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All answers are in the images: A review of deep learning for cerebrovascular segmentation

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ABSTRACT

Cerebrovascular imaging is a common examination. Its accurate cerebrovascular segmentation become an important auxiliary method for the diagnosis and treatment of cerebrovascular diseases, which has received extensive attention from researchers. Deep learning is a heuristic method that encourages researchers to derive answers from the images by driving datasets. With the continuous development of datasets and deep learning theory, it has achieved important success for cerebrovascular segmentation. Detailed survey is an important reference for researchers. To comprehensively analyze the newest cerebrovascular segmentation, we have organized and discussed researches centered on deep learning. This survey comprehensively reviews deep learning for cerebrovascular segmentation since 2015, it mainly includes sliding window based models, U-Net based models, other CNNs based models, small-sample based models, semi-supervised or unsupervised models, fusion based models, Transformer based models, and graphics based models. We organize the structures, improvement, and important parameters of these models, as well as analyze development trends and quantitative assessment. Finally, we have discussed the challenges and opportunities of possible research directions, hoping that our survey can provide researchers with convenient reference.

1. Introduction

Vascular malformations caused by vascular stenosis and aneurysms have become the main cause of cerebrovascular diseases. A population-based retrospective study in Adelaide, Australia showed that the annual incidence of cerebral thrombosis due to cerebral atherosclerosis reached 15.7 cases per million people (Devasagayam et al., 2016). According to the aging statistics of the Mayo Clinic, the proportion of middle-aged and elderly individuals with cerebral cavernous vascular malformation reached 0.46%. Vascular malformations have posed a great threat to human health (Flemming et al., 2017). Cerebrovascular imaging technology has been widely used in clinical practice, promoting the prevention and treatment of cerebrovascular diseases. With the development of computer technology, the clinical reconstruction and analysis of cerebrovascular have brought new challenges.

Cerebrovascular segmentation is an important prerequisite for the quantitative diagnosis and analysis of cerebrovascular diseases. There have been many clinical applications of cerebrovascular segmentation, such as: blood flow behavior detection and tumor evolution (Zhu et al., 2022), neurosurgery planning and navigation (Charles et al., 2019; Ganau et al., 2019), and the stent design (De Bock et al., 2012). Unlike semantic images, medical images have highly similar gray value distributions and non-uniform noise distributions. In addition, it is more challenging for cerebrovascular segmentation than conventional vascular tasks because of its variable shape and scale, and the existence of multi-level branches at the ends (Farajzadeh Khosroshahi et al., 2021; Prasad et al., 2015; Traystman, 2017). Exploring more accurate cerebrovascular segmentation has received extensive attentions.

In the past years, many methods have been proposed for cerebrovascular segmentation. Specifically, it is mainly based on statistical models (Gao et al., 2011; Hassouna et al., 2006; Cao et al., 2016), geometry (Xiao et al., 2018; Yang et al., 2014; Kugler et al., 2003), and graph theory (Franke, 2011; Fischer et al., 2011; Xiao et al., 2020). Lesage et al (Lesage et al., 2009). organized and discussed these methods in their review. During this period, many classic theories have been developed. However, they have shown some limitations: it is difficult for

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these algorithms to extract the original characteristics in cerebrovascular images, so they need to implement feature extractions, which leads to a lack of sufficient noise immunity. Moreover, since feature extraction cannot fully consider all features, these algorithms do not make full use of the information in cerebrovascular imaging, resulting in a lack of generalization. Some theories may rely on human-computer interaction. Recent studies (Zhou et al., 2019; Lv et al., 2020, 2019) based on the traditional theories have shown that these researches mainly lie in the optimization and improvement, and have not solved the problem of theoretical ductility and generalization. Therefore, they may not become the first choice of researchers before the establishment of a new theoretical system.

With the continuous improvement of computer technology, especially the proposal of U-Net in 2015 (Ronneberger et al., 2015), deep learning for cerebrovascular segmentation has been popularity. As a heuristic method, deep learning is mainly driven by datasets and find the answers from the original information. Different with traditional methods, researchers usually focus on model design and parameter optimization in order to make full use of the image. For deep learning models, the cerebrovascular characteristics are presented in the images, especially in their latent space. Therefore, how to use model to explore these features will be the key problem in the development of deep learning. Fig. 1 shows cerebrovascular-related publications since 2015. It can be seen that the deep learning provides a new development direction for cerebrovascular research, so the research of cerebrovascular segmentation is increasing year by year as an important research focus.

Surveys are invaluable references for researchers. For the cerebrovascular segmentation, Ajam (Ajam et al., 2017) and Taher et al (Taher et al., 2018). have made a detailed arrangement for traditional methods, but lacked a discussion of the latest advances in deep learning. Taher (Taher and Prakash, 2021) and Goni et al (Goni et al., 2022). took deep learning-centric survey on the development of cerebrovascular segmentation. However, their work does not cover the latest researches, especially the more novel models and semi-supervised learning methods for cerebrovascular segmentation in the past three years. Therefore, it is of significance to organize and discuss the comprehensive deep learning models for cerebrovascular segmentation.

This survey summarizes the deep learning for cerebrovascular segmentation since 2015. We focus on the cerebrovascular imaging modalities, deep learning models and open source. To cover a sufficient range of researches, the engines include PubMed, IEEE Xplore and Google Scholar. We aim to provide the latest researches of cerebrovascular segmentation, and discuss the development trend and quantitative assessment. It comprehensively covers most of the learned models for cerebrovascular segmentation, and discusses model innovation, loss functions, optimizers, and segmentation performance. It is expected to provide a convenient reference for researchers in the field.

The contributions of this survey are as follows:

(1) We focus on comprehensive deep learning for cerebrovascular segmentation and organize them.
(2) We collate most of the cerebrovascular imaging modalities of published researches.
(3) We have analyzed trends and quantitative assessments of cerebrovascular segmentation.
(4) We propose challenges and research directions for cerebrovascular segmentation based on existing developments.

The organization of this survey is as follows: Section 2 briefly summarizes the cerebrovascular imaging modalities reported in the researches; Section 3 introduce and summarize the deep learning models for cerebrovascular, which includes e eight categories as follows:

(1) Sliding window based model
(2) U-Net based model
(3) Other CNNs based models
(4) Small-sample based models
(5) Semi-supervised / unsupervised models
(6) Fusion based models
(7) Transformer based models
(8) Graphics based models

Sections 4 and 5 summarizes the open source and public datasets in cerebrovascular segmentation. Sections 6 and 7 analyze the development trend and quantitative assessment of deep learning for cerebrovascular segmentation. Section 8 puts forward the views for possible future directions. The last section concludes our survey.

2. Cerebrovascular imaging modalities

With the development of imaging technology, cerebrovascular imaging has also developed a variety of modalities to meet different clinical needs. We are roughly divided into four categories: digital subtraction angiography (DSA), computer tomography angiography (CTA), magnetic resonance imaging (MRI), and microscopy imaging according to their imaging principles (Lin et al., 2018).

2.1. DSA imaging

DSA takes the two frames of images taken before and after the injection of contrast agent through the subtraction, enhancement, and imaging, thereby eliminating bone and soft tissue images to obtain clear vessels (Fig. 2). DSA has the advantage of high resolution and is commonly used in diagnosis or surgical planning. Puncture complications may occur due to the need for arterial cannulation during DSA imaging (Schültke et al., 2010).

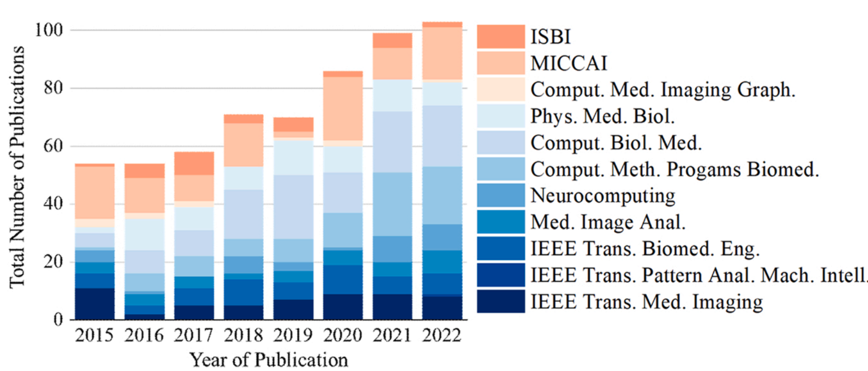

Fig. 1. Total number of publications for cerebrovascular or related researches.
The search was done using the three index terms of cerebrovascular, cerebral vessel and brain vessel.

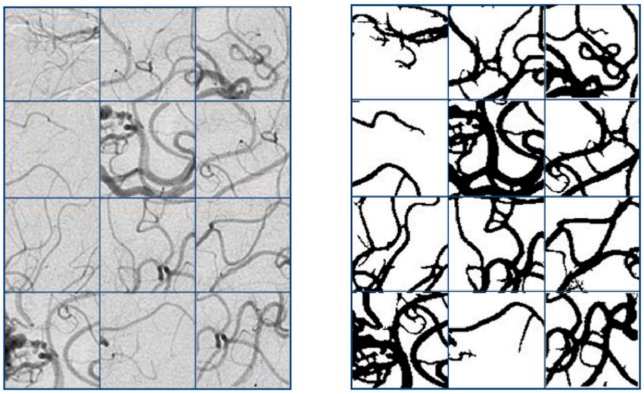

Fig. 2. DSA images and its segmentation edited from (Meng et al., 2020). require with (Meng et al., 2020) permission from Elsevier Neurocomputing

2.2. CTA imaging

CTA uses iodine-containing contrast agents to change the permeability of blood flow in computed tomography (CT) for imaging (Fig. 3). Due to the advantage of high speed, CTA is more common in the examination of emergency patients (O'Brien et al., 2010).

μCTA mainly refers to images collected by X-ray tomographic microscopy. Its resolution can reach the micron. μCTA is commonly used in the industrial application for the reconstruction and internal detection of small materials. In the cerebrovascular report, μCTA is applied in rat brain.

Contrast-enhanced cone beam CT (CE-CBCT) is a CT imaging of cone beam X-ray scanning and is assisted with the enhancement of iopamidole infusion injection. CBCT is more common in oral imaging. After iopamidole infusion injection, the vascular structure can also be better presented.

2.3. MRI imaging

MRI is an imaging technology that uses nuclear magnetic resonance phenomenon of hydrogen protons in organisms under specific radio frequency pulses, including regular scan and functional scan (Rauf et al., 2016).

T_2-weighted imaging (T_2WI) is a regular scan of MRI and usually shows high signal in the lesion region. It is often used in some cerebrovascular malformations and cerebral hemorrhage.

Vessel wall imaging (VWI) is a T_1-weighted imaging (T_1WI) (Fig. 4). It was first developed by Fan et al (Fan et al., 2017)., aiming to suppress cerebrospinal fluid and have better presentation of the vessel wall.

Susceptibility weighted imaging (SWI) is based on T2WI and provides enhancement based on different susceptibility differences between tissues. It has high clinical value in the display of intracerebral venous vessels and blood components.

Time-of-flight MRA (TOF-MRA) is the most commonly used MRA (Boeckh-Behrens et al., 2012). It saturates the static tissue through multiple excitation pulses, which weakens the imaging information. The flowing blood is not in a saturated state due to the dynamic transformation, thus showing a higher imaging signal.

Phase-contrast MRA (PC-MRA) are imaged by phase changes (El-Baz et al., 2009). During the imaging process, gradient pulses with equal and opposite magnitudes are applied. For stationary tissue, the phase changes cancel each other out, thereby forming inhibition; however, the flowing blood cannot eliminate the phase changes, resulting in strong information.

Contrast-enhanced MRA (CE-MRA) alters the imaging signal of the blood by injecting a paramagnetic contrast agent, allowing the blood

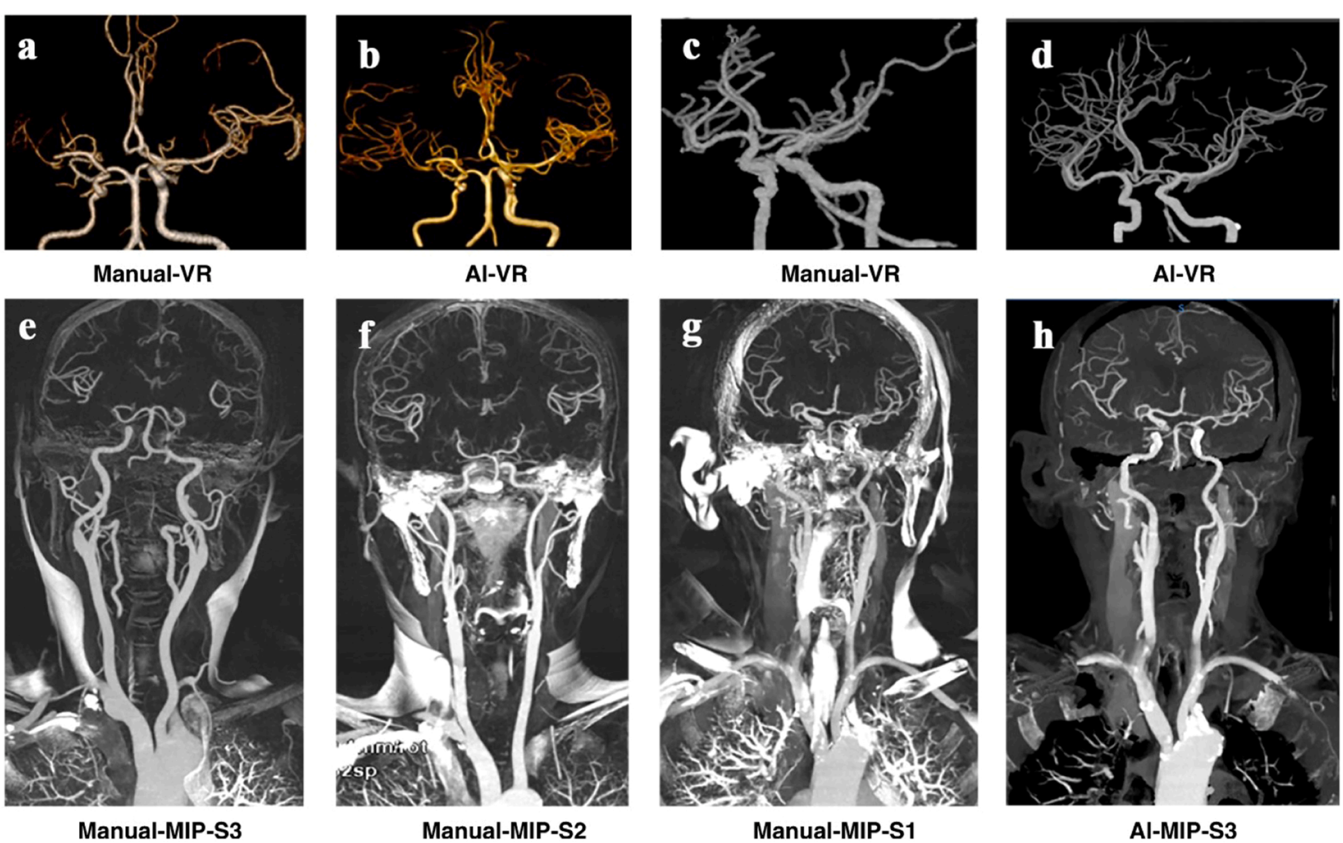

Fig. 3. CTA images and its segmentation edited from (Fu et al., 2020). (require with (Fu et al., 2020). permission from Nature Nature Communications.

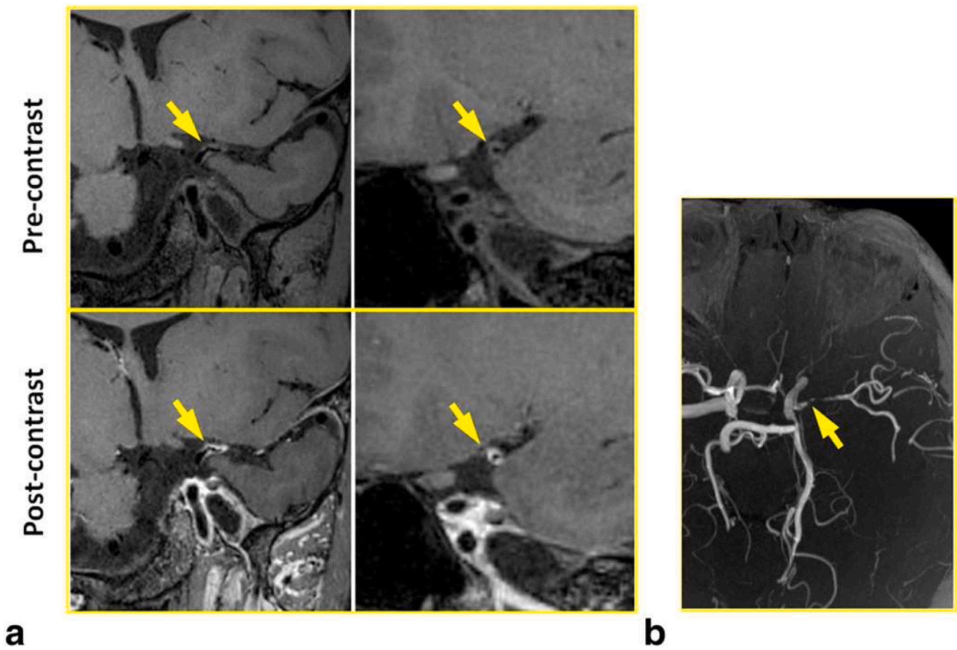

Fig. 4. MRIs processed by VWI from (Fan et al., 2017). (a)'s left column shows the stenotic lumen, and right column is stenotic lumen. (b) is the maximum intensity projection of TOF-MRA to prove that narrowness exists in the same place.
require with free access of (Fan et al., 2017) permission from Wiley Online Library Magnetic Resonance in Medicine.

vessel to form a distinct contrast with the surrounding tissue (Hoelter et al., 2017). Under the method of artificial injection and high-pressure injection of contrast agent, CE-MRA can better present the arterial and venous regions.

2.4. Microscopy imaging

Light-sheet microscopy (LSM) is used for microscale imaging. For cerebrovascular imaging, it was first reported by Todorov1 et al (Todorov et al., 2020). They applied mice as experimental subjects. To show clear vessel details, they stained the mice differently, so that the LSM imaging could clearly show the characteristics of vessels at the micrometer scale.

Two-photon microscopy (2PM)'s detectors are more sensitive and can record finer internal structures (Fig. 5). Gagnon (Gagnon et al., 2016) and Tahir et al (Tahir et al., 2021). reported the mouse brains imaging using 2PM. 2PM images collect faint photons from deep tissue, making the image brighter.

2.5. Other imaging

Craniotomy image (CI) refers to images of the cerebral epidermis taken after part of the skull has been removed during a craniotomy. Nercessian et al (Nercessian et al., 2021). firstly reported CIs for cerebrovascular segmentation in their research. CIs are mainly used to focus on cerebral epidermal vessels, which are of significance in preoperative navigation.

3. DL-based cerebrovascular segmentation model

In this section, we organize the deep learning methods for cerebrovascular segmentation, which are divide them into 8 types according to models or design methods.

3.1. Sliding window based models

The earliest deep learning segmentation model was implemented from the sliding window (Ciresan et al., 2012). As shown in the Fig. 6, it obtains the prediction of p point through the entire window area, and calculates the classification using calibration processing. Since no decoding is required, the model can be lightweight using sliding window. For example, Phellan et al (Phellan et al., 2017). built a sliding window based model using only two convolutional and two fully connected layers, which was remarkable in its storage contribution. Compared with the current popular end-to-end methods, the sliding window is almost no information loss, however, it needs to traverse each

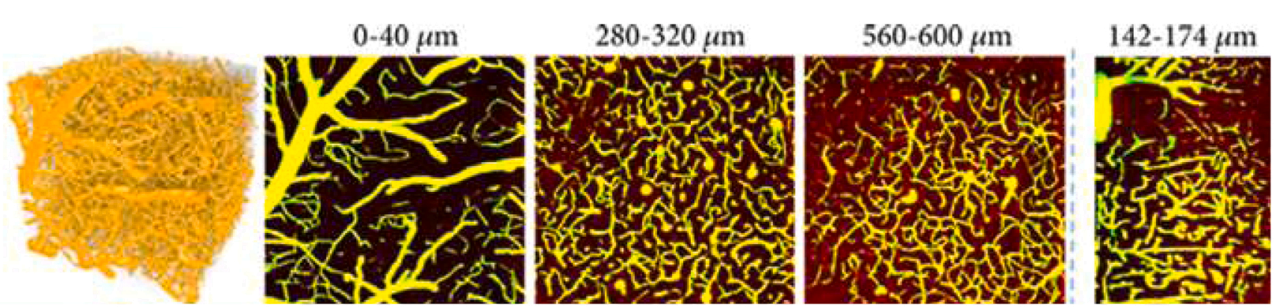

Fig. 5. 2PM images edited from Tahir et al. (2021).
require with open access of (Tahir et al., 2021) permission AAAS BME Frontiers.

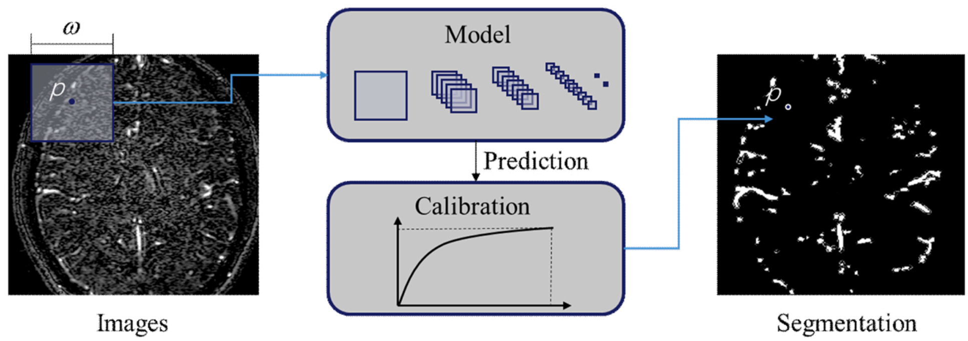

Fig. 6. Schematic diagram of FCN structure.

pixel, so it would consume expensive inference time.

3.2. U-Net based models

The proposal of the fully connected network (FCN) (Shelhamer et al., 2017) opened an end-to-end image segmentation network (Fig. 7). FCN uses up-sampling to restore the image resolution, so as to achieve the purpose of pixel-level classification. Due to the excessively large FCN up-sampling range, even the highest performance FCN-8 s is difficult for most precision tasks, especially in the medical field. To address the limitation, Ronneberger et al. proposed U-Net (Ronneberger et al., 2015), which became the most important backbone in medical segmentation tasks due to its high-resolution segmentation. As shown in the Fig. 8, U-Net has a symmetric structure with encoding and decoding path, which is an important reason for its high-resolution parsing. Moreover, U-Net uses skip connection to improve local features, causing U-Net perform well in most tasks. With these advantages, U-Net has been the most popular model for cerebrovascular segmentation tasks.

Table 1 summarizes all the works using U-Net in cerebrovascular segmentation, which can be roughly divided into two types: one is to directly use U-Net as the backbone. These researches applied U-Net to different cerebrovascular disease patients, such as steno-occlusive cerebrovascular (Livne et al., 2019), pediatric (Quon et al., 2020), stroke (Fan et al., 2020), epilepsy (Cui et al., 2021), arteriovenous malformation (Simon et al., 2022), and acute cerebrovascular (Aydin et al., 2021), etc. In Paetzold et al (Paetzold et al., 2019). ' study, U-Net is one of their backbones. They proposed a new similarity measure, named clDice, to better assess the topology and geometry. Guo et al (Guo et al., 2021). sampled TOF-MRA from different directions. They trained them on three separate U-Nets, and finally fused the three predictions. As one of the backbones of U-Net, Chen et al (Chen et al., 2022a). independently trained three models using PC-MRA. They applied Dempster/Shafer evidence theory (Zhao et al., 2022) to fuse different predictions. Aydin et al (Aydin et al., 2021). explored the consistency of different metrics with visual assessments. In their study, U-Net has become an important tool for making the ground truth. Therefore, these researches showed that U-Net usually satisfies most clinical needs.

The other type is usually an improvement on the U-Net backbone.

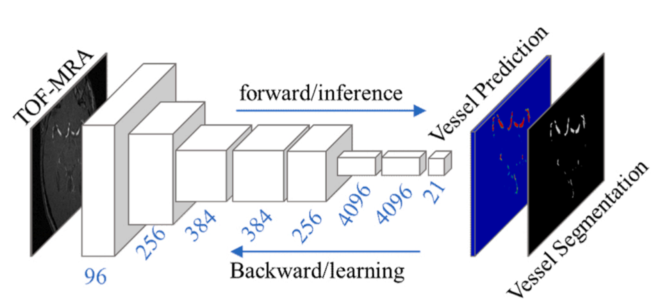

Fig. 7. Schematic diagram of FCN structure.

For example, Sanchesa et al (Sanchesa et al., 2019). inserted the Inception module into U-Net. It is well known that the Inception module proposed by GoogLeNet (Szegedy et al., 2015) can better adapt to feature textures of different sizes. Using this architecture, U-Net can select a more suitable convolution operation facing cerebrovascular regions of different scales. Zhang et al (Zhang et al., 2020a). extended U-Net to the 12-layer architecture. Since more parameters are acquired, the model is better able to learn from diverse data. Fu et al (Fu et al., 2020). and Hadji et al (Hadji et al., 2019). put more demands on computational efficiency. They added the bottleneck design (He et al., 2016) to the U-Net, thereby reducing parameters. As shown in X, the bottleneck design from ResNet uses two 1×1 convolution operations to compress and restore channels, so as to achieve the purpose of lightweight models, which has been widely applied in residual connection design. Shi et al (Shi et al., 2019). chose the PReLU activation in the convolutional layers of the U-Net, the purpose of which was to solve the ReLU information loss. In VWI of intracranial atherosclerotic disease patients, their improvement enhanced the extraction of outer wall boundaries. Tetteh et al (Tetteh et al., 2020). focused on improving the computational efficiency. They proposed the cross-hair convolution kernel, which used three 2D convolution operations to obtain 3D volume context, thereby reducing the computational burden (Fig. 9). In their work, U-Net improved by cross-hair convolution surpassed the regular 3D convolution in terms of speed, complexity and accuracy. Lee et al (Lee et al., 2021). proposed spider U-Net, which focused on the associations between slices (Fig. 10). They extracted the spatial features between each slice by stacking U-Nets. The long short-term memory (LSTM) was constructed between the encoder and the decoder to establish the connectivity of different slices. Huang et al (Huang et al., 2020). established double U-Net structure. The first U-Net improved the normalization operation for extracting coarse features. The second U-Net added attention module to further refine useful features. This structure enables the model to extract more details. Liu et al (Liu et al., 2022). added the spatial attention block to U-Net to reduce redundant use of low-level features. They employed multi-directional maximum intensity projections to improve the characteristic information of vessels.

For the convenience of reference and reproduction, Table 2 records the important parameters of these improved U-Net, including loss function, and optimizer of these improved U-Nets. In addition, the listed loss functions are their basis form. Some works have improved on these foundations. For example, Shi et al (Shi et al., 2019). designed a multi-category DSC loss, and Tetteh et al (Tetteh et al., 2020). added weights to CE loss. These algorithms pay more attention to a small number of cerebrovascular target regions, and is also an important inspiration for subsequent deep learning researches. As a milestone, U-Net is a popular choice as a backbone and comparative model. It also promotes the development of deep learning for cerebrovascular segmentation.

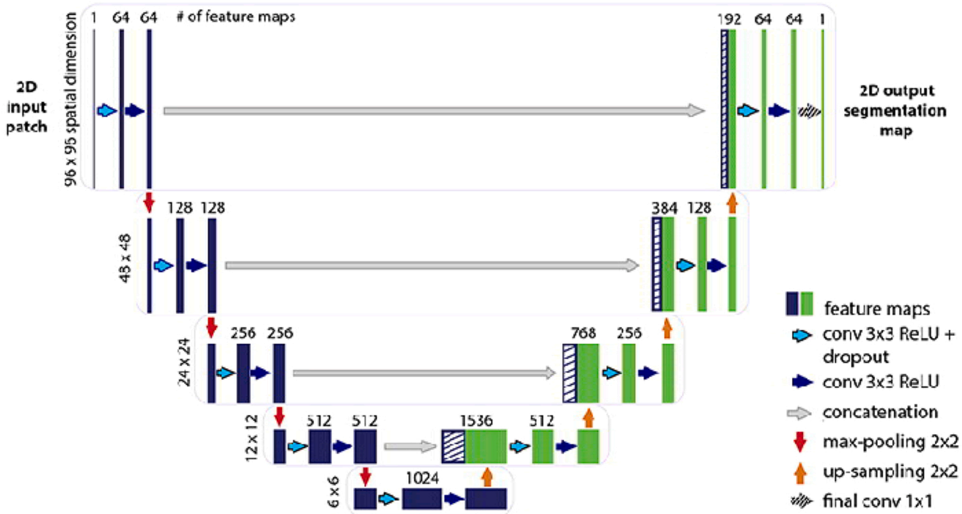

Fig. 8. U-Net structure from Livne et al. (2019) for cerebrovascular segmentation.
require with open access of (Livne et al., 2019) permission from Frontiers Frontiers in Neuroscience.

Table 1
Details of U-Net based models.

Author	Year	Modality	Training/Testing/ Validation Sets
Livne et al (Livne et al., 2019).	2019	TOF-MRA	41/14/11
Paetzold et al (Paetzold et al., 2019).	2019	LSM	11/4/2
Quon et al (Quon et al., 2020).	2020	T2WI	38/8/2
Guo et al (Guo et al., 2021).	2021	TOF-MRA	20/70/5
Chen et al (Chen et al., 2022a).	2022	PC-MRA	17/5/-
Chen et al (Chen et al., 2018).	2018	TOF, CTA	11/4/-
Fan et al (Fan et al., 2020).	2020	TOF	40/60/-
Cui et al (Cui et al., 2021).	2021	T1CE-MRA	15/5/5
Aydin et al (Aydin et al., 2021).	2021	TOF	-/10/-
Sanchesa et al (Sanchesa et al., 2019).	2019	TOF	32//3/1
Zhang et al (Zhang et al., 2020a).	2020	DSA	20/10/-
Fu et al (Fu et al., 2020).	2020	CTA	13146/1826/3287
Hadji et al (Hadji et al., 2019).	2019	CE-CBCT	15/5/5
Shi et al (Shi et al., 2019).	2019	VWI	30/20/6
Tetteh et al (Tetteh et al., 2020).	2018	TOF-MRA μCTA	20/15/5 20/4/-
Lee et al (Lee et al., 2021).	2021	TOF-MRA	18/4/4
Huang et al (Huang et al., 2020).	2020	CTA TOF-MRA	20/20/- 20/20/-
Simon et al (Simon et al., 2022).	2022	TOF-MRA	17/6/-

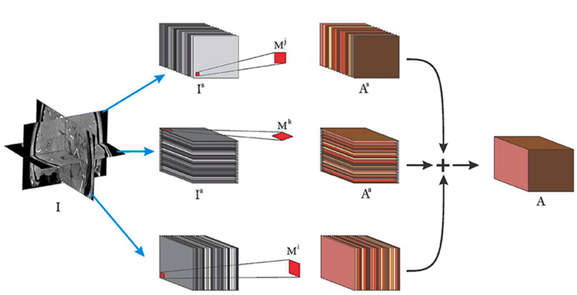

Fig. 9. The cross-hair convolution kernel structure from Tetteh et al. (2020).
require with open access of (Tetteh et al., 2020) permission from Frontiers Frontiers in Neuroscience.

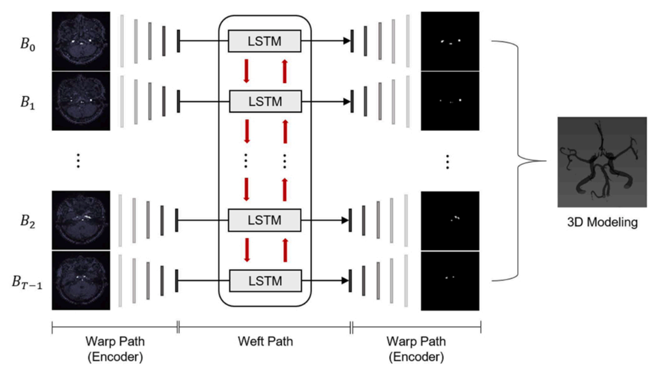

Fig. 10. The Structure of spider U-Net from Lee et al. (2021) for cerebrovascular segmentation.
require with open access of (Lee et al., 2021) permission from MDPI Applied Sciences.

Table 2
Details of U-Net improvement models.

Author	Improvement	loss	Optimizer
Sanchesa et al (Sanchesa et al., 2019).	Inception	Dice	Adam
Zhang et al (Zhang et al., 2020a).	The 12-layer architecture	CE	SGD
Fu et al (Fu et al., 2020).	Bottleneck	Dice	SGD
Hadji et al (Hadji et al., 2019).	Bottleneck	CE	Adam
Shi et al (Shi et al., 2019).	PReLU	Dice	Adam
Tetteh et al (Tetteh et al., 2020).	Cross-hair convolution	CE	SGD
Lee et al (Lee et al., 2021).	U-Net stacking LSTM	Focal dice	Adam
Huang et al (Huang et al., 2020).	Double U-Net	CE	Adam
Liu et al (Liu et al., 2022).	Spatial attention	Dice Tversky Focal Tversky	Adam

3.3. Other CNNs based models

Besides U-Net based model, other models have also been reported for cerebrovascular segmentation, such as V-Net. As a variant of U-Net, V-Net is also commonly used to deal with 3D volumes. Fig. 11 presents the V-Net structure, it is very similar in architecture to 3D U-Net. It mainly introduces residual connections and $5 \times 5 \times 5$ convolution kernels within layers, and replaces all pooling operations with convolution operations.

In Tetteh et al (Tetteh et al., 2020). 's research, V-Net was another backbone. They improved the computational efficiency of V-Net by replacing the regular convolution in cross-hair convolution. Tahir et al (Tahir et al., 2020). adjusted the channels of V-Net and reduced one layer in encoding and decoding path, respectively. This lightweight model enabled fast computation. Chen et al (Chen et al., 2022b). proposed SEVnet. It pays more attention to the squeeze-and-excite structure, which improve the correlation between channels.

In addition, there are some uncommon structures but also exhibit strong performance. For example, Chen et al (Chen et al., 2017). developed the 8-layer structure model based on convolutional autoencoder (CAE), which was first modified by Vincent et al (Vincent et al., 2008). It can extract effective information from voxels and has the potential to be extended for segmentation in other modalityities. As shown in Fig. 12, Ni et al (Ni et al., 2020). proposed a four-channel parallel structure. Since the features of each layer are fully utilized, this structure can minimize the information loss caused by successive convolution and pooling operations. Meng et al (Meng et al., 2020). developed MDCNN, which included dense blocks (Huang et al., 2017), skip connections, and multiscale atrous convolution (MAC) structures (Fig. 13). It adopts the improved MAC to obtain multi-scale features in DSA, which is designed based on Inception and dilated convolutions. In addition, they also reduce the number of connections, reducing redundant information. Nazir et al (Nazir et al., 2020). proposed OFF-eNet with dilated convolution and Inception module. As shown in Figure X, this is a model with a 22-layer structure. It contains 10 residual connected structures, connected by Inception modules. The model adopts different convolutional structures to learn multi-level features. Mou et al (Mou et al., 2021). proposed CS^2-Net, which generated channel and spatial representations using parallel spatial attention and channel attention (Fig. 14). This model has also been transformed into 2D and 3D models to suit different applications. Chen et al (Chen et al., 2022c). proposed A-SegAN, which is generative adversarial network (GAN)-based model. They incorporated feature attention block (FAB) for feature optimization, and filtered the predictions using the discriminator. Banerjee et al (Banerjee et al., 2022). added multi-task deep CNN (MSD-CNN). The model aids in learning the surface voxel-level centrality of cerebral vessels, leading to additional regularization.

We summarized these models in Table 3. Most of these models are pioneered from these researches. Although they are designed for cerebrovascular features, some general features are easily transplanted to other vascular structures, especially for imaging of small target areas. It makes them potentially important backbones in the future.

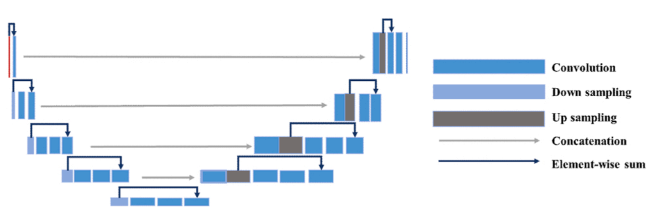

Fig. 11. The Structure of V-Net edited from Chen et al. (2022a) for cerebrovascular segmentation.
require with (Chen et al., 2022a) permission from Elsevier Computerized Medical Imaging and Graphics.

3.4. Small-sample based models

The acquisition of cerebrovascular datasets is not easy. For examples, the acquisition of magnetic resonance imaging is time-consuming and expensive. Some uncommon modalities are also difficult to form sufficient datasets, such as PC-MRA, VWI, and CIs, etc. In addition, cerebrovascular dataset also involves the patient privacy and the improvement of ethics.

To address the limitation, Tetteh et al (Tetteh et al., 2020). used synthetic data for model pretraining. Based on the vessel tree simulator (Schneider et al., 2012), they set random seeds and generated vessel structures adapted to the clinical dataset within random intervals. The synthetic data synchronously generated the corresponding labels, which was used for vessel segmentation. The experimental results show that it allows the model to obtain more information on the vascular texture, thereby improving the performance of cerebrovascular.

As shown in Fig. 15, Kossen et al (Kossen et al., 2021). used DCGAN (Frid-Adar et al., 2018; Sandfort et al., 2019), WGAN-GP (Gulrajani et al., 2017) and WGAN-GP-SN (Miyato et al., 2018) for image-label generation. These synthetic patches were pretrained and used for transfer learning. Compared to the baseline, the performance of applying transfer learning has been significantly improved. It is also beneficial to provide anonymized images and preserve the predicted properties.

Nercessian et al (Nercessian et al., 2021). explored cortical vessel segmentation in CIs. To expand the trainable dataset, they used style-enforced neural image analogy (Ma et al., 2020), which allowed it possible to obtain artificial datasets similar to real CIs by providing only some artificial labels.

Table 4 summarizes the details of these methods. They play an important heuristic role in small-sample datasets.

3.5. Semi-supervised / unsupervised models

Another important challenge for deep learning of cerebrovascular segmentation comes from labeled datasets. As shown in the Fig. 16, the cerebrovascular is multi-level branched and slender, and its geometry is very complex. Therefore, it is a tedious task in artificial cerebrovascular segmentation.

To reduce the dependence on labeled datasets, many researches have explored semi-supervised/unsupervised models (Ma et al., 2021). For example, Zhao et al (Zhao et al., 2018). extracted centerline (Mendonca and Campilho, 2006) and radius estimates (Lell et al., 2006) from cerebrovascular data for tube-level labels generation. They trained model using tube-level labels, and set stopping criteria using a small amount of artificial labels. This approach forces the model to mine valid information from the tube-level labels until it is consistent with the artificial label. Chen et al (Chen et al., 2018). acquired TOF-MRA and CTA simultaneously. They completed the registration of TOF-MRA to CTA using rigid registration, and used coarse segmentation to obtain incomplete vascular segmentation of TOF-MRA. By adjusting the model parameters, the model trained based on incomplete vascular segmentation can generate relatively complete CTA cerebrovascular without any artificial labels. Fan et al (Fan et al., 2020). applied hidden Markov random field to generate incomplete labels and used for model training. This method can rely on a small amount of artificial labels to achieve better segmentation results. Zhang et al (Zhang et al., 2020b). used the mixture probability model to obtain incomplete labels (Fig. 17). To improve the accuracy of incomplete labels, they designed clean mechanism by pretraining two models to supervise each other so that only consistent labels are retained. The model gets better results with augmented incomplete labels. Dang et al (Dang et al., 2022). proposed a weak patch-based segmentation method (Fig. 18). They apply K-means algorithm to synthesize incomplete labels based on 32-size patch labels input by the user, and train the classifier model synchronously. The classifier can obtain additional labels and use it as an additional

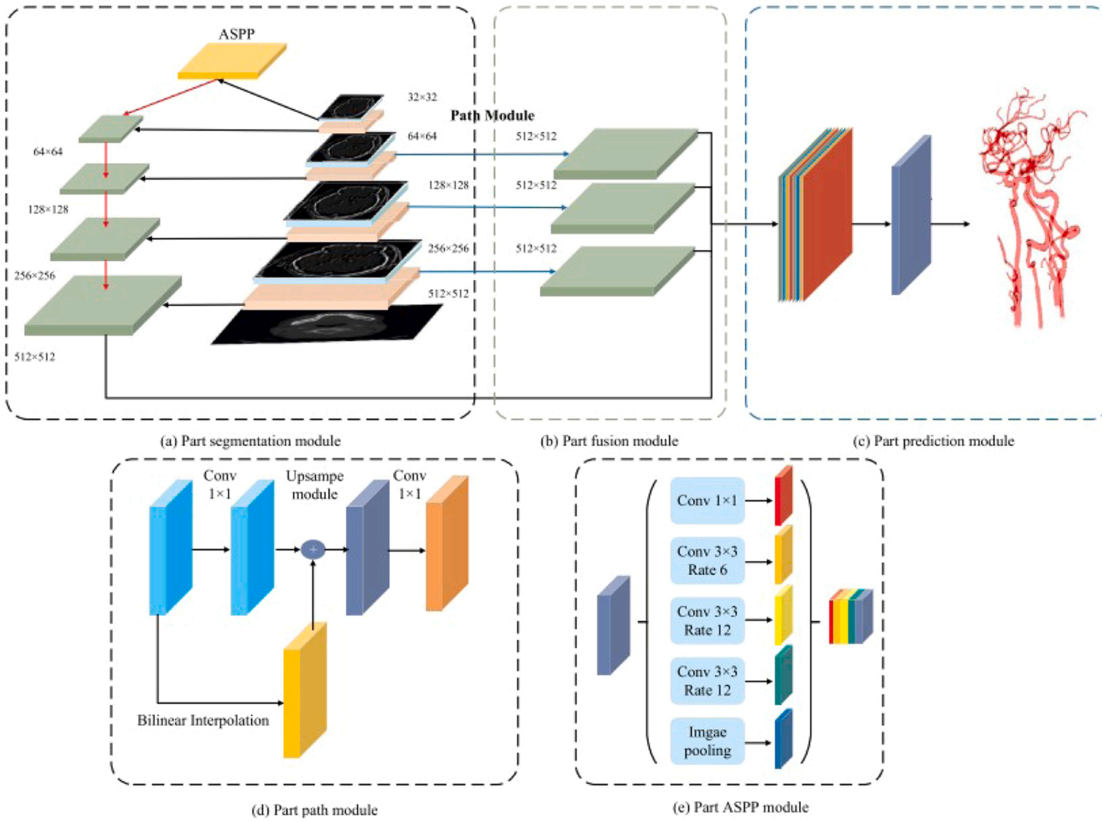

Fig. 12. The structure of GCA-Net from Ni et al. (2020).
require with (Ni et al., 2020) permission from Elsevier Computers in Biology and Medicine.

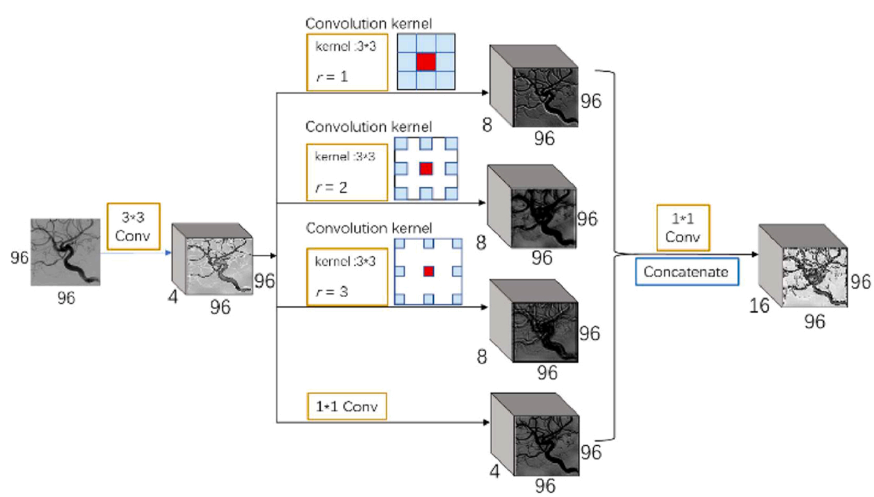

Fig. 13. The structure of MAC from Meng et al. (2020).
require with (Meng et al., 2020) permission from Elsevier Computers in Biology and Medicine.

criterion to optimize the segmentation effect. Chen et al (Chen et al., 2023). provided a semi-supervised learning method based on reconstruction consistency. They kept the predictions of the segmentation model and obtained the TOF-MRA images based on the reconstructed model. This strategy trended segmentation model obtained prediction results with more vessel information. Wu et al (Wu et al., 2022). developed an unsupervised framework, which employ Frangi enhanced images (Frangi et al., 1998) for soft supervision to gain the ability to extract tubular features. It completed cerebrovascular segmentation under the supervision of the statistical model. A small number of artificial labels validated the model and ensured the correct optimization. Li et al (Li et al., 2022). adopted clDice (Paetzold et al., 2019) to construct a hybrid loss function. They randomly generated sparse labels for supervised training, and computed the centerlines and radius of parts of the training set. Compared with pixel-level labels, the acquisition cost of the radius of the centerline is lower and more mature. Vepa et al (Vepa et al., 2022). used the active contour model to obtain weak labels. They proposed low-cost human-in-the-loop strategies to enhance the quality of labels. These improvements enabled the model to obtain enough vessel textures.

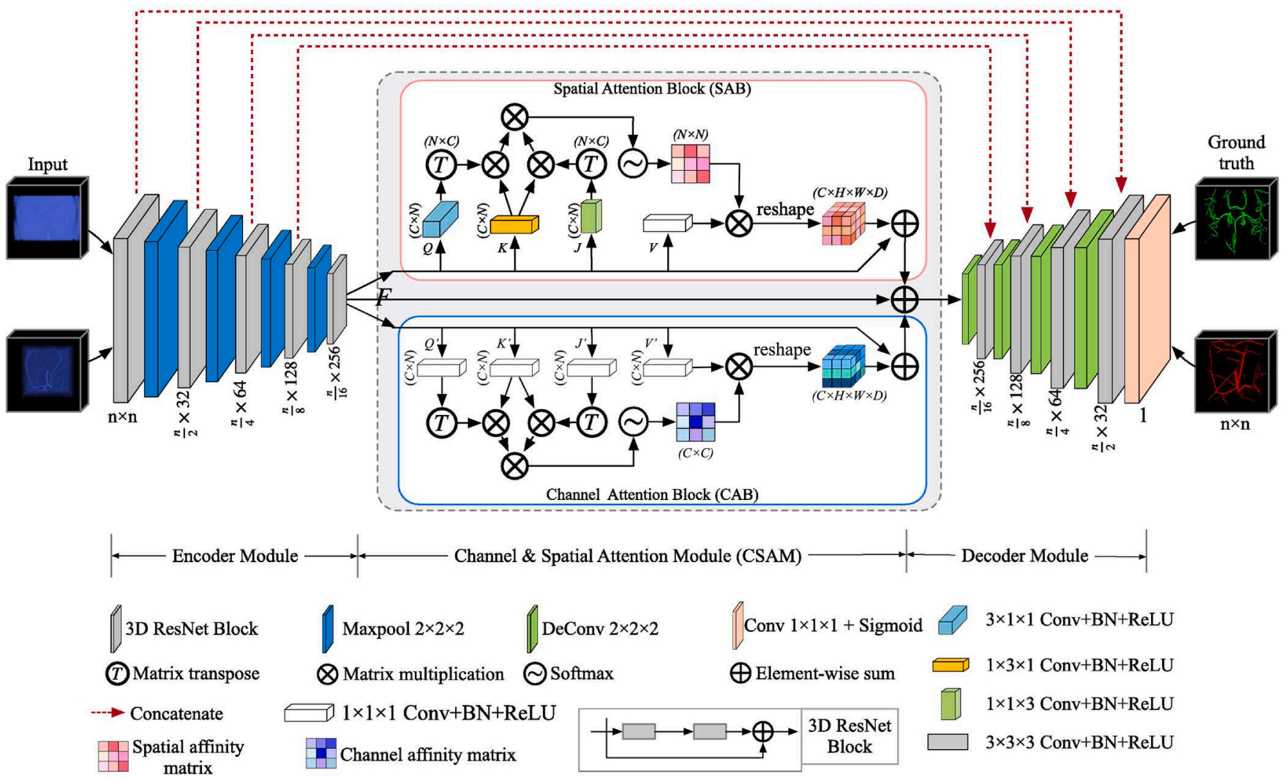

Fig. 14. The structure of CS^2-Net from Mou et al. (2021).
require with (Mou et al., 2021) permission from Elsevier Computers in Biology and Medicine.

Table 3
Details of other CNNs models.

Method	Year	Modality	Training/Testing/ Validation Sets
V-Net (Tahir et al., 2020)	2021	2PM	4/1/-
CAE (Chen et al., 2017)	2017	TOF-MRA	46/1/2
GCA-Net (Ni et al., 2020)	2020	CTA	9488/480/2372
MDCNN (Meng et al., 2020)	2020	DSA	18/10/2
OFF-eNet (Nazir et al., 2020)	2020	CTA	50/20/-
CS^2-Net (Mou et al., 2021)	2021	TOF-MRA	-
A-SegAN (Chen et al., 2022c)	2022	TOF-MRA	30/5/10
SEVnet (Chen et al., 2022b)	2022	TOF-MRA	56/46/-
MSD-CNN (Banerjee et al., 2022)	2022	TOF-MRA	30/4/8

This type of method can improve the generalization ability of the model, which effectively reduces the dependence on labeled datasets.

3.6. Fusion based models

Multi-information input can improve the representation ability of the model, which is a common method in cerebrovascular segmentation. As shown in Fig. 19, DeepMedic (Kamnitsas et al., 2017) is a classic two-branch structure, which is first used in the segmentation of brain lesions. Tatsat et al (Tatsat et al., 2020). explored the performance comparison of DeepMedic and U-Net in DSA. They verified the performance of DeepMedic in cerebrovascular segmentation. Ziegler et al (Ziegler et al., 2021). applied DeepMedic to CE-MRA and achieved multi-level segmentation of arteries. Zhao et al (Zhao et al., 2018). selected DeepMedic as backbone in their semi-supervised framework.

Zhang et al (Zhang et al., 2020b). designed a dual-branch DD-CNN. This structure uses dense connections and adds multi-rate dilated convolution to extract features at different scales. They adopted TOF-MRA images and Frangi enhanced images (Frangi et al., 1998) to different branches. Hilbert et al (Hilbert et al., 2020). proposed BRAVE-Net, a dual encoder model improved by U-Net. Specifically, they

Table 4
Details of small-sample based models.

Method	Year	Modality
Vessel tree simulator (Tetteh et al., 2020)	2021	TOF-MRA μCTA
GAN (Kossen et al., 2021)	2021	TOF-MRA
Neural image analogy (Nercessian et al., 2021)	2021	CI

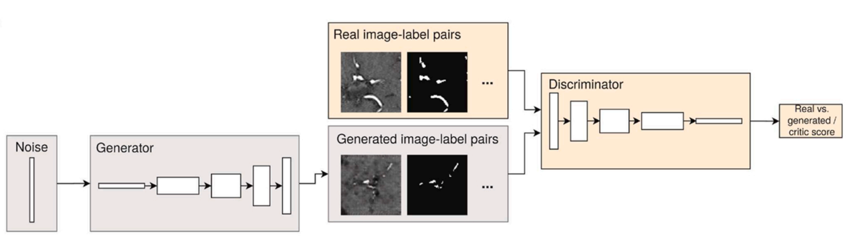

Fig. 15. The structure of GAN architecture (Kossen et al., 2021).
require with (Kossen et al., 2021) permission from Elsevier Computers in Biology and Medicine.

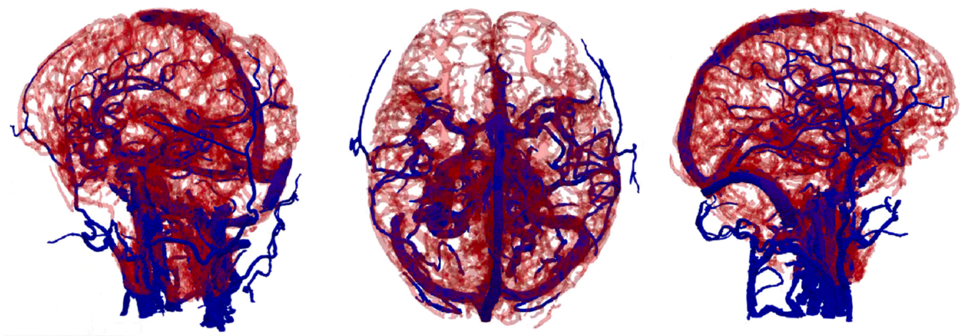

Fig. 16. The cerebrovascular reconstruction of PC-MRA and CE-MRA from Chen et al. (2022a)
require with (Chen et al., 2022a) permission from Elsevier Computerized Medical Imaging and Graphics.

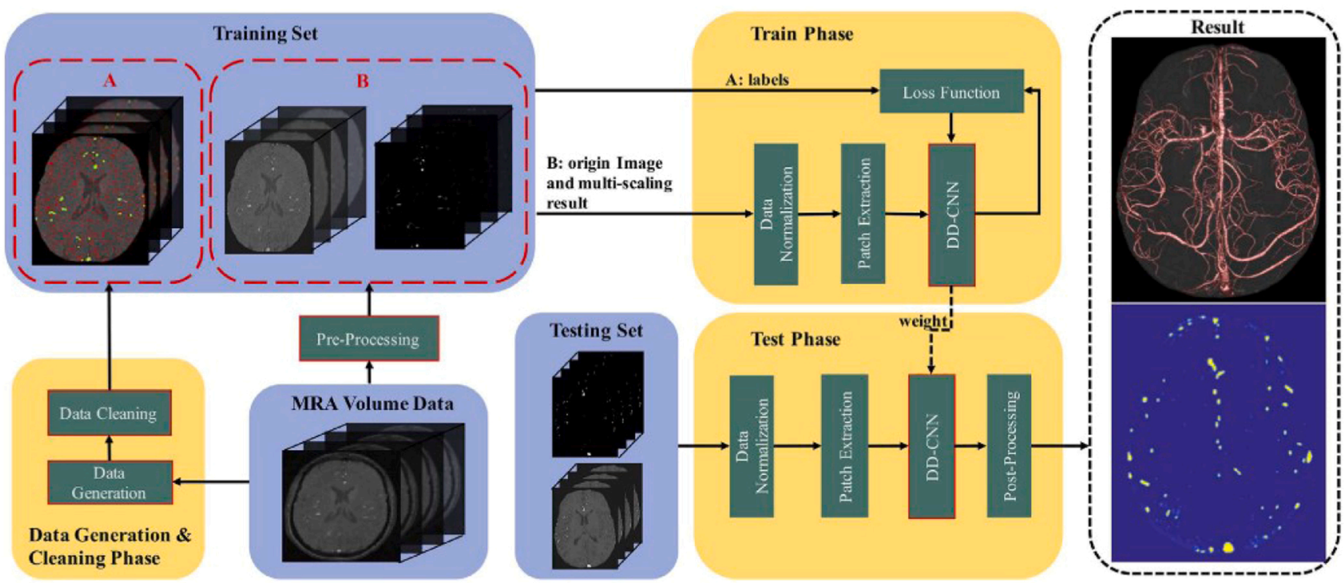

Fig. 17. The workflow of (Zhang et al., 2020b). They take cleaning strategy to correct weak labels.
require with open access of (Zhang et al., 2020b) permission from Elsevier Neurocomputing.

input a larger patch, which was input to the encoder after down-sampling. In addition, they took a central small patch as the input of another encoder. This strategy can better refine the contextual information of the 3D volume. As shown in Fig. 20, Todorov et al (Todorov et al., 2020). proposed VesSAP with two-branch input. They imaged the mouse with different stains to reveal fine vascular features in different regions. The various imaged LSMs were finally input into VesSAP for analysis and reconstruction of cerebrovascular.

3.7. Transformer based models

Transformer is a novel structure that uses self-attention to enhance the correlation between sequences and has important potential in cerebrovascular segmentation. Fig. 21 shows the schematics of MLP, CNN and Transformer. It can be seen that they have different arithmetic mechanisms in processing images.

Chen et al (Chen et al., 2023). proposed TRSF-Net, which applied Transformer to cerebrovascular segmentation. TRSF-Net consists of an encoder and a decoder. Its encoder performs feature extraction through successive Transformers and passes it to the decoder of the CNN structure, which parses feature maps and completes cerebrovascular segmentation.

Chen et al (Chen et al., 2023). and Wu et al (Wu et al., 2022). also tested cerebrovascular using UNETR (Hatamizadeh et al., 2022). The experiments proved that the cerebrovascular structure parsed by Transformer outperformed most CNNs. It may promote more Transformer-based cerebrovascular segmentation models.

3.8. Graphics based models

With the development of deep learning graphics, segmentation tasks are moving in the direction of 'depixelation' (Park et al., 2019). It has some advantages, the first is that the model has stronger anti-noise and not affect the overall geometry due to local pixel errors. Secondly, the reconstruction has a continuous representation without being limited by the sampling of pixels.

Although no graphics based models of cerebrovascular have been publicly reported, models applied to tubular structures have been developed that are similar to cerebrovascular. For example: Wang et al (Wang et al., 2020). used the spherical filling characteristics to construct the maximum radius of the sphere based on the shortest distance from the vessel samplings to the vessel surface (Fig. 22). They used the CNN to learn the mapping from the samplings to the vessel radius. Finally, the vessel model was formed by generating interlaced spherical stacks of samplings. The biggest advantage of this strategy is that accidental wrong pixel prediction can be filled with adjacent spheres, thereby reducing the missing segmentation.

Wang et al. (2019) captured the distance from the voxels to the

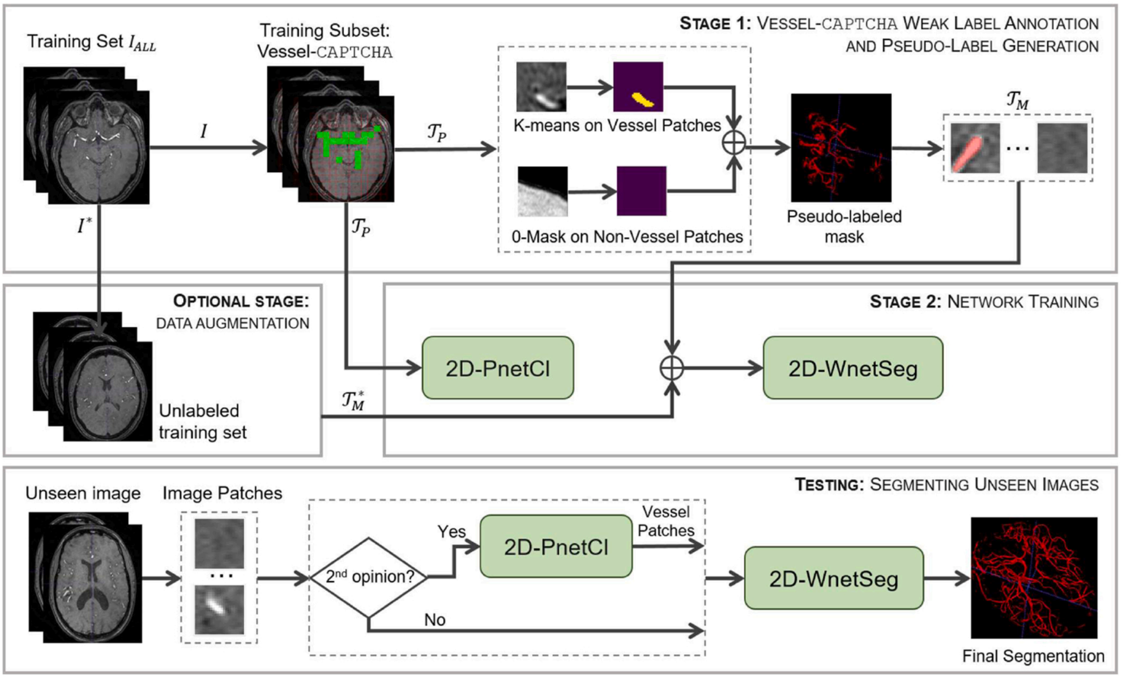

Fig. 18. The workflow of (Dang et al., 2022), witch co-trains two models for segmentation and augmentation.
require with open access of (Dang et al., 2022) permission from Elsevier Medical Image Analysis.

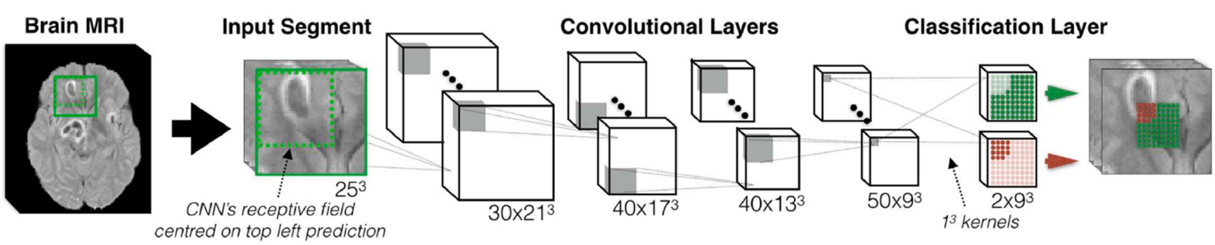

Fig. 19. The architecture of DeepMedic from Kamnitsas et al. (2017).
require with open access of (Kamnitsas et al., 2017) permission from Elsevier Medical Image Analysis.

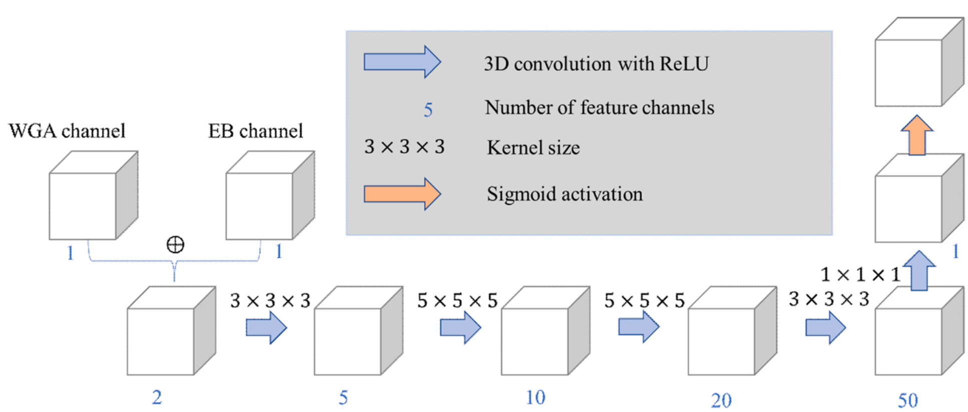

Fig. 20. The dual-branch structure of VesSAP CNN. WGA and EB are two color image using staining and clearing techniques.

tracheal wall to quantify the multi-scale tracheal target. By mapping the relationship between voxels and distance, deep learning models can pay more attention to small-scale targets, thereby implementing more effective segmentation. Shen et al (Shen et al., 2016). have realized the skeleton extraction of natural language images through deep learning models. The skeleton is the most important structure of the vessel model. It can analyze the connection relationship and topological structure of the vessel. This method has potential to be transplanted into medical images in the future.

Compared with the pixel-by-pixel segmentation model, graphics based models are usually unable to achieve end-to-end learning tasks. The combination of deep learning and graphics perfects the limitations of graphics in application, such as the discontinuity of voxels. Also, it has the theoretical basis of graphics, which has strong reasoning and

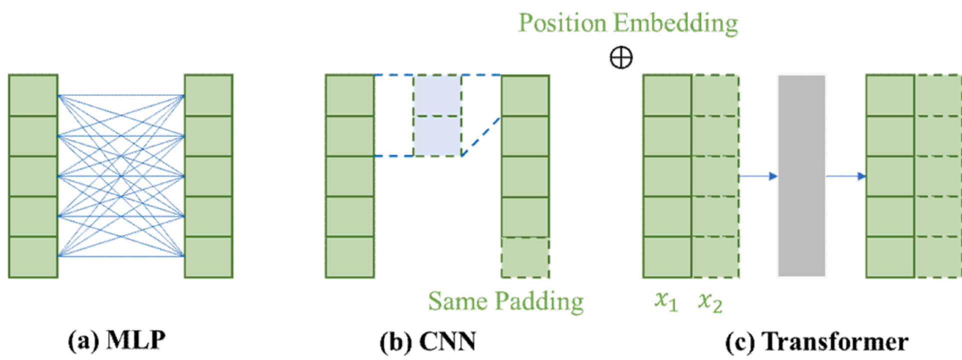

Fig. 21. Simple schematics of different models. (a) means MLP; (b) is CNN, and (c) introduces Transformer. All structures are drawn using vector.

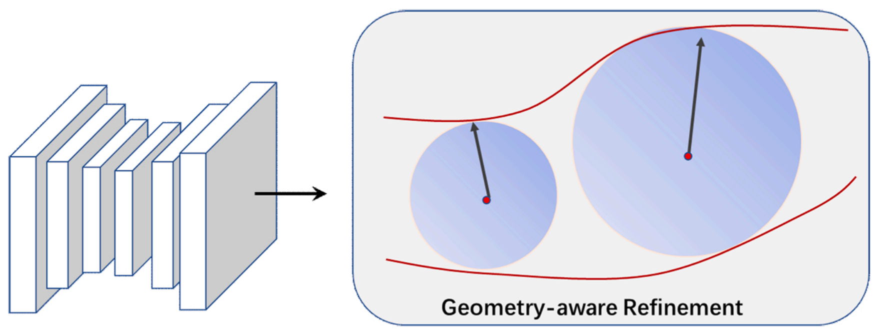

Fig. 22. CNN learned the smallest circle radius from the target voxel to the vessel wall.

robustness. Relevant studies have confirmed that there are important theoretical systems in cerebrovascular imaging, such as the vascular skeleton (Wang et al., 2016) and the gray-scale distribution of vessel (Friman et al., 2010) (Fig. 23). These theories provide great possibilities for the next step of graphics deep learning methods.

Finally, based on existing public reports and typical features, we summarized the general advantages and disadvantages of the eight models in Table 5.

4. Open source for cerebrovascular segmentation

Cerebrovascular segmentation is characterized by complex morphology and unbalance samples, so it is challenging for common segmentation frameworks to directly match cerebrovascular segmentation. We collected some typical frameworks that have been publicly reported for cerebrovascular segmentation. These open sources must have a complete framework, be directly used for cerebrovascular segmentation, and have strong expansibility to facilitate researchers' application and independent development.

Pytorch-Medical-Segmentation is our framework. It was first used in cerebrovascular segmentation, and later extended to any medical image. It is based on the Pytorch and has built-in more than 15 models including U-Net, V-Net, UNETR, MiniSeg, etc. Furthermore, the framework can freely switch between 2D and 3D, so it is not limited by the input modality of the data. The current limitation is that the validation set is not considered. We plan to derive more classic or mainstream models in the near future. The code is available at https://github.com/MontaEllis/Pytorch-Medical-Segmentation.

SSL-For-Medical-Segmentation is a semi-surprised learning framework from TRSF-Net (Chen et al., 2023). It combines the latest semi-supervised learning theory and is reproduced in the form for image segmentation. It was first applied in TOF-MRA images and now is available for different deep learning model and medical datasets. Code is available at https://github.com/MontaEllis/SSL-For-Medical-Segmentation.

Brain-vessel-segmentation is the open source for BRAVE-Net (Hilbert

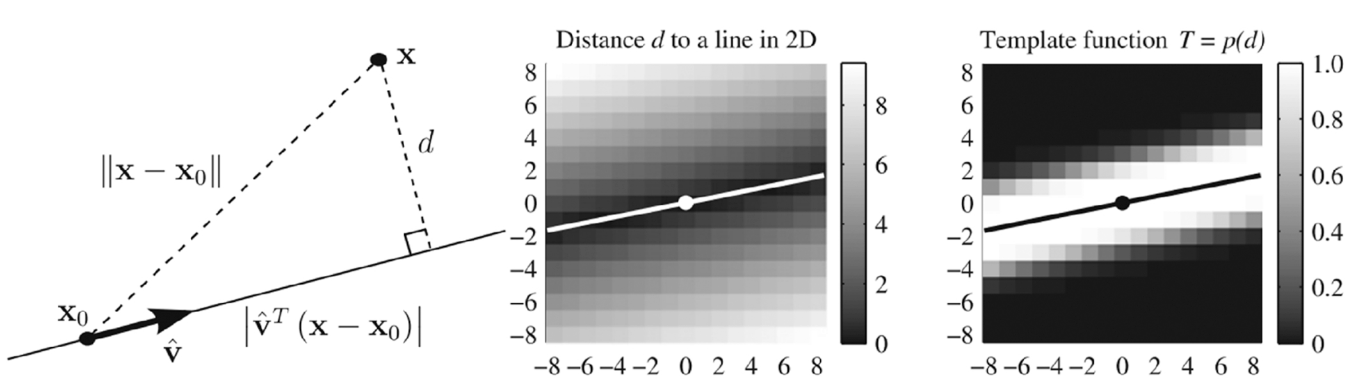

Fig. 23. Example of the vessel template edited from Friman et al. (2010). It explored the gray-scale distribution of vessels to obtain the vessel template. require with (Friman et al., 2010) permission from Elsevier Medical Image Analysis.

Table 5
General advantages and disadvantages of each model.

Models	Advantages	Disadvantages
Sliding window based models	Less information loss and global association	Expensive inference time and inefficient training
U-Net based models	A classic baseline for new theories and comparison	Feature redundancy
Other CNNs based models	Shared convolution for fewer parameters	Gradient extinction in deep structure and information loss in pooling
Small-sample based models	Data space expansion	Data space quality depends on generation techniques
Semi-supervised/ unsupervised models	Mining semantics from unlabeled datasets	Low training efficiency
Fusion based models	Diversity characteristics	Parameter redundancy
Transformer based models	Global feature combination, and self-attention mechanism	Low computational efficiency
Graphics based models	Priori semantics	Objective function complexity

et al., 2020). It provides the lightweight U-Net and context sampling strategy included in the study to achieve multi-scale feature extension. In addition, deep supervision is offered to force the intermediate layer to produce discriminant features to avoid gradient explosion and extinction. Code is available at https://github.com/hilbysfe/brain-vessel-segmentation.

A-SegAN is open code from A-SegAN (Chen et al., 2022c). It provides an attentional integration adversarial model for cerebrovascular segmentation from TOF-MRA images. The segmentation model combines multi-layer features with dense connections to establish local and global relevance. In the discriminator, the attention mechanism is used to filter low-level features to balance the proportion of vascular classes. Code is available at https://github.com/YingChen7/A-SegAN.

ISA-model is our new project derived from Pytorch-Medical-Segmentation. In this project, we offered an integration- and separation-aware adversarial model for cerebrovascular segmentation from TOF-MRA. Considering that adversarial training may lead to model degradation due to insufficient vascular semantics, we provided prior compensation for the model through texture and boundary separation. Code is available at https://github.com/MontaEllis/ISA-model.

5. Public cerebrovascular segmentation datasets

We have organized some common public datasets for cerebrovascular segmentation. We focused on screening them that included original angiography to satisfy the deep learning research. It is required that these datasets have been reported for cerebrovascular segmentation.

Healthy MR Database includes brain images of 100 healthy subjects with an age balanced distribution of 18–60 + , excluding diabetes, hypertension, head trauma, mental illness, etc. The images were obtained on the 3 T unit. In addition, eight patients are also included in datasets for generalization. Some of the images present motion artifacts. Data is available at https://public.kitware.com/Wiki/TubeTK/Data.

IXI dataset contains MR images from 600 healthy subjects. Images were collected from three different London hospitals, including Hammersmith Hospital using a Philips 3 T system, Guy's Hospital using a Philips 1.5 T system, and Guy's Hospital using a Philips 1.5 T system. It is available at https://brain-development.org/ixi-dataset/.

Cerebrovascular Segmentation Dataset is from A-SegAN (Chen et al., 2022c). Chen et al (Chen et al., 2022c). screened 45 TOF-MRA images from the IXI dataset and provided refined labels. Images were collected by 1.5 T GE MRI and manually annotated under the supervision of multiple radiologists. Data is available at https://xzbai.buaa.edu.cn/datasets.html.

CADA dataset is an open challenge from Medical Image Computing and Computer Assisted Intervention (MICCAI) for the detection and segmentation of cerebral aneurysms. It was scanned in contrast-enhanced cerebrovascular vessel tree, including 109 images and 127 tumor labels. CADA is applicable for localization and segmentation of local areas. Data is available at https://cada.grand-challenge.org/Dataset/.

ADAM dataset is another open challenge to the detection and segmentation of brain aneurysms from MICCAI, which contains 113 training and 142 testing sets. TOF-MRA images were scanned and labeled with experts in medical annotations. ADAM is applicable for the examination and segmentation of pathological cerebrovascular. Data is available at https://adam.isi.uu.nl/.

VesSAP data is from 3D VesSAP network (Todorov et al., 2020). It was collected from mice. By injecting different dyes, their brains were extracted and carried out with different emission filter in sequence for visualizations. All samples were imaged using light-sheet microscopy. VesSAP data presents micrometer-scale vessels for detailed structural analysis. Data is available at http://discotechnologies.org/VesSAP/.

6. Discussion of development trend

Fig. 24 plots the approximate statistical results of the deep learning for cerebrovascular segmentation through the incomplete statistics of search engines and our collections.

The first is the researcher's choice of deep learning methods and other methods when dealing with cerebrovascular segmentation. Although there are some challenging issues (Chen et al., 2023, 2022d), Fig. 24a shows that deep learning methods have emerged in large numbers since 2017 and almost reached their peak in 2019. In the past few years, there have been related public researches on other methods, but they are far less than deep learning methods. In addition, there are few reports after 2021 years about them. Taher (Taher et al., 2020), Kandil (Kandil et al., 2018), and Pei (Lu et al., 2016) et al. have incorporated prior probabilities through feature compensation, however, they still did not make full use of the structural features of vessels and the correlation of pixels. Therefore, the focus of researchers in the past few years has gradually begun to shift.

By observing the distribution of deep learning methods in Fig. 24b, about 51.35% are U-Net, and the U-Net improvement accounts for 24.32%. Therefore, U-Net has greatly promoted the advancement of this field. It can be seen that the exploration of deep learning is relatively late. This is because when studying the task of vascular segmentation, cerebrovascular segmentation is not the first choice due to the limitations of the dataset and public challenges. Common vascular research mainly focuses on hepatic vessels (Yan et al., 2021; Huang et al., 2018; Liu et al., 2020), retinal vessels (Dasgupta and Singh, 2017; Wu et al., 2020a; Jiang et al., 2018) and pulmonary vessels (Xu et al., 2018; Pawar and Talbar, 2021). They all have mature datasets and open challenges. In addition to U-Net, many excellent models have also emerged, which achieved satisfactory results in cerebrovascular segmentation.

7. Discussion of quantitative assessment

We count the evaluation results of deep learning for cerebrovascular segmentation. Most public reports use different assessment principles. For consistent comparison, we chose the DSC index (Chen et al., 2021a, 2021b), which has been discussed in almost all cerebrovascular segmentation, and is also the most classic index in image segmentation.

Table 6 summarizes the evaluation of TOF-MRA images in different researches, as this is the most frequently used modalityity. Other modalityities are listed in Table 7. It can be seen that some advanced 2D models perform strong, such as BRAVE-NET (Hilbert et al., 2020), CS^2-Net (Huang et al., 2020) etc. With the development of deep learning methods, the 3D models have gradually matured. It has increased from 67% to 93.20% for TOF-MRA images.

However, the reported indicators of these researches are hard to quantitatively evaluate each other. The most important thing is that the

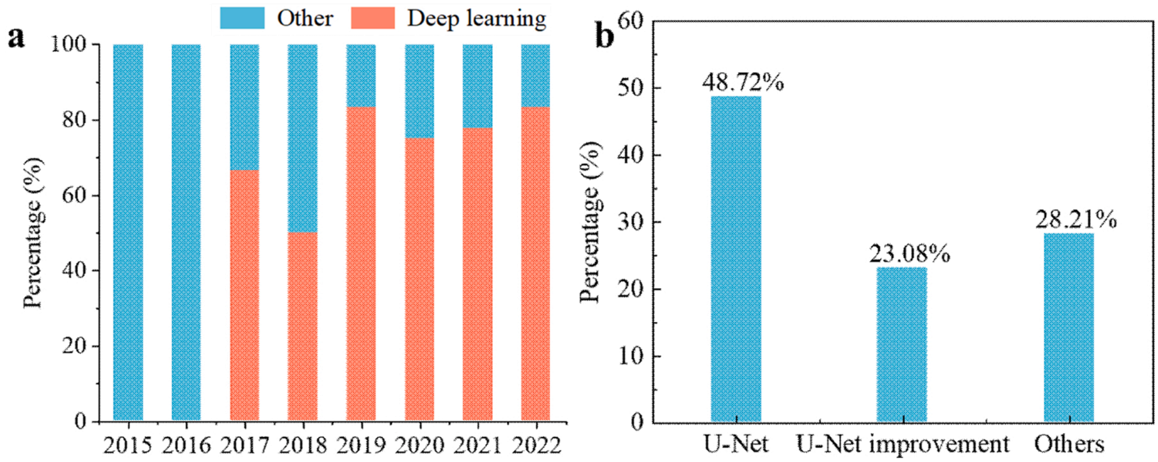

Fig. 24. Statistical distribution graph. (a) represents the publication ratio of the two types in different years. (b) represents the proportion of U-Net, U-Net improvement, and other models in deep learning.

Table 6
Quantitative assessment of different researches in TOF-MRA.

Author	Backbone	Dimension	DSC
Livne et al (Livne et al., 2019).	U-Net	2D	88.00
Guo et al (Guo et al., 2021).	U-Net	2D	87.93
Fan et al (Fan et al., 2020).	U-Net	3D	79.41
Sanchesa et al (Sanchesa et al., 2019).	U-Net	3D	67.00
Tetteh et al (Tetteh et al., 2020).	U-Net	3D	86.68
Zhao et al (Zhao et al., 2018).	DeepMedic	2D	-
Phellan et al (Phellan et al., 2017).	-	2D	78.60
Chen et al (Chen et al., 2017).	CAE	3D	82.84
Zhang et al (Zhang et al., 2020b).	DD-CNN	3D	93.20
Dang et al (Dang et al., 2022).	W-Net (Dias et al., 2019)	2D	79.32
Kossen et al (Kossen et al., 2021).	U-Net	2D	91.00
Hilbert et al (Hilbert et al., 2020).	BRAVE-Net	2D	93.10
Lee et al (Lee et al., 2021).	Spider U-Net	3D	79.30
Huang et al (Huang et al., 2020).	FAU-Net	2D	-
Mou et al (Mou et al., 2021).	CS^2-Net	3D	-
Chen et al (Chen et al., 2022c).	A-SegAN	3D	86.38
Chen et al (Chen et al., 2022b).	SEVnet	3D	89.89
Wu et al (Wu et al., 2022).	UNETR	3D	83.10
Li et al (Li et al., 2022).	GVC-Net	3D	67.66
Liu et al (Liu et al., 2022).	U-Net	3D	93.84
Banerjee et al (Banerjee et al., 2022).	MSD-CNN	3D	73.56
Simon et al (Simon et al., 2022).	U-Net	3D	88.50

Table 7
Quantitative assessment of different researches in others modality.

Author	Modality	Backbone	Dimension	DSC
Quon et al (Quon et al., 2020).	T2WI	U-Net	2D	75.00
Cui et al (Cui et al., 2021).	CE-MRA	U-Net	3D	79.40
Zhang et al (Zhang et al., 2020a).	DSA	U-Net	2D	82.68
Fu et al (Fu et al., 2020).	CTA	ResU-Net	2D	93.10
Hadji et al (Hadji et al., 2019).	CE-CBCT	FCNN	3D	79.00
Shi et al (Shi et al., 2019).	VWI	U-Net	2D	89.00
Tetteh et al (Tetteh et al., 2020).	µCTA	U-Net	3D	96.27
Tahir et al (Tahir et al., 2020).	2PM	V-Net	3D	68.40
Tatsat et al (Tatsat et al., 2020).	DSA	DeepMedic	2D	94.00
Ni et al (Ni et al., 2020).	CTA	GCA-Net	2D	96.51
Ziegler et al (Ziegler et al., 2021).	CE-MRA	DeepMedic	3D	80.00
Meng et al (Meng et al., 2020).	DSA	MDCNN	2D	88.13
Nazir et al (Nazir et al., 2020).	CTA	OFF-eNET	3D	99.75
Dang et al (Dang et al., 2022).	SWI	W-Net (Dias et al., 2019)	2D	-
Nercessian et al (Nercessian et al., 2021).	CI	U-Net	2D	86.00

relevant evaluations are not standardized. For example, Livne (Livne et al., 2019) and Huang (Huang et al., 2020) trained and tested their models using TOF-MRA slicers. This approach tends to be more performant because it avoids some invalid slicing areas. More are verified directly on the 3D volume. Therefore, it leads to differences even for the same modality. Also, most of them are verified on private labeled datasets, causing it difficult to form consistent assessments. We believe that with the improvement of public datasets, these evaluation methods will move towards standardization.

8. Challenges and opportunities

Based on the deep learning for cerebrovascular, we have sorted out some possible challenges in the future, hoping they are helpful and enlightening for next exploration.

8.1. Fusion of multimodal images

Cerebrovascular imaging technology has developed a variety of modalities to address different clinical needs, which has the potential to expand into fusion based models. However, multimodal images usually face irregular data structures such as physical space offsets and inconsistencies in sampling parameters. How to solve the fusion problem of irregular space between multimodal images will be an important exploration direction.

8.2. Semi-surprised and unsurprised models

Artificial labels of cerebrovascular datasets have long been the most costly and challenging topic. To avoid relying too much on labeled datasets, researchers have carried out preliminary explorations in semi-supervised or unsurprised learning. This type of algorithm has achieved some results, but it also puts forward higher requirements for computational efficiency and training cost. Exploring more effective image features to improve semi-supervised or unsupervised efficiency is a worthwhile direction to explore, which is also in line with clinical needs.

8.3. Models with geometric properties

Cerebrovascular contains rich geometric features, including shape, derivation law, and gray distribution features, etc. These properties for cerebrovascular have been extensively studied by researchers in the past years, but rarely reported in deep learning. Combining these attributes with deep learning will give the models more interpretability and break the current pixel-level prediction, which is expected to further improve the geometric characteristics of cerebrovascular reconstruction.

8.4. Efficient inference

Efficient inference is an important prerequisite for ensuring rapid clinical reconstruction of patients' cerebrovascular. Although the existing reported models have achieved lightweight structures, it still takes much inference time to fully reproduce the cerebrovascular in 3D volumes. How to efficiently represent the three-dimensional structure will be of value, for example, Tetteh et al (Tetteh et al., 2020). used 2D convolution to fit 3D convolution, which is an innovative of fitting and interpolation using deep learning.

8.5. Capsule model for cerebrovascular segmentation

CNN based structures may cause to lose spatial relationships of learned features. To overcome this, capsule models have been applied in different image segmentation and classification works (Duarte et al., 2019; Cai et al., 2021; Wu et al., 2020b). Therefore, new studies can be performed with efficient capsule networks to see their performance in segmentation of cerebrovascular structures.

9. Conclusions

This work summarizes the deep learning for cerebrovascular segmentation. We combed the cerebrovascular method based on deep learning model, and provided and discussed the improvement, loss function, optimization, quantitative assessment, and data modality, etc. These details are an important prerequisite for researchers to reproduce these researches. We hope that our review work can provide access to researchers in the field and inspire them to search for better models and theories to find the different answers or solutions in the images for diverse application scenarios. Also, it is expected that our thinking and understanding can provide a convenient reference for researchers trying new directions and new theories.

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.

Data availability

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

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