Lizhi Jia:** Visualization, Validation, Writing - original draft. **Ziming Li:** Formal analysis, Writing - review & editing. **Zishu Zhou:** Data curation, Writing - review & editing.

Data availability

No data was used for the research described in the article.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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