LIGHTVESSEL: EXPLORING LIGHTWEIGHT CORONARY ARTERY VESSEL SEGMENTATION VIA SIMILARITY KNOWLEDGE DISTILLATION

Hao Dang\textsuperscript{1,*}, Yuekai Zhang\textsuperscript{2,*}, Xingqun Qi\textsuperscript{2,†}, Wanting Zhou\textsuperscript{2}, Muyi Sun\textsuperscript{3}

\textsuperscript{1}School of Information Technology, Henan University of Chinese Medicine, Zhengzhou, China
\textsuperscript{2}Beijing University of Posts and Telecommunications, Beijing, China
\textsuperscript{3}Institute of Automation, Chinese Academy of Sciences, Beijing, China

ABSTRACT

In recent years, deep convolution neural networks (DCNNs) have achieved great prospects in coronary artery vessel segmentation. However, it is difficult to deploy complicated models in clinical scenarios since high-performance approaches have excessive parameters and high computation costs. To tackle this problem, we propose \textit{LightVessel}, a Similarity Knowledge Distillation Framework, for lightweight coronary artery vessel segmentation. Primarily, we propose a Feature-wise Similarity Distillation (FSD) module for semantic-shift modeling. Specifically, we calculate the feature similarity between the symmetric layers from the encoder and decoder. Then the similarity is transferred as knowledge from a cumbersome teacher network to a non-trained lightweight student network. Meanwhile, for encouraging the student model to learn more pixel-wise semantic information, we introduce the Adversarial Similarity Distillation (ASD) module. Concretely, the ASD module aims to construct the spatial adversarial correlation between the annotation and prediction from the teacher and student models, respectively. Through the ASD module, the student model obtains fine-grained subtle edge segmented results of the coronary artery vessel. Extensive experiments conducted on Clinical Coronary Artery Vessel Dataset demonstrate that LightVessel outperforms various knowledge distillation counterparts.

Index Terms—Coronary angiography, segmentation, knowledge distillation, lightvessel

1. INTRODUCTION

Coronary artery disease (CAD) is one leading cause of mortality and its prevalence is projected to increase worldwide gradually [1, 2]. To obtain accurate diagnosis results, coronary artery vessel segmentation is imperative from X-ary angiography images shown in Figure 1. There are various endeavors [3–7] which engage in vessel segmentation. CNN has become a milestone for this task in recent years. However, these methods always embrace complex computation and massive parameters, which are degraded or even incompetent in the scenes with limited computational resources. Meanwhile, the size of angiography images is usually larger than natural images. Therefore, the trade-off between performance and cost requires to be considered.

To tackle the above dilemma, lightweight networks are proposed to alleviate the burden. Model compression is one of the main directions to construct lightweight model, which is roughly categorized into three classes: pruning [8], quantization [9], and knowledge distillation [10–15]. Pruning and quantization try to adjust and modify the architecture of the networks, which leads to limitations on robustness and generalization. Knowledge distillation explores the knowledge transfer from a high-performance network to a non-trained lightweight network. This approach realizes high efficiency and accuracy, which also avoids designing new structures. Therefore, in this paper, we explore knowledge distillation to circumvent the trade-off between accuracy and efficiency in coronary artery vessel segmentation.

Motivated by the above observation, we propose \textit{LightVessel} for coronary artery segmentation. The framework of LightVessel is shown in Figure 2, which includes two modules: Feature-wise Similarity Distillation (FSD) and Adversarial Similarity Distillation(ASD). In the FSD module, we calculate feature similarity and distill it from the tangle-some teacher network to lightweight student network, which enhances the semantic correlation extraction ability of the student network. In the ASD module, we calculate the adversarial similarity through the predicted results and annotations. The semantic representations from the teacher and student are both associated with the semantic annotations, which promote

\begin{figure}[h]
\centering
\includegraphics[width=0.8\textwidth]{fig1.png}
\caption{The samples from X-ary coronary angiography images with low contrast, fuzzy vessel boundary, complex background, and structural interference.}
\end{figure}
Fig. 2. The pipeline of our proposed LightVessel. The feature distillation is the FSD module, which is committed to transmitting knowledge from a cumbersome teacher network to a non-trained lightweight student network. The adversarial distillation aims to compute the similarity between the predicted results and annotations.

The main contributions are as follows: (1) We propose LightVessel, a Similarity Distillation Framework, to perform efficient coronary artery vessel segmentation. (2) We design two collaborative modules, Feature-wise Similarity Distillation (FSD) and Adversarial Similarity Distillation (ASD), which perform high-quality and fine-grained semantic feature distillation. (3) The ablation and generalization experiments are implemented on Clinical Coronary Artery Vessel Dataset to verify the effectiveness and robustness of LightVessel.

2. RELATED WORKS

2.1. Coronary Artery Vessel Segmentation

With the dramatic development of CNN, coronary artery vessel segmentation has made great progress in recent years. Samuel et al. [13] leveraged a VSSC network to segment vessels from coronary angiographic images. Zhu et al. [4] used PSPNet to realize a parallel multi-scale CNN solving the problems of the complex structure of angiography images. Jun et al. [14] proposed an encoder-decoder architecture called T-Net, which consists of several small encoders. T-Net overcomes the limitation of U-Net [15], which has only one set of connection layers between encoder and decoder blocks. However, the prominent limitation of these models is the high complexity, which is caused by the excessive parameters and computational costs. Inspired by the above, we propose a novel lightweight method based on knowledge distillation.

2.2. Knowledge Distillation

Knowledge distillation is one of the most popular lightweight algorithms for CNN. Recently, this method has been applied to medical image analysis. Zhou et al. [16] proposed a knowledge distillation method to leverage both labeled and unlabeled data for overlapping cervical cell instance segmentation. Dou et al. [17] designed a learning scheme with a novel loss inspired by knowledge distillation, to implement multi-modal medical image segmentation. Hu et al. [18] established a knowledge distillation network to transfer knowledge from a trained multi-modal network to a mono-modal, which achieves accurate brain tumor segmentation. However, the challenges of these methods are two-fold. Firstly, the previous models ignore the whole transformation process of the teacher network for semantic information. Then, there is mismatching of feature dimensions between complex teacher models and lightweight student models. In this paper, we establish LightVessel method to circumvent these limitations.

3. METHODOLOGY

3.1. Overview

As illustrated in Figure 2, the LightVessel includes Feature-wise Similarity Distillation modules (FSD) and Adversarial Similarity Distillation modules (ASD). Specifically, the coronary angiography images $X$ are input to the teacher network $T$ and the student network $S$, simultaneously. To construct the semantic-shift of corresponding feature maps, the FSD module leverages the MLP to map the feature of the encoder and decoder into latent space. Then the feature similarity is calculated and distilled to $S$. Meanwhile, to establish pixel-level spatial correlations, the ASD module constructs adversarial similarity between the predicted results and annotations. The predicted results are projected into semantic space to ensure spatial consistency of the feature similarity with the ASD module.

3.2. Feature-wise Similarity Distillation

The FSD module is designed to transmit semantic-ware feature information (knowledge) from the cumbersome $T$ to the
lightweight $S$. Concretely, the corresponding feature maps from the encoder and decoder are projected into the latent space through two latent vectors. Thus, we obtain the semantic cosine similarity maps. It is defined as:

$$L_{	ext{Rec}} = \| F_{\text{ea}_i} - F_{\text{ea}_o} \|_1$$  \hspace{1cm} (1)

Where $F_{\text{ea}_i}$ denotes the features from $T$ and $S$, and $F_{\text{ea}_o}$ illustrates the reconstructed features with MLP. Further, the similarity distillation is illustrated in Figure 4. Concretely, the symmetric latent vectors $L_{e/d} = [l_1, l_2, \ldots, l_c] \in R^{1 \times 512}$ are transposed $(L_{e/d}^T)$ and multiply original $L_{e/d}$. The output is called $L_{\text{tra}} \in R^{512 \times 512}$. Meanwhile, We reshape $L_{\text{tra}} (512 \times 512)$ vector into a 1-dimensional vector ($L_1 - D$). Next, we calculate cosine similarity to obtain the feature dimension similarity maps. The cosine similarity is defined as:

$$\cos(L_e, L_d) = \frac{L_e \cdot L_d}{\|L_e\|_2 \cdot \|L_d\|_2}$$  \hspace{1cm} (2)

Where $L_e$ and $L_d$ denote the latent vectors from the encoder and decoder, respectively. The cosine similarity is calculated through two latent vectors. Thus, we obtain the semantic changes from the encoder to the decoder in $T$ and $S$. Given the cosine similarity maps of the corresponding feature dimension from $T$ and $S$, the $L2$ loss function is leveraged to constrain the cosine similarity maps. It is defined as:

$$L_{\text{FSD}} = \| \cos_{\text{tea}} - \cos_{\text{stu}} \|_2$$  \hspace{1cm} (3)

### 3.3. Adversarial Similarity Distillation

To further enhance $S$ to learn more refined semantic information from $T$, we propose the ASD module. More specifically, the ASD module calculates the pixel similarity between the prediction results of teacher network and annotations. Thus, the ASD module supervises the spatial correlation between predictions and annotations for pixel-level feature realignment. To retain abundant spatial semantic, the Euclidean distance is implemented as a metric. And it is defined as:

$$\text{Euc}(T, G) = \sqrt{\sum_{i=1}^{n}(T_i - G_i)^2}$$  \hspace{1cm} (4)

Where $T$ denotes the predictions of teacher, $G$ shows the annotations. The $L2$ loss function is carried out to supervise the pixel-wise knowledge transfer from $T$ to $S$. It is defined as:

$$L_{\text{ASD}} = \| \text{Euc}_{\text{tea}} - \text{Euc}_{\text{stu}} \|_2$$  \hspace{1cm} (5)

In addition, we utilize the labels and predictions of student to define the cross-entropy loss function. It is defined as:

$$L_{\text{CE}} = -\frac{1}{N} \sum(y_{i}\log(\overline{y}_{i}) + (1 - y_{i})\log(1 - \overline{y}_{i}))$$  \hspace{1cm} (6)

Where $y_i$ denotes ground truth, $\overline{y}$ shows predicted result. $N$ describes the number of samples. Last, the $L_{\text{CE}}$ is combined with $L_{\text{FSD}}$ and $L_{\text{ASD}}$ to construct the overall objective $L_{\text{total}}$:

$$L_{\text{total}} = L_{\text{CE}} + L_{\text{FSD}} + L_{\text{ASD}}$$  \hspace{1cm} (7)

### 4. EXPERIMENTS AND RESULTS

#### 4.1. Experiments Setup

**Dataset.** We employ Clinical Coronary Artery VesseDataset for experiments. The original dataset includes 240 images (992×992) and is augmented into 3864 images (256×256) for the experiment. The training and testing sets include 3200 and 640 images, respectively. In our experiments, we adopt patch-based method expressed as the original image is cropped into $256 \times 256$ patches.

**Implementation Details and Evaluation Metrics.** In the training phase, the initial learning rate is set as $1e - 3$. The total epoch is set to 200 with the batch size of 16. All the models.
are implemented on the Pytorch [22] platform with 2 Nvidia Titan XP GPUs. To verify the segmentation performance, we adopt five metrics: accuracy, sensitivity, AUC, mIOU, and F1-score. Furthermore, we leverage the sum of point operations (FLOPs) and the number of network parameters (Params) to measure lightweight.

### 4.2. Experiment Results

#### 4.2.1. Contrastive Analysis with KD Methods

In this section, we compare LightVessel with four state-of-the-art knowledge distillation approaches including SoftKD [12], ATKD [19], IFVKD [20], and SKD [21]. The four methods are performed with consistent original parameters. The backbone network is U-net. Specifically, the encoder is stacked with attention-based SKblock to establish a teacher network with large parameters. And the encoder of U-net is stacked with the inverted bottleneck block of lightweight MobileNetV2 [23] to construct the student network with slight parameters. The detailed experiment results are depicted in Table 1.

As reported in Table 1, our proposed LightVessel outperforms various knowledge distillation counterparts. Especially for the sensitivity, the student network increased by nearly 0.05. The other metrics have also been greatly improved, and even AUC has exceeded the teacher network. It is worth noting that our method achieves performance improvement without increasing the computation costs and parameters compared with the original student network. We also show the qualitative segmentation effectiveness described in Figure 5. The performance of student network(s) with LightVessel has significantly improved semantic information extraction ability. Meanwhile, compared with the other four methods, the LightVessel also has better performance.

#### 4.2.2. Feature-wise Similarity Distillation

We report the effectiveness of the FSD module in Table 2. The performance of the student network with FSD has a large improvement. Especially for the sensitivity, our student network with FSD increased by 0.034. Figure 6 illustrates the ablation experiment visualization result of the student network with FSD module (e). The segmentation ability of the student network with FSD module has been significantly optimized.

#### 4.2.3. Adversarial Similarity Distillation

As shown in Table 2, the quantitative analysis is carried out to validate the rationality and effectiveness of ASD module. Especially for the sensitivity, the student network with FSD and ASD modules (f) increased by nearly 0.05. Figure 6 also showcases the detailed qualitative results. The subtle edges of the vessels have been significantly optimized.

### 4.2.4. Generalization Analysis

To verify the generalization of our proposed methods, we construct different student models based on ENet [24] and ERFNet [25]. The experiment results are depicted in Table 3. Figure 7 shows the visualization results of generalization experiments. LightVessel has achieved significant performance compared with other student networks. This demonstrates that our proposed method has better generalization ability among different network models. It is worth noting that the FLOPs and Params are far less than the teacher network.

5. CONCLUSIONS

In this paper, we propose LightVessel, an efficient framework tailored for contrary artery vessel segmentation based on knowledge distillation. We present FSD module is tailored to promote the semantic extraction ability of the student network. Meanwhile, the ASD module is associated with the pixel semantic space of ground truth to enhance fine-grained predictions of the student network. Our method is demonstrated in Clinic Contrary Artery Vessel Dataset, which achieves higher performance compared with various knowledge distillation methods.

**Fig. 6.** The ablation analysis of FSD and ASD modules. Please zoom in for better visualization.

**Fig. 7.** The visualization results of generalization experiments. Student1, student2, and student3 are three different networks based on MobileV2, ENet, and ERFNet. Please zoom in for better visualization.

### Table 2. The ablation experiments of FSD and ASD modules

| Models       | ACC↑ | Se↑ | AUC↑ | mIOU↑ | F1-score↑ |
|--------------|------|-----|------|-------|-----------|
| Teacher      | 0.9835 | 0.8671 | 0.9929 | 0.8112 | 0.7801   |
| Student-scratch | 0.9804 | 0.8155 | 0.9865 | 0.7822 | 0.7378   |
| S w/ FSD     | 0.9826 | 0.8495 | 0.9917 | 0.8021 | 0.7670   |
| S w/ FSD + ASD | 0.9835 | 0.8620 | 0.9936 | 0.8106 | 0.7791   |

**Fig. 6.** The ablation analysis of FSD and ASD modules. Please zoom in for better visualization.

### Table 3. Generalization verification. St- (MobileV2, ENet, ERFNet) - scratch denotes three student networks without KD.

| Models       | ACC↑ | Se↑ | AUC↑ | mIOU↑ | F1-score↑ | FLOPs | Params |
|--------------|------|-----|------|-------|-----------|-------|--------|
| Teacher      | 0.9835 | 0.8671 | 0.9929 | 0.8112 | 0.7801 | 78.76G | 26.489M|
| St-MobileV2-scratch | 0.9804 | 0.8155 | 0.9865 | 0.7822 | 0.7378 | 0.804G | 4.682M |
| St-MobileV2-our | 0.9835 | 0.8620 | 0.9936 | 0.8106 | 0.7791 | 0.804G | 4.682M |
| St-ENet-scratch | 0.9816 | 0.8117 | 0.9892 | 0.7895 | 0.7484 | 0.516G | 0.349M |
| St-ENet-our | 0.9831 | 0.8688 | 0.9934 | 0.8082 | 0.7758 | 0.516G | 0.349M |
| St-ERFNet-scratch | 0.9814 | 0.8153 | 0.9900 | 0.7976 | 0.9558 | 1.344G | 2.063M |
| St-ERFNet-our | 0.9833 | 0.8696 | 0.9933 | 0.8075 | 0.7750 | 3.22G  | 2.063M |
6. REFERENCES

[1] H. Yang, X. J. Zhen, and et al., “Cpr-gcn: Conditional partial-residual graph convolutional network in automated anatomical labeling of coronary arteries,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020.

[2] S. Y. Xia, H. G. Zhu, and et al., “Vessel segmentation of x-ray coronary angiographic image sequence,” IEEE Transactions on Biomedical Engineering, vol. 67, no. 5, pp. 1338–1348, 2019.

[3] X. Q. Qi, Z. J. Wu, and et al., “Exploring generalizable distillation for efficient medical image segmentation,” arXiv preprint arXiv:2207.12995, 2022.

[4] X. L. Zhu, Z. Y. Cheng, and et al., “Coronary angiography image segmentation based on psynet,” Computer Methods and Programs in Biomedicine, vol. 200, pp. 105897, 2021.

[5] Z. J. Wu, Z. J. Wang, and et al., “Paenet: A progressive attention-enhanced network for 3d to 2d retinal vessel segmentation,” in 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2021, pp. 1579–1584.

[6] M. Y. Sun, K. Q. Li, and et al., “Contextual information enhanced convolutional neural networks for retinal vessel segmentation in color fundus images,” Journal of Visual Communication and Image Representation, vol. 77, pp. 103134, 2021.

[7] K. Q. Li, X. Q. Qi, and et al., “Accurate retinal vessel segmentation in color fundus images via fully attention-based networks,” IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 6, pp. 2071–2081, 2020.

[8] Z. Liu, M. J. Sun, and et al., “Rethinking the value of network pruning,” arXiv preprint arXiv:1810.05270, 2018.

[9] A. Gholami, S. Kim, and et al., “A survey of quantization methods for efficient neural network inference,” arXiv preprint arXiv:2103.13630, 2021.

[10] W. X. Zou, X. Q. Qi, and et al., “Graph flow: Cross-layer graph flow distillation for dual efficient medical image segmentation,” IEEE Transactions on Medical Imaging, pp. 1–1, 2022.

[11] W. X. Zou, X. Q. Qi, and et al., “Coco distillnet: a cross-layer correlation distillation network for pathological gastric cancer segmentation,” in 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2021, pp. 1227–1234.

[12] G. Hinton, o. Vinyals, and et al., “Distilling the knowledge in a neural network,” arXiv preprint arXiv:1503.02531, vol. 2, no. 7, 2015.

[13] P. M. Samuel and T. Veeramalai, “Vssc net: vessel specific skip chain convolutional network for blood vessel segmentation,” Computer methods and programs in biomedicine, vol. 198, pp. 105769, 2021.

[14] T. J. Jun, J. Kweon, and et al., “T-net: Nested encoder-decoder architecture for the main vessel segmentation in coronary angiography,” Neural Networks, vol. 128, pp. 216–233, 2020.

[15] O. Ronneberger, P. Fischer, and et al., “U-net: Convolutional networks for biomedical image segmentation,” in International Conference on Medical image computing and computer-assisted intervention. Springer, 2015, pp. 234–241.

[16] Y. N. Zhou, H. Chen, and et al., “Deep semi-supervised knowledge distillation for overlapping cervical cell instance segmentation,” in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, 2020, pp. 521–531.

[17] Q. Dou, Q. D. Liu, and et al., “Unpaired multi-modal segmentation via knowledge distillation,” IEEE transactions on medical imaging, vol. 39, no. 7, pp. 2415–2425, 2020.

[18] M. H. Hu, M. Maillard, and et al., “Knowledge distillation from multi-modal to mono-modal segmentation networks,” in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, 2020, pp. 772–781.

[19] S. Zagoruyko and N. Komodakis, “Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer,” arXiv preprint arXiv:1612.03928, 2016.

[20] Y. Y. Wang, W. Zhou, and et al., “Intra-class feature variation distillation for semantic segmentation,” in European Conference on Computer Vision. Springer, 2020, pp. 346–362.

[21] Y. F. Liu, C. Y. Shu, and et al., “Structured knowledge distillation for dense prediction,” IEEE transactions on pattern analysis and machine intelligence, 2020.

[22] A. Paszke, S. Gross, and et al., “Automatic differentiation in pytorch,” 2017.

[23] M. Sandler, A. Howard, and et al., “Mobilenetv2: Inverted residuals and linear bottlenecks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 4510–4520.

[24] A. Paszke, A. Chaurasia, and et al., “Erfnet: A deep neural network architecture for real-time semantic segmentation,” arXiv preprint arXiv:1606.02147, 2016.

[25] E. Romera, J. M. Alvarez, and et al., “Erfnet: Efficient residual factorized convnet for real-time semantic segmentation,” IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 1, pp. 263–272, 2017.