Federated Learning on Brain Disease Research: Segmentation of Cerebral Small Vessel Diseases (CSVD) using Multi-scale Hybrid Spatial Deep Learning Approach

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Abstract

Federated learning is an emerging approach that enables large-scale decentralized learning without the need to share data among different data owners. This approach is particularly valuable in addressing data privacy concerns in medical image analysis. However, existing methods often impose a strict requirement for label consistency across clients, which significantly limits its applicability. Various clinical sites may only provide annotations for specific organs of interest, and there may be limited or no overlap in the labeled data among different sites. The human brain receives nutrients and oxygen through blood vessels in the brain. The pathology of small vessels, i.e. mesoscopic scale, is a vulnerable component of the cerebral blood supply and can result in major complications such as Cerebral Small Vessel Diseases (CSVD). In this paper, we propose a hybrid architecture for medical image segmentation to produce efficient representations from global and local features and adaptively aggregate them, aiming to fully exploit their strengths to obtain better segmentation performance in federated learning. Furthermore, we propose a multi-scale feature extraction module embedded at the bottom of the proposed model, which can efficiently extract hidden multi-scale contextual information and aggregate multi-scale features. Experiments on segmentation over three-dimensional rotational angiography of internal Carotid Artery with aneurysm (SHINY-ICARUS) challenge dataset show the effectiveness of the proposed multiscale framework.

Keywords: Federated Learning, Deep Learning, Medical Image Analysis, 3D volume Segmentation, Cerebral Small Vessel Diseases, Brain angiography.

1. Introduction

Distributed big data and digital healthcare technologies hold immense potential for advancing medical services. However, challenges arise when attempting to develop predictive models from diverse and intricate e-health datasets. Federated learning (FL) [1] has emerged as a decentralized learning paradigm that enables multiple data owners to collectively train deep learning (DL) models without sharing the raw data. Previous studies [1], [2] have showcased the viability of FL, particularly the federated averaging (Fe-dAvg) algorithm in the context of medical image segmentation. Federated Learning (FL), as a collaborative machine learning technique, aims to tackle these challenges by creating a joint predictive model across clients at multiple sites, especially within distributed medical institutions or hospitals. FL allows for the collective training of deep learning models using distinct patient data from various hospitals for various clinical applications, including medical image segmentation. Given the non-convex nature of the training objective in deep neural networks, averaging locally trained models can result in suboptimal solutions within the parameter space, potentially leading to performance degradation [1]. However, a significant issue with FL is the performance degradation it may experience when dealing with data that are not independently and identically distributed (non-iid), a situation commonly encountered in medical image datasets. Recent publications by various authors [2], [3], [4], [5] have focused on federated deep learning, especially for segmentation and classification tasks. Wicaksana et al. [3] introduced "FedMix: Mixed Supervised Federated Learning for Medical Image Segmentation," while Xu et al. [4] presented "Federated Cross Learning for Medical Image Segmentation." Additionally, Qiu et al. [5] proposed "Federated Semi-Supervised Learning for Medical Image Segmentation via Pseudo-Label Denoising."

As the expert knowledge usually required for annotating medical images is much more demanding and difficult to obtain, various medical institutions have very limited strong pixel-level annotated images and most available images are unlabeled or weakly annotated. Therefore, a realistic clinical mechanism that utilizes every available supervision for cross-institutional collaboration without data sharing is highly desirable. We propose to develop a label-agnostic Mixed Supervised Federated Learning approach that efficiently uses data labeled in any form for medical image segmentation. Specifically, in the absence of pixel-level labels, it will effectively utilize unlabeled images as well as useful information contained in the weakly labeled for producing and selecting high-quality pseudo labels. We will devise an effective adaptive weight assignment across clients, where each client can learn an aggregation weight. Adaptive weight assignment is essential to handle inter-client variations in supervision availability. Recently, the SHINY-ICARUS challenge was organized to analyze vascular morphology and topology efficiently to provide a platform and benchmark for brain vascular segmentation [6]. Recent advancements in deep learning and imaging technology have enabled the development of advanced deep learning models and large-scale datasets [6], [7], [8]. Recently a lot of work proposed deep learning-based segmentation methods for medical imaging and signals [8], [9], [10], [11], [12]. In this work, we present an efficient hybrid attention and multi-scale feature aggregation 3D deep learning framework for automatic brain vascular segmentation. Experiments are conducted on the SHINY-ICARUS challenge which shows the effectiveness of the proposed framework.

The key contributions of this work are:

1. Present a 3D UNet-based segmentation framework aided with hybrid attention and multi-scale features for automatic brain vascular segmentation in the federated learning environment.
2. The attention-guided feature fusion module exploits the most useful features (both high-level features and low-level features) between two adjacent layers and the multiscale feature module assists the model in extracting precise features at different scales and training on each client and communicating with the server model using the weighting aggregation approach.
3. Extensive experiments were conducted on the SHINY-ICARUS challenge dataset which showed efficient segmentation of brain vascular.

2. Methodology

3D angiographies of brain vasculature segmentation especially segmentation of visible vasculature connected to one or more of the main feeding arteries of the brain is a challenging problem due to its complex nature. To effectively analyze the vascular morphology and topology, we present an efficient hybrid attention and multi-scale feature aggregation 3D deep learning framework for automatic brain vascular segmentation. In the following section, we first present the overall framework followed by details of each component. The proposed vascular segmentation architecture is based on a classical U-shape encoder–decoder structure [13], [14], [15]. Besides, we have also integrated two core modules (hybrid spatial and channel attention module, multi-scale feature extractor module) subtly and seamlessly which helps to select important multiscale contextual spatial information and semantic information adaptively. The hybrid spatial and channel attention module (HSCA) suppresses the low-level background noise and retains local semantic information of vessel structure, whereas the multiscale feature extractor module (MSFE) assists in the effective extraction of concealed multi-scale contextual information as well as aggregating multi-scale features. As a results, it helps to enhance the capability of the network to deal with complex cases where vascular heavily varies in shape and size, and many are intertwined. Figure 1 illustrates the proposed framework. To extract different feature maps from each convolutional block in the encoder, each block consists of 3D convolutional layers with batch-normalization and ReLU activation functions. We have used the 3D max-pooling layer to reduce the input spatial size of the image. Notice that we have reduced the size of spatial input with the increase in several layers and we have recovered the spatial resolution in the decoder. To recover the spatial resolution in the decoder, we have applied 3D up-sampling using bi-linear up-sampling. In this experiment, we have used $3 \times 3 \times 3$ kernel size in both the encoder and decoder and the number of feature map numbers to 16, 32, 64, 128, and 256 for each encoder. To down-sample the spatial resolution. we have set the kernel size to $2 \times 2 \times 2$ for the 3D-MaxPool layer on encoder side.

Finally, we have used a transpose3D convolutional layer with stride 2 and 2 × 2 × 2 kernel size for up-sampling the size of each decoder. At the end, we have concatenated the output of each encoder block to the corresponding decoder block. To generate the final output segmentation map, we have used a 1 × 1 convolutional layer with softmax function.

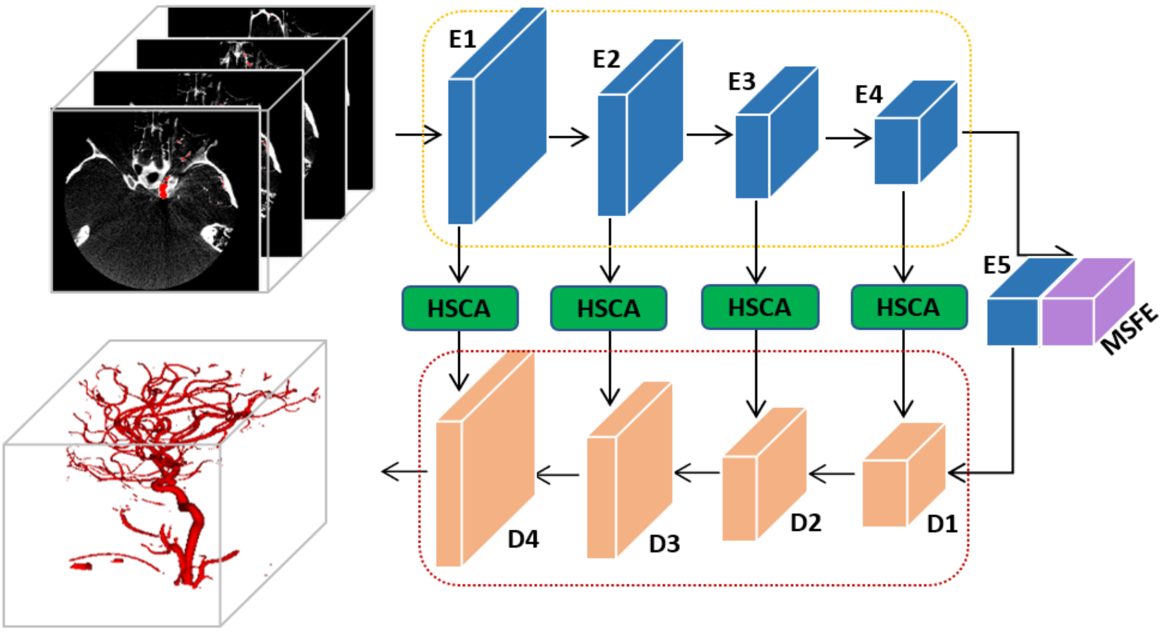


Fig. 1. Proposed Multi-scale Feature extraction Module (MSFE) and hybrid spatial and Channel attention module (HSCA) aided brain vascular segmentation framework. E1, E2, E3, E4 are encoders blocks and D1, D2, D3 and D4 are decoders blocks respectively.

Our approach follows the structure of the FedAvg [1] algorithm, a widely recognized benchmark in the field of Federated Learning (FL). This approach involves a central server node and K client nodes. The central server's main role is to manage the communication and computation processes among the various client nodes. Meanwhile, the client nodes are primarily responsible for training the model using their local data and computing devices. With a universal label set encompassing M organs, each client node possesses a local dataset D_k, which is labeled with a subset of $N_k(\leq M)$)organs. Our objective is to develop a segmentation network F(.,θ) for all M organs by leveraging the labeled datasets $\{D_k\}_{k=1}^{K}$, which are distributed across distinct client nodes and cannot be joined or centralized for training purposes. The training process within the Federated Learning (FL) framework is comprised of Tcommunication rounds between the server and client nodes. In each communication round, denoted as the t_{th} round, each client node k initially downloads the parameters of the current segmentation network, represented as $F(.,\theta^t)$ from the server (referred to as the global model). This process results in a local copy of the model, denoted as the local model.

Subsequently, the client node proceeds to train its local model using its local dataset, Dk, for a specified number of E epochs. Following the local training, the server collects the trained local models, $F(.,\theta_k^t)$, from all Kclient nodes and combines them into a new global model through a parameter-wise averaging process.

$$\theta^{t+1} = \sum\nolimits_{k}^{K} \frac{|D_k|}{\sum_j^K |D_j|} . \theta_t \tag{1}$$

Since the local models are trained separately on the client nodes, the server node is only required to transmit the model parameters, as opposed to the raw data, from the clients. This approach allows the Federated Learning (FL) model to gain insights from distinct client datasets without compromising data privacy. Figure 2 showed the process of federated learning environment for brain tumor segmentation.

As labels for regions in brain vascular are sparse, hence, we have used binary cross-entropy and weighted binary cross-entropy loss [14] which can adjust the learning bias between vessels and background. Besides, we also used dice similarity coefficient loss [15] to ensure the segmentation of small vessels. Finally, we define the 3D optimization loss function.

$$L = BCE + \alpha WBCE + (1 - \alpha)LDSC \quad (2)$$

where α is the weight balance parameter between weighted binary cross entropy (WBCE) and LDSC (Dice loss). We have empirically set $\alpha = 0.6$.

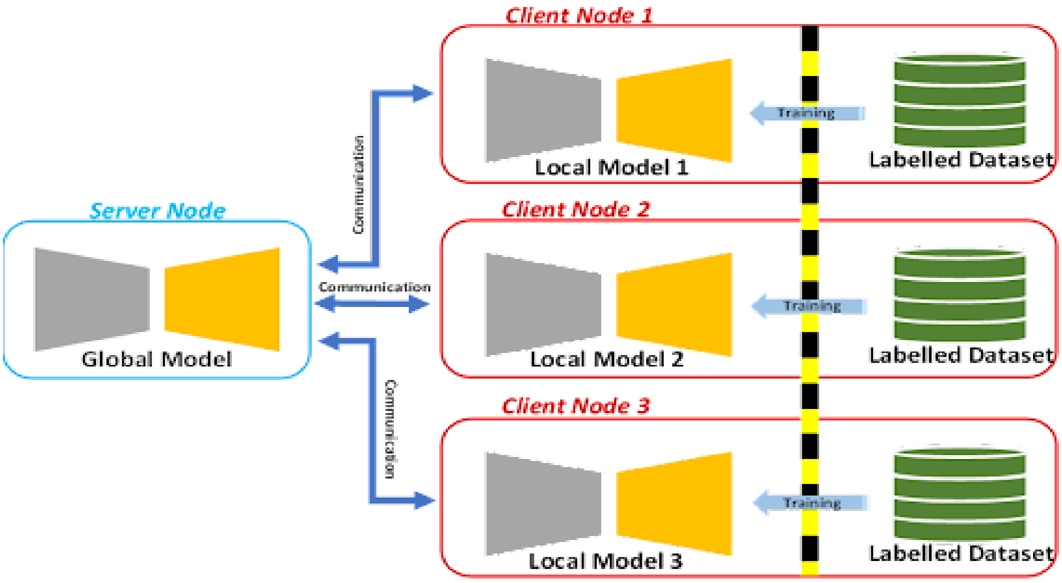


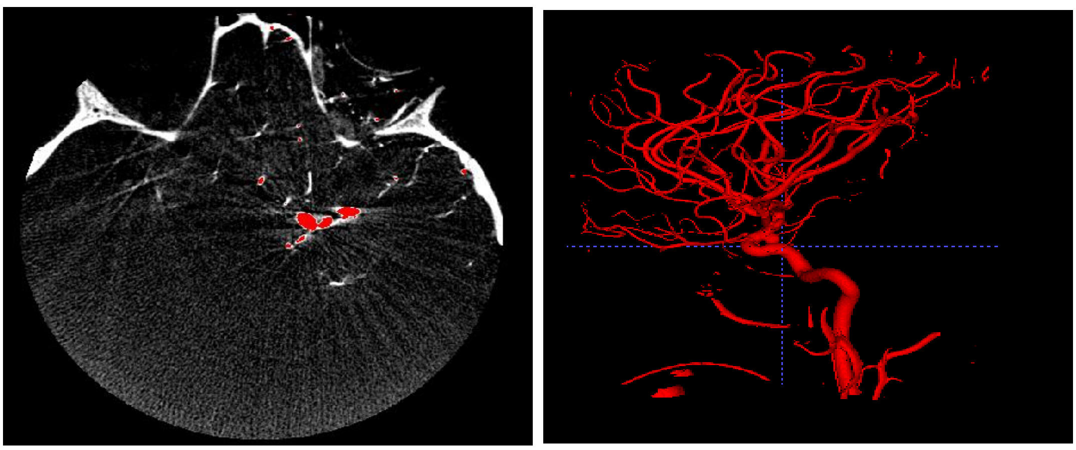
Fig. 2 Federated Learning environment for brain tumor segmentation

3. Results and Discussion

In this section, we first present details of the dataset followed by the experiment and results. We have evaluated and compared the performance using the Dice, Jaccard index, volumetric similarity coefficient, and balanced average Hausdorff distance (HD). SHINY-ICARUS challenge evaluation is based on two overlapping matrices such as clDice5 and Dice. ClDices measure the similarity while favoring both connectivity and topology. Both clDice5 and Dice carry the same weight for the evaluation.

3.1. Dataset

SHINY-ICARUS dataset consists of manually segmented cerebral arteries NIfTI volumes with 16-bit representation. The images (resolution 0.227 × 0.227 × 0.227mm) are acquired by interventional neuroradiologists from patients presenting intracranial aneurysms, using a GE INNOVA 3D. The dataset consists of contract images of most of the patient's head. In this experiment, we have divided the dataset into five-fold cross-validation based on the best validation score, the proposed model uploaded in a docker container. The challenge organized provided 35 volumes for training the proposed model. A detailed description of the dataset can be found [6]. A sample dataset with manual annotation is shown in Figure 3.



(a) image (b) mask

Fig. 3 A sample dataset was used in our proposed model.

3.2. Experimental Results

For evaluation purposes, the SHINY-ICARUS challenge provides two test sets (primary and secret). We have trained the proposed model using patches of input volume due to the limitation of memory. We have found 160 × 160 × 160 the best patch for training. We have generated 10 random patches with a single epoch during training and optimization. In this experiment, we used Adam optimizer, batch size 2, and set the learning rate to 0.0001 and epoch to 1000. We have used a combined loss functions function between the prediction mask and the ground truth. We have used early stopping criteria and training was ended after 20 epochs on similar validation dice. We have used NVIDIA GTX 3070 GPU having a 24GB memory machine and developed the model in PyTorch library and trained from scratch. Figure 4 illustrates the visualization of the validation set. Table 1 shows the results of the proposed model using the validation dataset.

Figure 4 shows the predicted and ground truth segmentation for subject1 and subject2 validation datasets. The proposed model produced a similar segmentation mask as compared to ground truth segmentation. Our proposed model produced overestimated some branches and we can remove these extra segmentation branches using connected components.

Table 1. Results on the proposed model on the validation dataset.

Models	**Dice**	**Re**	**Pr**	**clDice**	**clRe**	**clPr**
3DUNet+MSFE	0.8674	0.9990	0.7664	0.8496	0.9988	0.7392
3DUNet+HSCA	0.8969	0.9882	0.8210	0.8573	0.9890	0.7566
3DUNet+HSCA+MSFE	0.9374	0.9432	0.9317	0.8968	0.9567	0.8440

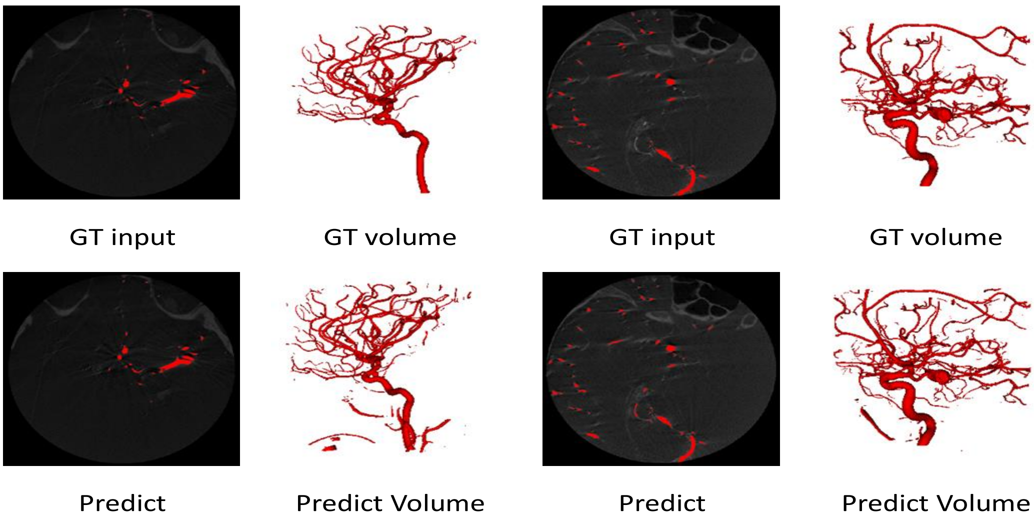


Fig. 4 The first shows the prediction and ground truth (GT) segmentation mask for validation subject 1 and the second row shows results on subject 2.

4. Conclusion

In this paper, we presented an efficient brain vascular segmentation deep framework aided with hybrid attention and multi-scale feature aggregation modules. Experiments are conducted on the SHINY-ICARUS challenge which shows that our model is ranked 2nd on the secret test and 3rd on the combo test that validates the effectiveness of the proposed framework. We have divided the dataset into five-fold cross-validation and based on the best validation score, the proposed model was uploaded in a docker container. Experiment results showed efficient (dice and clDice5) segmentation of brain vascular.

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Authors Introduction

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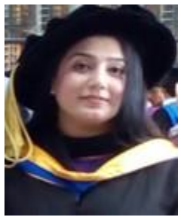

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