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SEMI-SUPERVISED SEGMENTATION OF MEDICAL IMAGES

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***Abstract*—*This article is devoted to the development of a method (algorithm) of medical image segmentation based on semi-supervised learning. Semi-supervised learning methods are shown to have significant potential for improving medical image segmentation through effective use of unlabeled data. However, challenges remain in adapting these methods to the specific characteristics of medical images, such as high variability, class imbalance, and the presence of noise and artifacts. To overcome these difficulties, it is proposed to integrate several approaches (consistency regularization, pseudo-labeling, average teacher model) into a single structure. To increase the robustness and generalizability of the model for different imaging methods, we include industry-specific data supplements tailored to the unique characteristics and challenges of each method. Large-scale experiments on magnetic resonance imaging, computed tomography, and optical coherence tomography datasets demonstrate that the proposed framework significantly outperforms fully supervised and individual semisupervised learning methods, especially in scenarios with low data labeling.*

Index Terms—Semi-supervised learning; medical image segmentation; consistency regularization; pseudo-labeling; mean teacher; deep learning.

I. INTRODUCTION

Medical image segmentation is a critical task in medical image analysis, serving as a foundation for numerous clinical applications such as disease diagnosis, treatment planning, and patient monitoring. By precisely delineating anatomical structures and pathological regions, segmentation provides essential information that aids healthcare professionals in making informed decisions. For example, accurate segmentation of tumors in MRI scans can significantly influence surgical planning and radiotherapy targeting, directly impacting patient outcomes [1].

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs) like the U-Net architecture [2], have revolutionized medical image segmentation. These models have demonstrated remarkable success due to their ability to learn complex hierarchical features from imaging data. The encoder-decoder structure with skip connections in U-Net enables efficient capture of both global context and fine-grained details, leading to high-performance segmentation results. However, the effectiveness of these models heavily depends on large amounts of labeled data.

Acquiring extensive annotated datasets in the medical domain poses significant challenges. The annotation process is time-consuming and requires specialized expertise from medical professionals who must meticulously label images at the pixel or voxel level. Moreover, ethical considerations and patient privacy concerns often restrict data sharing between institutions, further limiting the availability of labeled data. This scarcity hinders the training of deep learning models and restricts their applicability across diverse medical imaging tasks.

Semi-supervised learning (SSL) offers a promising solution to mitigate the reliance on large labeled datasets by leveraging unlabeled data, which is more abundant. SSL methods aim to enhance model performance by incorporating the vast amounts of unlabeled data into the training process without necessitating proportional increases in annotation efforts. While SSL has shown considerable success in natural image processing, its application to medical image segmentation is less explored and presents unique challenges due to the specific characteristics of medical imaging data [3], such as high intra-class variability, low inter-class contrast, and the presence of imaging artifacts.

In this paper, we propose a comprehensive semi-supervised segmentation framework tailored to the complexities of medical images. Our approach integrates multiple SSL techniques-consistency regularization, pseudo-labeling, and the Mean Teacher model – to effectively harness the information present in unlabeled data. Consistency regularization encourages the model to produce stable predictions under various perturbations of the input data, enhancing robustness and generalization.

Pseudo-labeling involves generating labels for unlabeled data based on high-confidence model predictions, which are then used to further train the model. The Mean Teacher model maintains an exponential moving average of the model weights, providing more stable targets and reducing the risk of overfitting.

We enhance the framework with domain-specific data augmentations appropriate for different medical imaging modalities. Our contributions are:

1) An integrated SSL framework that combines multiple methods to effectively utilize unlabeled medical images.

2) Domain-specific data augmentations to improve model robustness and generalization.

3) Extensive evaluation on diverse medical imaging datasets to demonstrate the effectiveness of the proposed framework.

II. Problem Statement

Developing accurate medical image segmentation models is hindered by the limited availability of labeled data, as manual annotation is time-consuming and requires specialized medical expertise. Deep learning models, such as convolutional neural networks (CNNs), rely on large labeled datasets to achieve high performance. The challenge is to create a semi-supervised learning framework that effectively leverages unlabeled medical images to enhance segmentation accuracy under limited labeled data conditions. Specifically, we aim to integrate methods like consistency regularization, pseudo-labeling, and the Mean Teacher model, along with domain-specific data augmentations, to address the unique complexities of different medical imaging modalities and improve the utilization of unlabeled data in the training process.

III. Related Work

The goal of this article is to build an ensemble of neural networks with an optimal architecture for classifying data.

A. Medical Image Segmentation

Medical image segmentation has undergone significant transformation with the advent of deep learning techniques, particularly Convolutional Neural Networks (CNNs). Before deep learning became prevalent, segmentation tasks relied on manual delineation by experts or traditional image processing methods such as thresholding, region growing, and edge detection. These conventional approaches often struggled with variability in image quality, noise, and complex anatomical structures, leading to inconsistent and less accurate results.

The introduction of CNN-based architectures revolutionized medical image segmentation by enabling models to learn hierarchical and abstract features directly from data. One of the most influential architectures is the U-Net [2], proposed by Ronneberger et al., which has become a foundational model in biomedical image segmentation. The U-Net architecture features a symmetric encoder-decoder structure with skip connections that facilitate the combination of low-level and high-level feature information. This design allows the network to capture both the global context and fine-grained details essential for precise segmentation. Subsequent adaptations of U-Net have been developed to address specific challenges, such as 3D U-Net for volumetric data [4], Attention U-Net incorporating attention mechanisms to focus on relevant regions [5], and Residual U-Net integrating residual connections to improve training convergence [6]. Despite the success of these models, they typically require large amounts of annotated data to achieve optimal performance, which is a significant limitation in the medical imaging domain where labeled data is scarce.

B. Semi-supervised Learning

Semi-supervised learning (SSL) has emerged as a promising approach to mitigate the dependency on large labeled datasets by leveraging unlabeled data, which is often more readily available. In the context of medical imaging, SSL methods aim to enhance model performance by extracting meaningful information from unlabeled images, thereby reducing the burden of manual annotation. Various SSL techniques have been explored in medical image segmentation, each addressing the unique challenges posed by medical data [7].

One common SSL approach is consistency regularization, which encourages the model to produce consistent outputs when inputs are subjected to perturbations or augmentations. For instance, Li et al. [8] applied transformation-consistent self-ensembling to cardiac MRI segmentation, where the model's predictions remained stable under different transformations of the input data. This method improved the generalization of the model by making it robust to variations commonly encountered in medical images.

Another widely used technique is pseudo-labeling, where the model generates labels for unlabeled data based on its confident predictions. Bai et al. [9] utilized pseudo-labeling for semi-supervised cardiac MR image segmentation, iteratively refining the model with newly labeled data. This approach effectively expanded the training dataset without additional manual annotations, leading to improved segmentation accuracy.

The Mean Teacher model [10], originally proposed for natural image classification, has also been adapted for medical image segmentation. Perone et al. [11] employed a Mean Teacher framework for spinal cord gray matter segmentation in MRI scans. By maintaining a teacher model as an exponential moving average of the student model's weights, they achieved more stable and accurate predictions, particularly when labeled data was limited.

In addition to these methods, adversarial learning has been explored in SSL for medical imaging. Zhang et al. [12] introduced a deep adversarial network for biomedical image segmentation, where a discriminator network guides the segmentation model to produce outputs that are indistinguishable from ground truth labels. Although effective, adversarial approaches can be complex to train and may require careful tuning to achieve convergence.

Overall, SSL methods have shown significant potential in enhancing medical image segmentation by effectively utilizing unlabeled data. However, challenges remain in adapting these techniques to the specific characteristics of medical images, such as high variability, class imbalance, and the presence of noise and artifacts. Our work builds upon these SSL approaches, integrating multiple techniques within a unified framework and incorporating domain-specific data augmentations to address modality-specific challenges.

IV. METHODOLOGY

A. Overview

Our proposed semi-supervised segmentation framework integrates multiple SSL techniques-consistency regularization, pseudo-labeling, and the Mean Teacher model – to effectively leverage unlabeled medical images. We also incorporate domain-specific data augmentations tailored to different imaging modalities to enhance model robustness and generalization. The overall architecture is based on the U-Net model, which is well-suited for segmentation tasks due to its encoder-decoder structure with skip connections.

B. Semi-supervised Learning Methods

1) Consistency Regularization

We enforce the model to produce consistent outputs when the input is subjected to perturbations. The unsupervised consistency loss L_{consist} is defined as:

$$L_{\text{consist}} = \mathbb{E}_{(x \sim D_u)}\left[\left\| f_\theta(x+\delta) - f_\theta(x)^2 \right\|\right],$$

where D_u is the unlabeled dataset; δ represents perturbations, and f_θ is the model.

Perturbations include:

- *Spatial Transformations*: Random rotations, scaling, and elastic deformations.
- *Intensity Transformations*: Brightness and contrast adjustments, Gaussian noise.

2) Pseudo-Labeling

We assign pseudo-labels to unlabeled data based on model predictions with high confidence. The steps are:

- *Model Prediction*: Obtain softmax outputs on unlabeled data.
- *Confidence Thresholding*: Select predictions with confidence above a threshold τ.
- *Label Assignment*: Assign pseudo-labels to selected predictions.
- *Training Update*: Use pseudo-labeled data to update the model.

The pseudo-label loss L_{pseudo} is calculated using cross-entropy between the model's predictions and the pseudo-labels.

3) Mean Teacher Model

The Mean Teacher model [5] maintains a teacher model whose weights are an exponential moving average (EMA) of the student model's weights. The student model is trained to minimize the difference between its predictions and those of the teacher model.

The teacher model provides more stable targets for the student model. The consistency loss between the student and teacher models is:

$$L_{MT} = \mathbb{E}_{x \sim D_u}\left[\left\| f_\theta(x) - f_{\theta'}(x)^2 \right\|\right],$$

where θ′ are the teacher model's weights, D_u is the unlabeled dataset.

C. Domain-Specific Data Augmentations

To enhance the model's robustness and generalization across different imaging modalities, we incorporate domain-specific data augmentations tailored to the unique characteristics and challenges of each modality.

For MRI brain scans, we simulate realistic variations and artifacts commonly encountered in clinical settings. This includes introducing motion artifacts to mimic patient movement during scanning, adjusting for intensity inhomogeneities that result from scanner-related variations, and adding Gaussian noise to reflect inherent acquisition noise. These augmentations help the model become invariant to such variations, improving its ability to generalize to new, unseen data.

In the case of CT liver images, the augmentations focus on addressing variability in contrast levels and the presence of pathological features. We adjust contrast settings to simulate different phases of contrast enhancement, which is critical for liver imaging where timing of the contrast agent affects image appearance. Synthetic lesions are introduced to increase the diversity of pathological cases, enabling the model to better detect and segment liver lesions. Additionally, simulating metal artifacts, such as streaks caused by implants, makes the model robust against common imaging artifacts that can obscure anatomical details.

For retinal OCT images, the augmentations aim to replicate noise patterns and structural deformations typical of OCT imaging. Adding speckle noise mimics the characteristic granular appearance of OCT images due to the coherent nature of the imaging process. Simulating deformations of retinal layers helps the model handle anatomical variations and pathological changes, such as those caused by macular degeneration or edema. Introducing small artifacts resembling vitreous floaters addresses common issues that degrade image quality, ensuring the model can maintain performance despite such challenges.

By integrating these domain-specific augmentations into the training process, the model is exposed to a wide range of realistic variations and artifacts. This exposure encourages the learning of invariant features crucial for accurate segmentation across diverse imaging conditions. Consequently, the model's robustness and generalizability are enhanced, which is essential for reliable performance in clinical applications where imaging conditions and patient anatomies can vary significantly.

D. Loss Functions

The total loss L combines supervised and unsupervised components:

$$L = L_{\text{supervised}} + \lambda_{\text{consist}} L_{\text{consist}} + \lambda_{\text{pseudo}} L_{\text{pseudo}} + \lambda_{MT} L_{MT}.$$

where $L_{\text{supervised}}$ is the dice loss and cross-entropy loss on labeled data, λ are the weights for each unsupervised loss term, determined empirically.

E. Training Procedure

The training involves:

1) Initialization: Train the student model on labeled data.

2) Unlabeled Data Integration: Incorporate unlabeled data using corresponding SSL methods.

3) Teacher Model Update: Update the teacher model's weights using EMA of the student model.

4) Iterative Optimization: Continue training with both labeled and unlabeled data.

F. *Network Architecture*

We employ the U-Net architecture [2] due to its effectiveness in biomedical image segmentation. The U-Net consists of a contracting path (encoder) to capture context and an expansive path (decoder) to enable precise localization. Skip connections between corresponding layers in the encoder and decoder paths allow for the preservation of spatial information.

To accommodate the different characteristics of the datasets, we adjust the number of filters and layers accordingly. For example, deeper networks are used for higher-resolution images to capture more complex features.

V. EXPERIMENTS AND RESULTS

A. Datasets

To evaluate the effectiveness of our proposed semi-supervised learning framework for medical image segmentation, we conducted extensive experiments on three publicly available datasets representing different imaging modalities: MRI brain scans from the BraTS dataset, CT liver images from the LiTS dataset, and retinal OCT images from the Duke OCT dataset. Each dataset presents unique challenges due to variations in imaging techniques, anatomical structures, and pathological conditions.

B. Data Splitting and Preprocessing

For each dataset, we divided the available data into training, validation, and test sets. The training set comprised a small portion of labeled data and a larger portion of unlabeled data to simulate limited annotation scenarios. The validation set was used for hyperparameter tuning and early stopping, while the test set provided an unbiased evaluation of the model's performance.

Preprocessing steps were applied to standardize the data across samples. Images were resampled to a consistent resolution to account for variations in voxel size. Intensity normalization was performed to adjust for differences in scanner settings and patient-specific characteristics. For MRI images, skull stripping was applied to remove non-brain tissues, and for CT images, windowing techniques were used to enhance the visibility of liver structures.

C. Evaluation Metrics

To quantitatively assess the segmentation performance, we employed several widely used metrics:

- *Dice Similarity Coefficient (DSC):* Measures the overlap between the predicted segmentation and the ground truth, ranging from 0 (no overlap) to 1 (perfect overlap).
- *Hausdorff Distance (HD):* Evaluates the maximum distance between the boundary points of the predicted segmentation and the ground truth, indicating the worst-case boundary error.
- *Average Surface Distance (ASD):* Computes the average distance between the surfaces of the predicted segmentation and the ground truth, providing a measure of overall boundary accuracy.

These metrics collectively offer a comprehensive evaluation of both the volumetric overlap and the boundary accuracy of the segmentation results.

D. Baseline Models and Comparative Methods

To demonstrate the effectiveness of our proposed framework, we compared its performance against several baseline models and existing semi-supervised learning methods:

- *Fully Supervised Learning (FSL):* A model trained solely on the labeled data without utilizing unlabeled data.
- *Consistency Regularization Only:* A semi-supervised model employing only consistency regularization as the SSL method.
- *Pseudo-Labeling Only:* A semi-supervised model utilizing only pseudo-labeling for leveraging unlabeled data.
- *Mean Teacher Only:* A model using only the Mean Teacher approach for SSL.
- *Combined SSL Methods:* Our proposed framework integrating consistency regularization, pseudo-labeling, and the Mean Teacher model.

All models shared the same network architecture (U-Net) and were trained under identical conditions to ensure a fair comparison.

E. Training Details

Training was conducted using an NVIDIA GPU to handle the computational demands of deep learning models. We employed the Adam optimizer with an initial learning rate set to 1e-4. Learning rate decay strategies, such as cosine annealing, were used to improve convergence. The batch size was selected based on memory constraints and set to 4 for 3D images (MRI and CT) and 16 for 2D images (OCT).

To balance the supervised and unsupervised loss components, we empirically determined the weights $\lambda_{\text{consistency}}$, λ_{pseudo}, λ_{MT} through cross-validation. Data augmentation was applied on-the-fly during training, incorporating both general augmentations (e.g., flipping, rotation) and the domain-specific augmentations described in the methodology.

Early stopping was implemented based on the validation loss to prevent overfitting. The best-performing model on the validation set was saved and later evaluated on the test set.

The results of the research are presented in Tables I – III.

Table I. TEST SAMPLE RESULTS ON MRI BRAIN SCANS

Method	DSC (%)	HD (mm)	ASD (mm)
FSL	75.4	12.3	1.8
Consistency Regularization Only	78.1	10.9	1.5
Pseudo-Labeling Only	77.5	11.2	1.6
Mean Teacher Only	78.8	10.7	1.4
Proposed Framework	**83.2**	**8.5**	**1.1**

Table II. TEST SAMPLE RESULTS ON CT LIVER IMAGES

Method	DSC (%)	HD (mm)	ASD (mm)
FSL	82.1	9.7	1.6
Consistency Regularization Only	85.0	8.5	1.3
Pseudo-Labeling Only	84.6	8.8	1.4
Mean Teacher Only	85.5	8.2	1.2
Proposed Framework	**88.7**	**6.4**	**0.9**

Table III. TEST SAMPLE RESULTS ON RETINAL OCT IMAGES

Method	DSC (%)	HD (mm)	ASD (mm)
FSL	80.3	11.0	1.7
Consistency Regularization Only	83.0	9.6	1.4
Pseudo-Labeling Only	82.5	9.8	1.5
Mean Teacher Only	83.7	9.2	1.3
Proposed Framework	**86.9**	**7.8**	**1.0**

F. Analysis and Discussion

Our proposed semi-supervised learning framework demonstrated consistent and significant performance improvements across all three datasets – MRI brain scans, CT liver images, and retinal OCT images – compared to both the fully supervised baseline and models utilizing individual SSL methods. Specifically, the framework increased the Dice Similarity Coefficient (DSC) from 75.4% to 83.2% on MRI brain scans, from 82.1% to 88.7% on CT liver images, and from 80.3% to 86.9% on retinal OCT images. These enhancements indicate that the integrated use of consistency regularization, pseudo-labeling, and the Mean Teacher model effectively leverages unlabeled data to improve segmentation accuracy. Additionally, reductions in the Hausdorff Distance (HD) and Average Surface Distance (ASD) across all datasets reflect improved boundary precision and overall segmentation quality.

The inclusion of domain-specific data augmentations further improves the model's robustness by exposing it to a variety of realistic variations and artifacts. This exposure enables the model to learn invariant features that are crucial for accurate segmentation across different imaging conditions.

Our framework consistently outperformed the baselines across all datasets, indicating its versatility and effectiveness across different imaging modalities and segmentation tasks. The improvements in both overlap measures (DSC) and boundary accuracy metrics (HD and ASD) suggest that the model not only segments the regions of interest more completely but also delineates their boundaries more precisely.

These results have significant implications for clinical applications. Improved segmentation accuracy can enhance the reliability of computer-aided diagnosis systems, assist in precise treatment planning, and contribute to better patient outcomes. By reducing the dependency on large labeled datasets, our framework makes it more feasible to develop high-performing segmentation models in scenarios where annotated data is scarce.

VI. CONCLUSION

We presented a semi-supervised segmentation framework for medical images that effectively leverages unlabeled data by integrating consistency regularization, pseudo-labeling, and the Mean Teacher model. Domain-specific data augmentations further enhance model robustness and generalization. Extensive experiments on MRI, CT, and OCT datasets demonstrate that our framework significantly outperforms fully supervised and individual SSL methods, particularly in low-labeled-data scenarios. This work highlights the potential of SSL in reducing the dependency on large annotated datasets, facilitating wider adoption of deep learning in medical imaging applications.

Future work could explore the extension of the framework to three-dimensional (3D) segmentation tasks in volumetric data, which are common in medical imaging. Additionally, incorporating other SSL techniques, such as graph-based methods or adversarial training (with careful consideration of training stability), may further improve performance.

Investigating the application of the framework to other medical imaging modalities, such as ultrasound or positron emission tomography, could demonstrate its generalizability. Finally, collaborating with clinical experts to evaluate the practical impact of the improved segmentation in real-world clinical workflows would provide valuable insights.

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О. І. Чумаченко, К. Д. Рязановський. Напівконтрольована сегментація медичних зображень

Цю статтю присвячено розробці методу (алгоритму) сегментації медичних зображень на основі напівконтрольованого навчання. Показано, що методи напівконтрольованого навчання мають значний потенціал для покращення сегментації медичних зображень за рахунок ефективного використання немаркованих даних. Однак залишаються проблеми з адаптацією цих методів до конкретних характеристик медичних зображень, таких як висока мінливість, дисбаланс класів та наявність шуму і артефактів. Для подолання зазначених труднощів запропоновано інтегрувати кілька підходів (регуляризація узгодженості, псевдомаркування, модель середнього вчителя) до єдиної структури. Для підвищення надійності та узагальнення моделі для різних методів візуалізації включаємо доповнення до даних, специфічні для конкретної галузі, адаптовані до унікальних характеристик та проблем кожного методу. Масштабні експерименти з наборами даних магнітно-резонансної томографії, комп'ютерної томографії та оптично

когерентної томографії демонструють, що розглянута структура значно перевершує повністю контрольовані та індивідуальні методи напівконтрольованого навчання, особливо у сценаріях з низьким рівнем маркування даних.
Ключові слова: напівконтрольоване навчання; сегментація медичного зображення; регулярізація узгодженості; псевдомаркування; середній учитель; глибоке навчання.

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