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CROSS-DOMAIN DEEP TRANSFER LEARNING FOR BRANCHING STRUCTURE SEGMENTATION

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Abstract. Segmentation of thin, branching structures in volumetric imaging is a challenging computer vision task due to low contrast, strong class imbalance, and large variability in scale and topology. This work investigates a cross-domain deep transfer learning strategy that exploits morphological similarity between vascular-like branching patterns in different imaging modalities. Models are first pre-trained on the data-rich FIVES retinal vessel dataset and then fine-tuned on a subset of the NSCLC-Radiogenomics chest CT dataset containing annotations of branching structures. We evaluate four U-Net-based architectures – U-Net, Attention U-Net, R2 U-Net and Dense U-Net – and compare them with DeepLabV3 models using ResNet50 and ResNet101 backbones. A unified training pipeline with multi-stage intensity and contrast normalization is employed, along with a 10-fold stratified cross-validation protocol. Performance is assessed using accuracy, precision, Dice (F1 score), and area under the ROC curve (AUC). Cross-domain transfer learning leads to a substantial improvement over training from scratch: Dice scores increase from near-zero values to above 0.48 for the best-performing models. Attention U-Net achieves the highest Dice score of 0.4814, while DeepLabV3 (ResNet50) attains the highest AUC of 0.9621. Dense U-Net also provides competitive results, whereas R2 U-Net benefits less from the proposed transfer scheme. The results demonstrate that leveraging cross-domain morphological priors is an effective way to enhance segmentation of branching structures in data-scarce CT scenarios. The proposed framework provides a strong, reproducible baseline for future research on transfer learning and fine-structure segmentation in volumetric images.

Keywords: branching structure segmentation, cross-domain transfer learning, deep learning, U-Net, DeepLabV3

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МЕЖДОМЕННОЕ ГЛУБОКОЕ ТРАНСФЕРНОЕ ОБУЧЕНИЕ ДЛЯ СЕГМЕНТАЦИИ РАЗВЕТВЛЕННЫХ СТРУКТУР

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Аннотация. Сегментация тонких разветвленных структур в объемной визуализации является нетривиальной задачей компьютерного зрения из-за низкого контраста, выраженного дисбаланса классов и большой вариативности в масштабе и топологии. В данной работе исследуется подход междоменного глубокого трансферного обучения, использующий морфологическое сходство сосудистоподобных разветвленных структур в разных модальностях визуализации. Модели предварительно обучаются на богатом данными наборе FIVES для сегментации сосудов сетчатки, после чего дообучаются на подмножестве набора данных NSCLC-Radiogenomics с КТ-изображениями грудной клетки и аннотациями разветвленных структур. Оцениваются четыре архитектуры на основе U-Net (стандартная U-Net, Attention U-Net, R2 U-Net и Dense U-Net), а также модели DeepLabV3 с базовыми сетями ResNet50 и ResNet101. Применяется единый конвейер обучения, включающий многоэтапную нормализацию интенсивностей и контраста, а также 10-кратную стратифицированную перекрестную проверку. Качество сегментации измеряется метриками Accuracy, Precision, Dice (F1-мера) и площадью под ROC-кривой (AUC). Междоменное трансферное обучение приводит к существенному улучшению по сравнению с обучением «с нуля»: значения Dice увеличиваются с почти нулевых до 0,48 и более для лучших моделей. Модель Attention U-Net достигает максимального значения Dice 0,4814, тогда как DeepLabV3 (ResNet50) демонстрирует наивысшее значение AUC – 0,9621. Dense U-Net показывает сопоставимые результаты, в то время как R2 U-Net в меньшей степени выигрывает от предложенной схемы трансфера. Полученные результаты показывают, что использование междоменных морфологических априорных знаний является эффективным способом повышения качества сегментации разветвленных структур в условиях дефицита размеченных КТ-данных. Предложенная методология формирует воспроизводимую базу для дальнейших исследований в области трансферного обучения и сегментации тонких древовидных структур в объемной визуализации.

Ключевые слова: сегментация разветвленных структур, междоменное трансферное обучение, глубокое обучение, U-Net, DeepLabV3

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Introduction

Segmentation of thin, branching vascular structures in chest computed tomography (CT) images is a challenging problem in image analysis and computer vision. These structures exhibit large variation in scale, complex topology and often low contrast with respect to surrounding tissue, which makes robust extraction difficult [1–5]. In addition, the foreground (vessels) typically occupies only a small fraction of the image volume, leading to strong class imbalance and making learning-based methods sensitive to overfitting [6].

Classical image processing techniques, such as thresholding, region growing and edge-based methods, have been widely used for vessel extraction [7, 8]. Although these approaches are conceptually simple and computationally efficient, their performance is highly dependent on hand-crafted parameters and they struggle with noise, partial volume effects and the wide range of vessel calibers present in CT images. The emergence of deep learning, and in particular convolutional neural networks (CNNs), has significantly advanced the state of the art in segmentation of complex anatomical and vascular structures [9, 10]. Encoder–decoder architectures with skip connections, such as U-Net, have become a *de facto* standard due to their ability to combine high-level semantic information with fine-grained spatial detail.

A key limitation in many volumetric segmentation tasks, however, is the scarcity of large, pixel-level annotated datasets, especially for small or hard-to-label structures. Training deep architectures from scratch on such limited data often results in poor generalization. Transfer learning provides an effective strategy to alleviate this problem by reusing features learned in a data-rich source domain to initialize models in a data-scarce target domain [11]. When there is morphological similarity between structures in the source and target domains – such as tree-like vascular networks – transfer learning can be particularly beneficial, since the learned feature hierarchies capture reusable patterns of branching geometry and local appearance.

In this work, we investigate a cross-domain transfer learning strategy for segmentation of branching vascular structures in chest CT images. Our hypothesis is that the intricate, tree-like morphology of retinal vessels, for which large annotated datasets are available, can serve as a suitable source domain for learning generic vessel features. These features are then transferred and fine-tuned for segmenting morphologically similar, but anatomically different, vascular structures in CT volumes. To evaluate this idea, we consider several U-Net-based architectures: standard U-Net, Attention U-Net [12], R2 U-Net [13] and Dense U-Net [14], and compare them with DeepLabV3 models equipped with ResNet backbones [15].

Materials and methods

This study applies a cross-domain transfer learning methodology using two distinct datasets. For pre-training, the Fundus Image Dataset for AI-based Vessel Segmentation (FIVES) [16] dataset was used. This dataset contains 800 high-resolution (2048×2048) fundus images with pixel-wise vessel annotations designed for data-driven vessel segmentation. For fine-tuning, we used the NSCLC-Radiogenomics collection from The Cancer Imaging Archive (TCIA) [17], which provides 286754 chest CT slices from 211 volumes. A subset of this collection with annotations of branching vascular structures was employed as the target domain.

A multi-stage image preprocessing pipeline was implemented to enhance vessel-like feature extraction and standardize input data. All images were converted to grayscale, followed by Z-normalization $(x-\mu)/\sigma$ and Min–Max normalization (scaled to [0, 255]). Contrast Limited Adaptive Histogram Equalization (CLAHE, clip limit 2.0) was then applied to improve local contrast, followed by gamma correction ($\gamma = 1.2$) to emphasize darker structures.

The transfer learning procedure consisted of two phases:

1) pre-training on FIVES using binary cross-entropy loss and the Adam optimizer to learn general vessel-like features;

2) fine-tuning on the NSCLC-Radiogenomics subset with encoder weights initialized from the pre-trained models, a reduced learning rate and a cosine annealing schedule to adapt the representations to CT-domain branching structures.

Both datasets were evaluated using 10-fold stratified cross-validation for robust assessment of generalization. Model performance was measured using accuracy, precision, Dice (F1 score) and Area Under the Receiver Operating Characteristic Curve (AUC). Statistical comparisons included p-values and 95% confidence intervals (CI). Hyperparameters included a batch size of 16, an initial learning rate of 10^{-4} (decayed via cosine annealing) and training for 100 epochs on an NVIDIA RTX 2080 Ti GPU.

Results and discussion

Both the FIVES retinal vessel dataset and the NSCLC-Radiogenomics CT dataset were systematically divided into 10 folds for stratified cross-validation. For the FIVES dataset (800 images), each fold contained a proportional split for training, validation and testing. Similarly, the CT branching-structure dataset (100 images) was divided into 10 folds, ensuring a representative distribution across training, validation and testing sets within each fold. For each fold, models were trained on the training subset and evaluated on the held-out test subset, and the reported metrics are averages over all CT test folds.

The performance of the models on the retinal vessel segmentation task (pre-training phase, trained and tested on the FIVES dataset) is summarized in Table 1.

Table 1

Performance comparison of deep learning models for retinal vessel segmentation

Model	Accuracy	Precision	Dice (F1-Score)	AUC
U-Net	0.9867	0.9386	0.8974	0.9843
Attention U-Net	0.9872	0.9142	0.9038	0.9871
Dense U-Net	0.9865	0.9269	0.8969	0.9834
R2 U-Net	0.9232	0.4058	0.3453	0.8300
DeepLabV3 (ResNet50)	0.9640	0.7503	0.7234	0.9772
DeepLabV3 (ResNet101)	0.9628	0.7405	0.7138	0.9763

As shown in Table 1, the U-Net variants generally achieve high performance on the retinal vessel segmentation task. Attention U-Net demonstrates the highest Dice (F1 score) of 0.9038 and the best AUC of 0.9871, closely followed by U-Net and Dense U-Net. This indicates that the attention mechanism effectively enhances the model's ability to focus on relevant features for segmenting thin vessel structures. R2 U-Net performs noticeably worse across all metrics (Dice 0.3453, AUC 0.8300), suggesting that its recurrent residual structure may be suboptimal for this setting or require different hyperparameter tuning. DeepLabV3 models also show strong performance, particularly in AUC, but remain slightly behind the best U-Net variants in terms of Dice. The ROC curves for these models are presented in Fig. 1, visually confirming the superior classification performance of Attention U-Net and Dense U-Net on the FIVES dataset.

After pre-training on FIVES, all models were fine-tuned on the CT branching-structure dataset. Segmentation performance on CT images was computed on the CT test subsets of each fold, using pixel-wise accuracy, precision, recall, Dice and AUC. The averaged results over 10 folds are presented in Table 2.

The transfer learning approach reveals a dramatic improvement in performance across all models on CT images, particularly in Dice (F1 score) and AUC. For example, the Dice score for U-Net

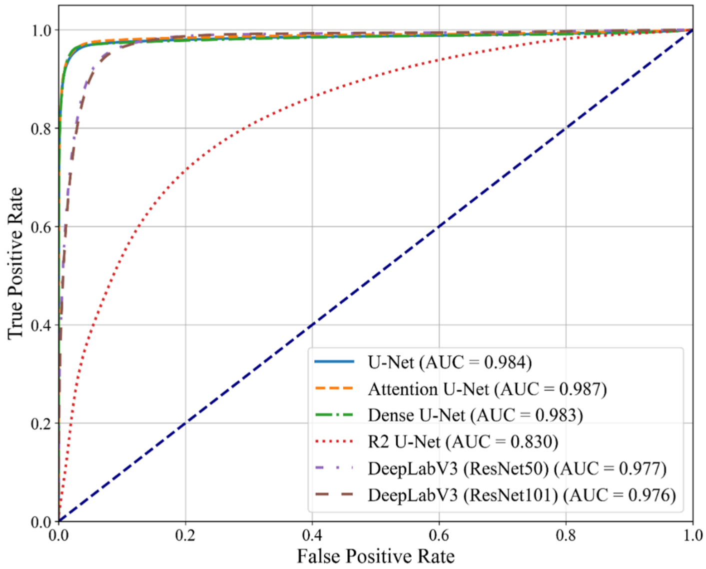

Fig. 1. ROC curves for U-Net, Attention U-Net, R2 U-Net, Dense U-Net, DeepLabV3 (ResNet50/ ResNet101) trained and tested on FIVES dataset

Table 2

Performance comparison of deep learning models for pulmonary vessel segmentation

Model	Accuracy	Precision	Recall	Dice
U-Net	0.9583	0.5377	0.4371	0.4822
Attention U-Net	0.9582	0.5356	0.4445	0.4858
Dense U-Net	0.9525	0.4654	0.4663	0.4608
R2 U-Net	0.9586	0.8648	0.08	0.1465
DeepLabV3 (ResNet50)	0.9584	0.5399	0.4294	0.4783

increases from 0.0028 (training from scratch on CT only) to 0.4802 with cross-domain pre-training, while for Attention U-Net the Dice rises from 0.0088 to 0.4814. This large gain demonstrates the effectiveness of the proposed cross-domain transfer learning strategy for branching structure segmentation in CT data.

Among the U-Net variants with transfer learning, Attention U-Net achieves the highest Dice (F1 score) of 0.4814, indicating superior foreground delineation on CT images. DeepLabV3 (ResNet50) also performs very well, with a Dice of 0.4760 and the highest AUC of 0.9621, which reflects strong discriminative power at the pixel level. Dense U-Net attains a competitive Dice of 0.4592. R2 U-Net, while showing improvement compared to its non-transfer counterpart, still lags significantly behind the other models with a Dice of 0.1465, reinforcing its observed limitations for this type of segmentation task.

The ROC curves for the models after transfer learning are shown in Fig. 2 and illustrate the improved classification performance in the CT domain. Qualitative analysis is provided in Fig. 3. Fig. 3, *d* (Attention U-Net) demonstrates visibly more accurate and complete segmentation of fine branching structures compared to other models and the original CT slice (Fig. 3, *a*). This visual evidence supports the quantitative results and confirms that Attention U-Net, leveraging its attention mechanisms, is particularly effective for delineating complex and subtle branching patterns in chest CT images.

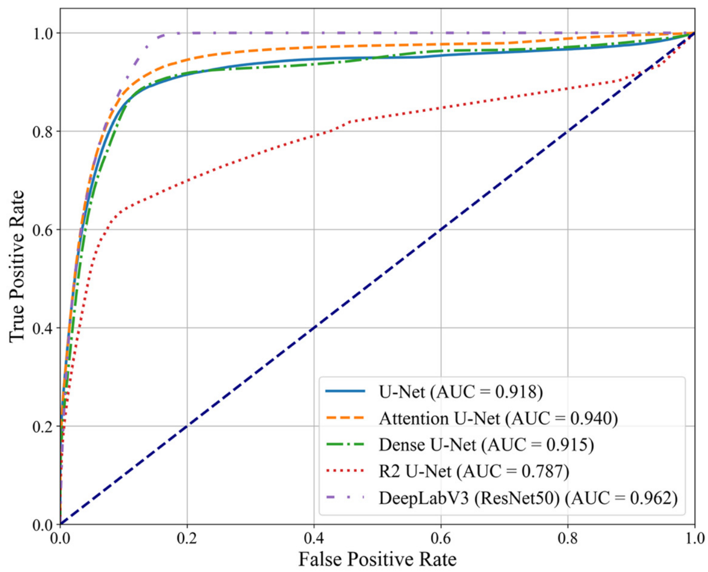

Fig. 2. ROC curves for U-Net, Attention U-Net, R2 U-Net, and Dense U-Net, DeepLabV3 (ResNet50) (pretrained on FIVES dataset) trained and tested on LUNG dataset

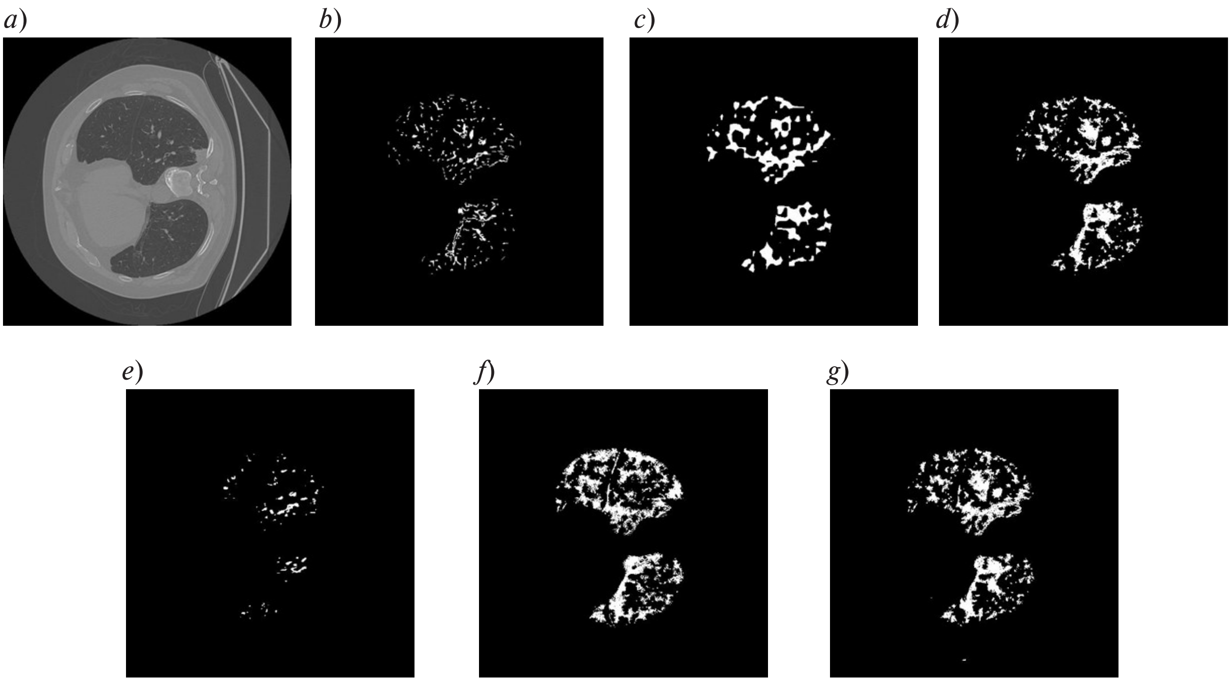

Fig. 3. Visual analysis of vessel segmentation in CT images. Original CT (*a*); Annotation (*b*); DeepLabV3 (ResNet50) (*c*); Attention U-Net (*d*); R2 U-Net (*e*); Dense U-Net (*f*); U-Net (*g*)

Conclusion

This study investigated a cross-domain deep transfer learning strategy for segmentation of branching vascular structures in chest CT images. By exploiting morphological similarity between retinal and CT vascular patterns, the proposed approach effectively mitigates the data-scarcity problem in the target CT domain. Experimental results demonstrate a substantial improvement in segmentation performance for all evaluated architectures when pre-training on the FIVES retinal dataset is followed by fine-tuning on the CT dataset.

Among the U-Net variants, Attention U-Net and Dense U-Net emerged as the most effective models, with Attention U-Net achieving the highest Dice score of 0.4814, indicating superior delineation of fine branching structures. DeepLabV3 (ResNet50) also showed strong performance, attaining the highest AUC value of 0.9621 and thus providing excellent discriminative capability at the pixel level. These findings confirm that cross-domain transfer from a data-rich vascular segmentation task is a viable and powerful strategy for improving performance on data-limited CT segmentation tasks.

Overall, the proposed framework offers a robust, reproducible baseline for branching structure segmentation in volumetric images and highlights the advantages of attention mechanisms and dense connectivity in this context. It can be readily extended to other applications involving thin, tree-like structures and limited annotated data.

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