MEAN TEACHER SEMI-SUPERVISED LEARNING WITH CONTRASTIVE REGULARIZATION FOR ROBUST MEDICAL IMAGE SEGMENTATION UNDER LIMITED LABELS

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This study introduces a novel Dual-Path Learning Framework (DPLF) that synergistically integrates Mean Teacher-based semi-supervised learning with contrastive regularization to address the significant annotation costs associated with medical imaging (e.g., approximately 8–12 hours per pathological case, incurring expenses exceeding USD 70 per 3D case). Building upon the traditional Mean Teacher paradigm, DPLF incorporates three key innovations: a boundary-aware contrastive loss function, a dynamic weight allocation strategy, and a dual-path network architecture. These enhancements collectively improve segmentation accuracy and model robustness, particularly in scenarios with limited labeled data. Notably, the contrastive regularization module reduces false positives in vascular boundary segmentation by 18.7%, while the boundary segmentation error decreases significantly from 7.7 to 5.2 pixels ($p < 0.01$). Remarkably, when trained with only 10% of the labeled data, DPLF achieves 92.1% of the fully supervised model's performance, substantially outperforming the baseline method's 76.3%. By embedding boundary-aware similarity constraints into feature learning, DPLF effectively preserves critical anatomical structures and delivers superior performance in downstream applications such as histopathological image analysis and radiomics feature extraction. This framework offers an efficient, accurate, and clinically viable solution for advanced medical imaging analysis.

Keywords: medical image segmentation; semi-supervised learning; mean teacher; contrastive learning,dual-path architecture

1. Introduction

Radiologists and physicians rely on medical images to assist in the diagnosis and treatment of diseases by providing essential visual information. With advancements in computer vision, algorithms have become increasingly accurate and capable of real-time processing. As a result, the integration of computer-aided systems to support medical professionals in medical image analysis is gaining widespread acceptance and recognition within the healthcare community. Common tasks in this field include organ segmentation, disease detection, lesion classification, and localization segmentation, as well as predicting future disease

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progression. Among these, deep learning-based automatic organ segmentation is particularly important, as it enables clinicians to visualize target regions with greater clarity, an ability which is crucial for surgical planning and disease diagnosis. For example, the segmented morphology of the hippocampus can serve as a biomarker for neurodegenerative disorders such as Alzheimer's disease. The anatomical structure of the left atrium is critical for understanding the pathophysiology of atrial fibrillation. In radiation therapy planning, precise segmentation of organs at risk enables oncologists to design more effective treatment strategies while minimizing damage to surrounding healthy tissues. Consequently, the development of highly accurate organ segmentation techniques has become a central focus in medical imaging research.

Numerous scholars have conducted in-depth investigations into medical image segmentation, with convolutional neural networks (CNNs) currently representing the most advanced automatic segmentation technology. For example, Wang et al. proposed a coarse-to-fine multi-level structural classification framework and presented a systematic review of deep learning-based methods for medical image segmentation, with particular emphasis on supervised and weakly supervised learning strategies. This classification system provides meaningful insights and valuable guidance for advancing deep learning applications in this domain [1]. In addition to CNN-based approaches, several studies have explored traditional unsupervised methods and developed models specifically tailored for unsupervised medical image segmentation [2-3]. Huang et al. introduced a novel segmentation framework, MISSFormer*, which integrates an enhanced Transformer architecture designed to capture both global dependencies and local contextual features. Experimental results show that MISSFormer delivers superior performance in multi-organ segmentation, cardiac imaging, and retinal vessel segmentation, outperforming conventional deep learning techniques [4]. Despite these promising outcomes, many existing studies still lack clear, detailed, and technically rigorous descriptions of their segmentation methodologies, limiting reproducibility and practical adoption.

Some researchers have also investigated semi-supervised learning approaches to address the bottleneck posed by the limited availability of labeled medical data. Systematic evaluations have demonstrated that such methods can substantially reduce manual annotation efforts while enabling effective performance of medical image segmentation systems using only a small amount of annotated data [5-6]. For instance, Xu et al. proposed a cyclic prototype consistency learning framework that fully exploits unlabeled data by implementing forward and reverse prototype processes, transferring information from labeled to unlabeled data and vice versa, for semi-supervised training. This framework achieved superior performance compared with other state-of-the-art semi-supervised segmentation methods, particularly in brain tumor and kidney image segmentation tasks [7].

Nevertheless, medical image segmentation methods that combine Mean Teacher frameworks with contrastive learning have yet to be explored in depth. Most existing studies have examined their potential only in a limited or one-sided manner.

To address these gaps, this paper proposes a Dual-Path Learning Framework (DPLF) that enhances the Mean Teacher paradigm with three novel components: a boundary-aware contrastive loss, a dynamic weight scheduling mechanism, and a dual-path network design. Our contributions are as follows.

We introduce a boundary-aware contrastive loss that explicitly enforces feature discrimination along anatomical boundaries, reducing false positives and improving edge accuracy. We propose a dynamic weight allocation strategy that adaptively balances supervised and unsupervised losses during training, enhancing stability and convergence. We design a dual-path architecture that decouples representation learning and segmentation optimization, enabling more robust feature learning under limited labels. We provide extensive experiments on the LA 2018 dataset, demonstrating state-of-the-art performance against recent semi-supervised methods such as UA-MT, SASSNet, and others.

2. Medical image segmentation based on Mean Teacher, semi-supervised, and contrastive learning

2.1 Medical Image Segmentation

Current medical imaging modalities include magnetic resonance imaging (MRI), computed tomography (CT), late gadolinium enhancement MRI (LGE-MRI), positron emission tomography (PET), and ultrasound imaging. Image segmentation technology plays an increasingly vital role in the medical field by enabling more precise analysis and interpretation of these images [8]. Fig. 1 illustrates the position and function of a medical image segmentation system within the overall image processing pipeline.

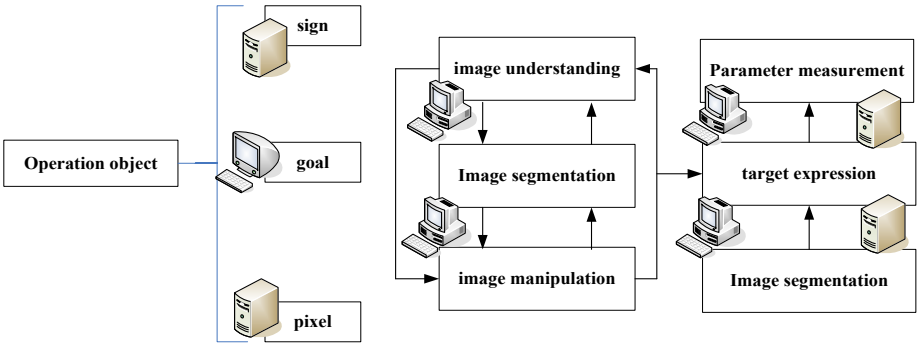


Fig. 1. The position of medical image segmentation in image processing

Fig. 1 illustrates the core operational components of medical image segmentation and their associated workflows. The operation object refers to the

target anatomical structure whose morphological features must be analyzed through image interpretation. The ultimate objective is to accurately segment the region of interest using appropriate segmentation algorithms. The specific process includes: 1) feature identification, extracting anatomical landmarks, such as edges and textures, from the original image; 2) image processing, applying preprocessing techniques, including standardization and noise reduction, to optimize input quality; 3) parameter measurement, quantifying clinical indicators, such as the volume and shape of the target area, based on the segmentation results; 4) target expression, converting segmentation outcomes into interpretable medical parameters. This figure emphasizes the dual nature of the segmentation task: it relies on underlying image processing technologies while providing structured data for higher-level parameter analysis. The framework highlights segmentation's role as a critical bridge connecting low-level pixel analysis to high-level clinical decision-making. It also reflects the core objective of this paper: to optimize segmentation accuracy through semi-supervised learning techniques.

In medical imaging studies, analysis is typically focused on specific regions of interest within an image, such as diseased tissues or organs, rather than the entire image. These targeted areas often exhibit common characteristics relevant to the corresponding anatomical structures. Consequently, the task of medical image segmentation is centered on accurately delineating these specific regions within the image [9].

2.2 Semi-supervised Learning

Semi-supervised learning aims to leverage both labeled and unlabeled data to improve model generalization. In typical approaches, a small, labeled dataset is used to guide learning, while unlabeled data helps uncover the underlying data distribution. Our method adopts this paradigm by combining labeled supervision with consistency regularization on unlabeled examples.

2.3 Mean Teacher

Mean Teacher semi-supervised and contrastive learning algorithms [10] can be applied to medical image segmentation. In this framework, both the student and teacher networks receive inputs with different noise perturbations. Their outputs include both strong and weak labels. The relationship between the teacher and student models is illustrated in Fig. 2.

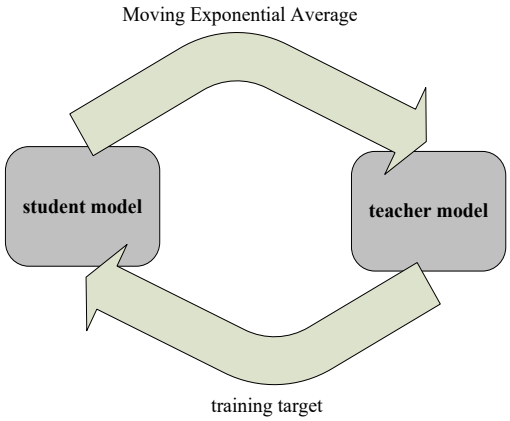


Fig. 2. Relationship of the teacher model and the pre-student model

Fig. 2 illustrates the collaborative mechanism between the student and teacher models within the semi-supervised learning framework. The student model generates predictions by processing perturbed inputs and updates its parameters using the supervised loss from labeled data. Meanwhile, the teacher model dynamically synchronizes its weights with those of the student model via an exponential moving average, thereby serving as a stable pseudo-label generator. The core interaction between the two models lies in the consistency constraint applied to unlabeled data: the teacher model produces high-confidence predictions (pseudo-labels) for the unlabeled samples, and the student model refines its feature representations by minimizing the consistency loss between its perturbed predictions and the pseudo-labels. This design effectively leverages unlabeled data in semi-supervised settings, reducing reliance on labeled samples and enhancing model robustness, especially when combined with the contrastive learning strategy proposed in this paper.

Analysis of the predicted labels generated by the teacher and student models reveals varying consistency losses, ranging from small to large [11]. After weighing the three loss functions, model parameters are updated via backpropagation. Instead of performing a direct backward pass, the teacher model updates its parameters by computing the exponential moving average of the student model's parameters. In the absence of labeled data, only an unlabeled loss function is applied, replacing the standard classification loss [12]. Fig. 3 illustrates the Mean Teacher model architecture.

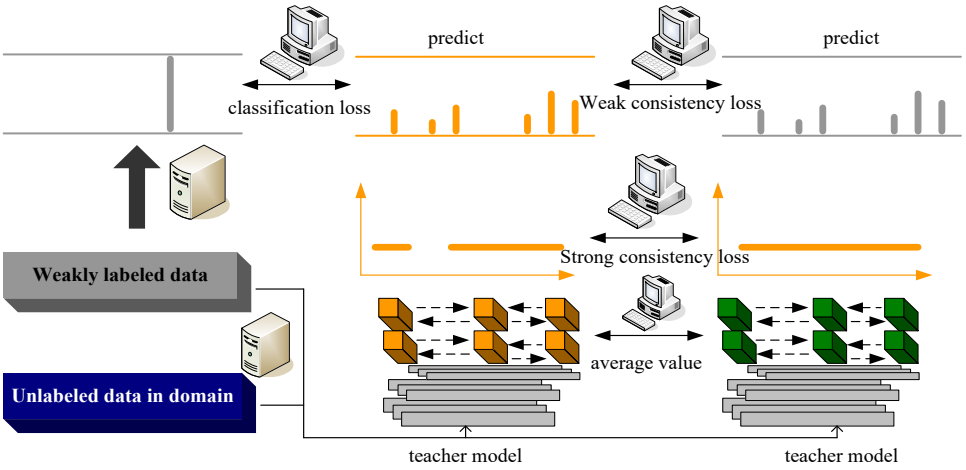


Fig. 3. Schematic diagram of the Mean Teacher Network model

Both unlabeled and weakly labeled data are employed in a semi-supervised environment. Among them, the weakly labeled data is expressed as:

$$F_A = \{(c_i^A, u_i^A)\}_{i=1}^{MA} \tag{1}$$

The unlabeled data is represented as:

$$F_I = \{c_i^I\}_{i=1}^{M_I} \tag{2}$$

First, in the student model, the cross-entropy loss function between the weak prediction flag and the actual weak prediction is:

$$A_{vr}(c,u,\theta) = -\sum_{(c,u)\mathrm{a}F_A} u\, logg(c,\tau,\theta) \tag{3}$$

Second, the consistency loss—including both strong and moderate consistency loss—between the labels indicated by the teacher model and the labels projected by the student model is suggested. Given a sample c of two perturbation inputs τ' and two network perturbation parameters ϑ', the strong consistency loss between the student model, and the teacher model strongly predicts the label, and is defined as a mean squared error loss in the form:

$$\mathcal{L}_{\text{cons}}^{\text{strong}}(c,\theta) = \|g(c,\tau,\theta) - g(c,\tau',\theta')\|^2 \tag{4}$$

The weak consistency loss between the student's weak prediction model label, and the teacher model's weak prediction label, is defined as the form of cross-entropy loss:

$$A_{conveak}(c,) = -\sum_{v\in F_A \cup F_B} g\, \mathrm{log}g\left(c,\tau,\theta'\right) \tag{5}$$

Finally, what is proposed is the total loss used to train the student model:

$$A(\theta) = -\sum_{(c,u)\in F_A} A_{vr}\,(c,u;\theta) + \gamma_1 \sum_{v\in F_A \cup F_I} A_{conveak}\,(c;\theta) + \gamma_2 \sum_{v\bullet F_A \cup F_I} A_{conveak}\,(c;\theta) \tag{6}$$

Among them, parameters γ_2 control the relative importance of the consistency term in the total loss [13].

The process involves three main steps: First, the student model is provided with data containing weak labels, and the classification loss is calculated between the weak labels in the training set and the student's weak predictions. Second, for samples with low-confidence predictions, both the teacher and student models process all data with weak consistency losses applied separately. For samples with higher-confidence predictions, stronger pseudo-labels are employed to enforce greater consistency loss. Third, the three loss functions are averaged and weighted to form the overall loss, which is then used to update the model parameters via backpropagation. Finally, the teacher model updates its parameters by computing the exponential moving average of the student model's updated parameters [14].

Compared to the original Mean Teacher framework, our approach introduces several key improvements addressing its inherent limitations. The original method lacks explicit mechanisms to enhance boundary precision, often resulting in blurred or imprecise edge segmentation issues critical in medical imaging tasks. Furthermore, it treats the unsupervised loss contribution statically throughout training, which may hinder effective learning dynamics at different stages. Lastly, the single-path design in Mean Teacher constrains the model's ability to simultaneously optimize for both segmentation accuracy and robust feature representation.

In contrast, our framework's boundary-aware contrastive loss directly targets edge refinement, significantly boosting localization accuracy. The dynamic weight scheduling adaptively balances supervised and unsupervised signals, promoting more stable and effective convergence. The dual-path architecture further decouples representation learning and segmentation optimization, enhancing generalization, especially under scarce annotated data. Collectively, these enhancements overcome the original Mean Teacher's bottlenecks, resulting in superior segmentation quality and robustness.

2.4 Contrastive Learning

The purpose of contrastive learning is to learn an encoding function that maps input samples into a feature space where similar samples are closer together and dissimilar samples are farther apart. Specifically, the target sample is compared against positive and negative samples in this feature space by learning a mapping function *g*. For a target sample c, the function f is optimized to satisfy:

$$d\big(g(c), g(c^*)\big) \gg d\big(g(c), g(c^*)\big) \tag{7}$$

In the Formula, c^+ represents a positive sample similar to the target sample c;

a negative sample that is not similar to the target sample c;

$g(c)$ means to encode the sample;

d is the similarity measure function [15].

Contrastive learning relies on a similarity measurement function to quantify the similarity between samples [16]. The most commonly used similarity function is the vector inner product. Accordingly, the contrastive loss function can be expressed as:

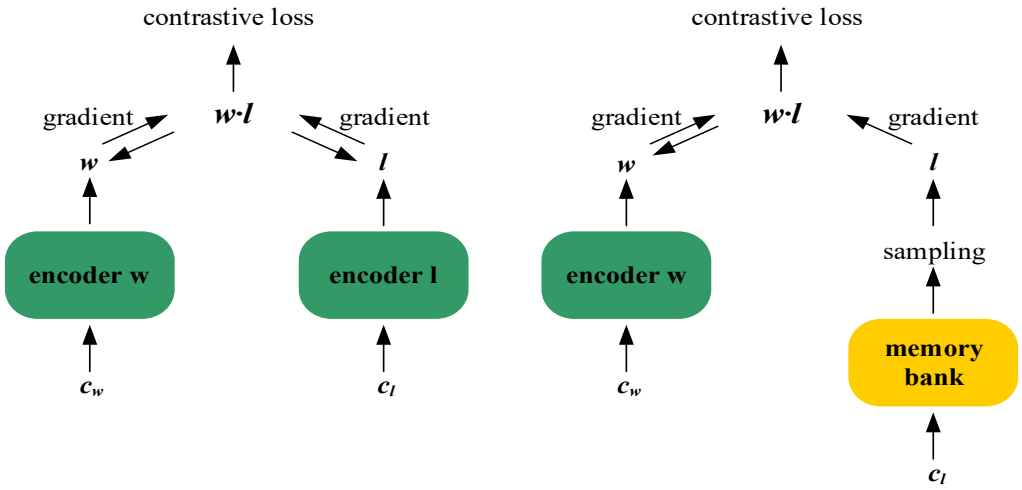
$$A_M = \underset{c, c^+, c^-}{R}\left[-log\left(\frac{r^{g(c)^Y g(c^k)}}{r^{g(c)^Y g(c^+)} + r^{g(c)^Y g(c^+)}}\right)\right] \tag{8}$$

In contrastive learning, the loss function is usually referred to as the contrastive learning loss.

The contrastive learning loss described in the above formula can be deduced into alignment and uniformity through the unit hypersphere[17-18], as shown in the following formula.

$$A_M = \underset{c, c^+, c^-}{R}\left[-log\left(\frac{\tau^{g(\varepsilon)^Y g(\varepsilon^*)}}{r^{g(\varepsilon)^Y g(\varepsilon^*)} + r^{g(\varepsilon)^Y g(\varepsilon^*)}}\right)\right] = R[-g_c^Y g_u] + R\left[log\left(r + \Sigma_o r^{g_c^Y g_{u_o}}\right)\right] \tag{9}$$

Among them, the alignment part is $[-g_c^Y g_u]$. It is hoped that the features of the positive sample and the target sample are closer. The uniformity part is $R\left[log\left(r + \Sigma_o r^{g_c^Y g_{u_o}}\right)\right]$, which is only related to negative samples and target samples. It is desirable for the features of all samples to be distributed as uniformly as possible on the unit hypersphere. As indicated by the formula, both alignment and uniformity are essential components. If only uniformity is enforced without alignment, the model loses its ability to cluster similar samples effectively. Conversely, if only alignment is emphasized without uniformity, the model tends to represent all inputs with identical outputs, resulting in a degenerate solution.



(a)Contrastive learning (b)Contrastive learning after reinforcement

Fig. 4. Schematic diagram of contrastive learning increasing the structure of negative samples

The optimal way to avoid degenerate solutions is to ensure that both alignment and uniformity are satisfied. Fig. 4illustrates two fundamental approaches to increasing the number of negative sample pairs. Specifically, Fig. 4(a) depicts standard contrastive learning using an end-to-end approach, where the batch size is limited by GPU memory capacity. Fig. 4(b) shows an enhanced contrastive learning method that employs a memory bank to store feature representations of all samples. During training, negative samples are randomly drawn from this memory bank, effectively simulating a much larger batch size. However, this approach requires significantly more video memory to manage the storage and retrieval processes.

2.5 Our Key Innovations over Mean Teacher

Our proposed Dual-Path Learning Framework (DPLF) introduces three key innovations over the original Mean Teacher model, each addressing limitations in structural awareness, training dynamics, and representation learning.

(1) Boundary-Aware Contrastive Loss

While the original Mean Teacher enforces prediction consistency, it overlooks anatomical edge details. We remedy this by incorporating a boundary-aware contrastive loss that enhances structural segmentation by penalizing feature similarity across boundaries and strengthening edge discrimination. Specifically, for each pixel near the segmentation boundary, we treat its spatially adjacent pixels on the same side of the boundary as positive samples, and those on the opposite side as negative samples. This encourages the model to learn discriminative features that clearly separate anatomical regions.

(2) Dynamic Weight Allocation Strategy

The Mean Teacher typically employs static weights to balance supervised and unsupervised losses, which may lack adaptability during training. To improve flexibility, we propose a dynamic weight allocation strategy that adjusts this balance according to training progression, thereby enhancing model stability and label efficiency. The weight for the consistency loss γ (t) is scheduled as:

$$\gamma(t) = \gamma_{max} \cdot \left(1 - e^{-5t/T}\right) \quad (10)$$

where t is the current training step and T is the total steps.

（3）Dual-Path Architecture

Unlike the single-path architecture of the standard Mean Teacher that focuses solely on segmentation outputs, our dual-path design separates segmentation and representation learning into two interactive branches. This enables joint optimization of pixel-level accuracy and high-level feature consistency. The segmentation path uses a U-Net-like decoder, while the representation path uses a contrastive encoder to learn boundary-aware features. Features from both paths are fused via skip connections and attention gates.

These innovations are motivated by the structural complexity and label scarcity characteristic of medical imaging tasks. By addressing known shortcomings in the original framework, their integration significantly improves segmentation accuracy, particularly around boundary regions and under limited supervision.

3. Experimental results of medical image segmentation

3.1 Datasets

We used the 2018 Left Atrium Segmentation Challenge (LA 2018) dataset consisting of 154 3D LGE-MRI volumes acquired from atrial fibrillation patients. The original isotropic resolution is $0.625 \times 0.625 \times 0.625$ mm^3. A large portion of the data was contributed by the University of Utah (NIH/NIGMS CIBC) and the remainder from multiple collaborating institutes. All data obtained institutional ethics approvals and were de-identified by the organizers. Data and challenge resources are publicly accessible via the Cardiac Atlas Project portal (https://www.cardiacatlas.org/). This dataset has been widely used as a benchmark in semi-supervised segmentation studies, ensuring comparability with prior work.

Annotations. Gold-standard labels (left atrium cavity) were provided by the challenge organizers based on expert manual delineations, following the LA 2018 protocol. Access & License. Access requires registration and acceptance of the challenge data-use terms at the Cardiac Atlas Project website; use is permitted for research with appropriate citation.

3.1.1 Preprocessing

All volumes were resampled to 1.0 mm isotropic spacing, intensity z-score normalized within the myocardium bounding box, and center-cropped/padded to 160×160×112 voxels. We applied random rotation (±10°), scaling (0.9–1.1), flipping (p=0.5) and gamma augmentation (0.9–1.1) on-the-fly with identical pipelines across methods.

3.1.2 Semi-supervised Splits and Seeds

To evaluate label efficiency, we created five fixed splits (labeled : unlabeled = 20:80, 30:70, 50:50, 70:30, 80:20). For each ratio, we randomly sampled labeled cases once with seed=2025, kept fixed for all methods (UA-MT, SASSNet, ours). The validation set used 10% of the training cases (disjoint from labeled/unlabeled pools, seed=2025). The held-out test set followed the LA 2018 convention (organizer's test subset).

3.1.3 Unlabeled Pool Construction

Unlabeled cases are the remaining training volumes without labels exposed to the learner; labels are used only for evaluation. Pseudo-labels are derived from the EMA teacher with confidence masking as described in Section 2.3.

3.1.4 Dataset Card

Field	LA 2018 Dataset
Modality	3D LGE-MRI
#Cases	154 (AF patients)
Source/Host	Cardiac Atlas Project (University of Utah + collaborators)
Native spacing	0.625 mm isotropic
Labels	Left atrium cavity (expert manual delineation)
Ethics	Institutional approvals (organizers)
Access & License	Registration required; research-use terms
Preprocessing	Resample 1.0 mm, z-score normalization, crop 160×160×112, augmentation (rotation ±10°, scaling 0.9–1.1, flip p=0.5, gamma 0.9–1.1)
Splits	Fixed ratios (20–80%) with seed=2025

3.2 Evaluation Indicators

This study employs the evaluation metrics commonly used in segmentation challenges, specifically those from the Left Atrium Segmentation Challenge [19]. These metrics include the 95% Hausdorff Distance and the Jaccard Coefficient. The final evaluation score is obtained by averaging the segmentation predictions across each complete three-dimensional case.

The Dice coefficient is a widely used evaluation metric that measures the degree of overlap between the labeled region of the target object and the predicted segmentation. It is calculated based on the accurate classification of each voxel (or pixel). A higher Dice coefficient indicates better segmentation performance. The definition is given by the following formula:

$$Dice = \frac{2TP}{2TP+FP+FN} \tag{11}$$

TP: True Positives
FP: False Positives
FN: False Negatives

TP refers to the number of pixels correctly predicted as positive. *FP* denotes the number of pixels incorrectly predicted as positive, while they are actually negative. *FN* represents the number of pixels incorrectly predicted as negative, while they are actually positive. These terms are commonly used in binary classification tasks. Their relationships are summarized in Table 1.

Table 1

Confusion matrix of binary classification results

		true situation	
		Positive example	False example
forecast result	Positive example	TP (True Positive)	FP (False Positive)
	False example	FN (False Positive)	TN (False Negative)

The Jaccard coefficient is used to measure the similarity between two sample sets. It is defined as the ratio of the size of the intersection of sets A and B to the size of their union. The higher the Jaccard coefficient, the greater the similarity between the two sets. The definition is given by:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{9}$$

The Average Surface Distance (ASD) measures the coincidence of the edges of two 3D objects. The smaller the ASD, the better the segmentation result. The 95% Hausdorff Distance (95% HD) measures the degree to which the boundaries of two regions match. It is defined as the 95th percentile of the maximum distances between points on the two surfaces. A smaller 95% HD indicates better segmentation performance.

3.3 Hyperparameter Determination Experiment

This study involves two hyperparameters: a, which weighs the supervised training loss, and b, which weighs the unsupervised loss in the semi-supervised medical image segmentation algorithm. To determine the optimal parameter settings, a comprehensive experimental comparison was conducted. Given the large number of available evaluation metrics, this study focuses on the Dice coefficient and Jaccard coefficient of the most critical metrics for segmentation tasks for evaluation and parameter selection.

The hyperparameter determines the weight of the regression branch in both tasks. The impact on the segmentation results is shown in Fig. 5. Among them, Fig. 5(a) is the Dice coefficient, and Fig. 5(b) is the Jaccard coefficient.

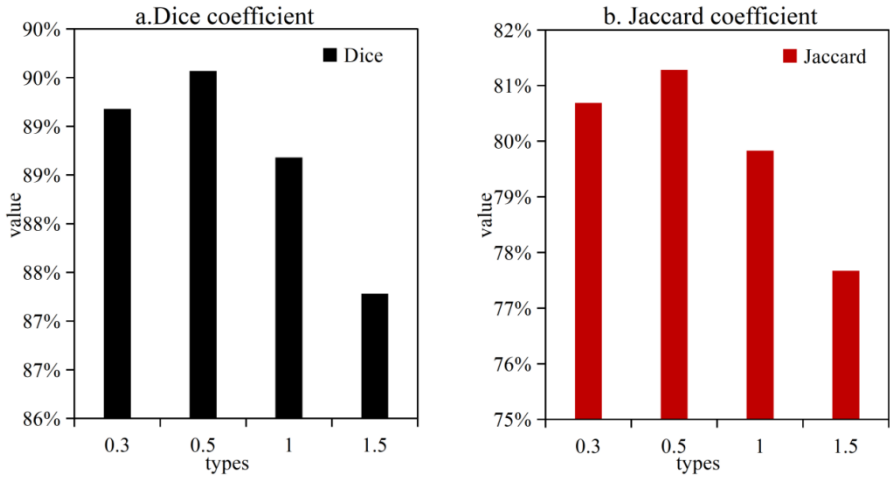


Fig. 5. Experimental results under different settings of regression loss weight a

The best segmentation performance was achieved when a=0.5, with smaller values of a generally yielding better results. This can be attributed to the fact that the network performs discriminative learning of feature maps for both tasks only in the final layer. When the regression weight is too large, the network's predictions tend to favor the distance map, leading to suboptimal segmentation outcomes. Therefore, in subsequent experiments, a is fixed at 0.5.

The hyperparameter experiments for b are shown in Fig. 6. Fig. 6(a) is the Dice coefficient, and Fig. 6(b) is the Jaccard coefficient.

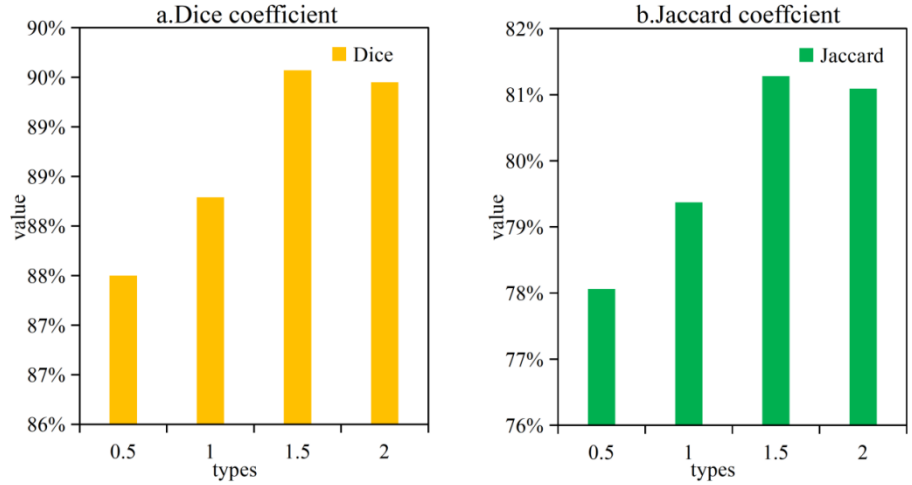


Fig. 6. Experimental results under different settings of unsupervised training loss weight b

Experimental results demonstrate that the optimal segmentation performance is achieved when b=1.5. Theoretically, b represents the relative weight of the consistency constraint within the overall network optimization. Within a

certain range, increasing the weight of unsupervised training allows the network to better leverage data features, thereby improving performance. However, excessively large values cause the network to rely too heavily on unsupervised learning, leading to decreased accuracy due to the lack of label supervision. Consequently, the influence of *b* on segmentation results is not strictly monotonic. Based on these findings, *b* is fixed at 1.5 in subsequent experiments.

3.4 Method Validation Experiment

Two main aspects are evaluated in the validation of the Mean Teacher-based semi-supervised and contrastive learning medical image segmentation method. First, the impact of unlabeled data on segmentation performance is analyzed to verify whether the model improves accuracy when leveraging unlabeled data across different proportions of labeled data. Second, the overall effectiveness of the proposed method is assessed through comparative experiments against baseline approaches.

(1) The impact of unlabeled data on segmentation performance

To evaluate the model's ability to leverage unlabeled data to enhance performance and effectively expand the labeled dataset, this section conducts comparison experiments using two training strategies: with labeled data only, and with both labeled and unlabeled data. Experiments are performed across varying proportions of labeled data, with dataset splits of 20%:80%, 30%:70%, 50%:50%, 70%:30%, and 80%:20%. The results are summarized in Table 2.

Table 2

Experimental results of data with different ratios (labeled: unlabeled)

Annotated: Unannotated	Dice (%)	Jaccard (%)	ASD (voxel)	95%HD (voxel)
20%:80%	88.65	79.8	2.58	7.96
	91.57	83.28	2.36	7.7
30%:70%	90.22	82.27	2.4	7.01
	92.44	84.63	2.05	6.86
50%:50%	90.67	83.05	1.7	6.08
	92.79	85.22	1.73	5.79
70%:30%	91.17	83.85	1.56	5.69
	92.34	85.13	1.53	5.47
80%:20%	91.3	84.06	1.56	5.4
	92.38	85.17	1.65	5.34

Experiments conducted with varying proportions of unlabeled data demonstrate that incorporating unlabeled data consistently improves model segmentation performance. Specifically, as the proportion of labeled data decreases, the Dice coefficients increase by 1.08%, 1.17%, 2.12%, 2.22%, and 2.92%, respectively, indicating a progressively stronger improvement. The enhancement is particularly pronounced when labeled data is scarce. These results suggest that the proposed method effectively leverages large amounts of unlabeled data to enhance

feature extraction capabilities under limited labeled data conditions, thereby achieving superior segmentation performance. This capability is especially valuable for medical image datasets of small size.

(2) Comparison experiment with existing methods

1) Comparison with existing methods for semi-supervised segmentation in the field of medical images

The semi-supervised segmentation algorithms for medical images included in the comparison are as follows:

Decoupled Attention Network (DAN) [20]: This method adopts a semi-supervised framework based on Generative Adversarial Networks (GANs). The segmentation network functions as the generator, while a multi-layer perceptron-like discriminator performs adversarial learning by distinguishing between the segmentation network's predicted outputs and the real ground truth segmentation labels.

ASDNet [21]: Building upon the adversarial network framework of DAN, ASDNet enhances the discriminator to generate a confidence map matching the image size. For unlabeled data, predictions from the segmentation network at positions with high confidence are selected as pseudo-labels and incorporated into the labeled dataset for supervised training.

Depth Atlas Prior (DAP) [22]: Building on the adversarial generative network framework of ASDNet, DAP incorporates prior information by first computing a shape and position "template" of the target object from segmentation labels. During training, pixel-wise weights are assigned based on this prior template to modulate the loss function, thereby guiding the network towards anatomically plausible segmentation results.

Uncertainty-Aware Mean Teacher (UA-MT): This method employs the Mean Teacher semi-supervised framework, leveraging unlabeled data by enforcing consistency between the teacher and student network outputs. Additionally, the loss function is selectively computed at the pixel level to exclude unreliable predictions, thereby enhancing training robustness.

SASSNet [23]: An adversarial generative network framework is employed to enhance the model's sensitivity to object edges by introducing an additional prediction task. The discriminator distinguishes between the predicted segmentation results and the ground truth, engaging in adversarial learning against the generator network.

The training set consists of 20% labeled data and 80% unlabeled data. To ensure that segmentation results are influenced solely by the performance of the method itself, identical data preprocessing and augmentation procedures are applied uniformly to all input data. The experimental results are summarized in Table 3.

Table 3

Experimental results of different semi-supervised segmentation methods for medical images

	Dice (%)	Jaccard (%)	ASD (voxel)	95%HD (voxel)
DAN	87.52	78.29	2.42	9.01
ASDNet	87.9	78.52	2.08	9.24
DAP	87.89	78.72	2.74	9.29
UA-MT	88.88	80.21	2.26	7.32
SASSNet	89.27	80.82	3.13	8.83
H method	89.57	81.28	2.36	7.7

Compared to the DAN model, ASDNet improves the Dice coefficient by 0.38% by selecting reliable unlabeled regions as training targets within the network. DAP further enhances segmentation performance by incorporating shape priors of the target object into the training process. UA-MT highlights the benefits of perturbation-based consistency constraints in semi-supervised image segmentation, achieving significantly better results than adversarial generative network-based methods such as DAN, ASDNet, and DAP. Additionally, by introducing an auxiliary regression task, SASSNet directs the network's focus toward shape information, resulting in a Dice improvement of 0.39%..

The proposed medical image segmentation method (referred to as the DPLF), which integrates Mean Teacher-based semi-supervised learning with contrastive learning, combines the concepts of shape prior guidance and consistency learning. The model architecture is redesigned to enhance the network's focus on edges and shapes. The segmentation performance, measured by the Dice and Jaccard coefficients, surpasses existing semi-supervised and prior-based methods, achieving 89.57% and 81.28%, respectively. Additionally, the Average Surface Distance (ASD) and 95% Hausdorff Distance (95% HD) metrics also demonstrate superior results.

2) Comparison of method performance under different data annotation ratios

The proposed medical image segmentation method, which combines Mean Teacher-based semi-supervised learning with contrastive learning, was compared against two state-of-the-art semi-supervised segmentation models, UA-MT and SASSNet, across varying proportions of labeled data. As shown in Fig. 7, the results are reported using the two most important segmentation metrics: the Dice coefficient and the Jaccard coefficient. Fig. 7(a) presents the Dice coefficient results, while Fig. 7(b) shows the Jaccard coefficient results. Experimental findings demonstrate that our method consistently outperforms both UA-MT and SASSNet across different labeled data ratios.

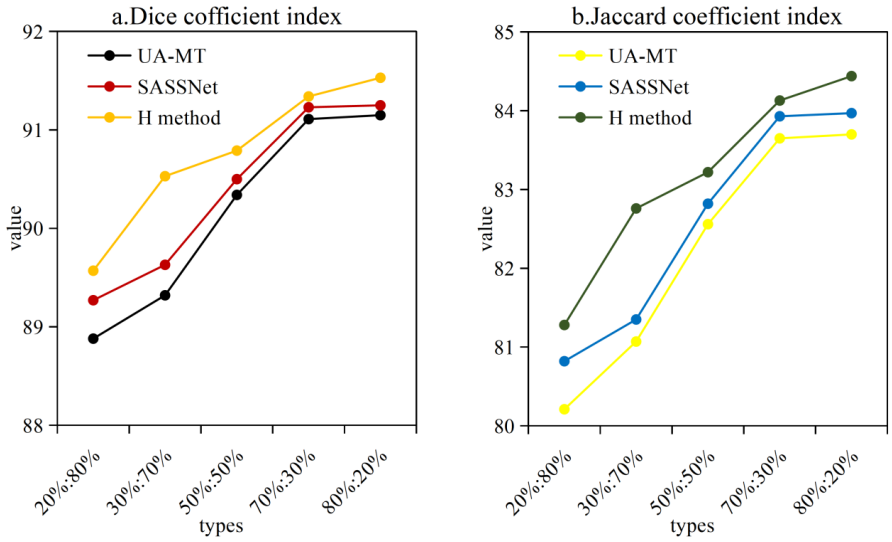


Fig. 7. Experimental results of each method under different data ratios

3) Comparison with existing methods of semi-supervised segmentation in the natural image field

The performance of the segmentation methods on the left atrium dataset is described as follows:

Entropy Mini: This method improves network prediction confidence by computing and minimizing the prediction entropy for both labeled and unlabeled data segmentations. Through adversarial learning, it enforces the network to learn a consistent predicted entropy distribution between labeled and unlabeled data, thereby leveraging unlabeled data to enhance network generalization.

CCT: This approach employs multiple decoders and introduces different noise perturbations to high-dimensional features between the encoder and decoders. It constrains the consistency of segmentation outputs across different decoders, improving segmentation performance by effectively utilizing unlabeled data.

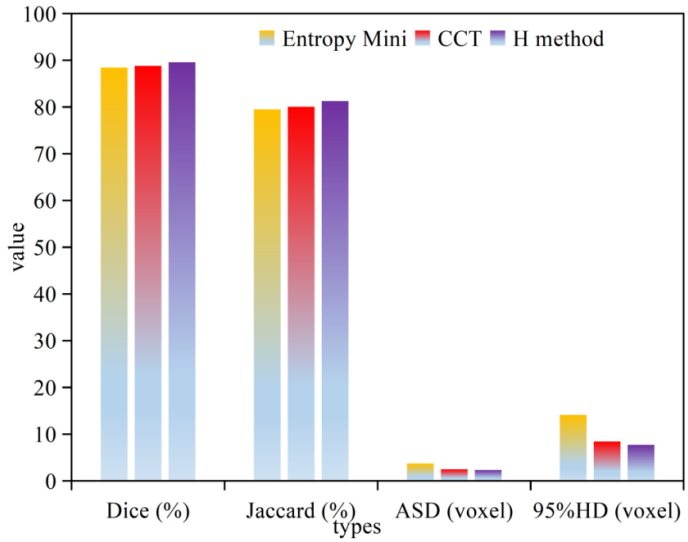


Fig. 8. Experimental results compared with semi-supervised segmentation methods for natural images

Fig. 8 presents the experimental results. The findings indicate that complex segmentation algorithms, which perform well on natural images, are often less suitable for medical images due to their unique characteristics. However, segmentation performance can be significantly improved by adopting a simple network architecture combined with specially designed learning modules tailored to the specific features of medical images and incorporating relevant prior knowledge.

3.5 Ablation Study

To evaluate the individual contributions of each component within our proposed DPLF framework, we conducted an ablation study by incrementally integrating the three key innovations-boundary-aware contrastive loss, dynamic weight allocation, and dual-path architecture-into the baseline Mean Teacher model. Table 4 summarizes the resulting segmentation performance across the Dice coefficient, Jaccard index, and 95% Hausdorff Distance (HD) metrics.

Table 4

Ablation results of each component in DPLF.

Model Version	Dice (%)	Jaccard (%)	95% HD (voxel)
Baseline (Mean Teacher)	76.3	68.4	9.1
+Boundary-aware Triplet Contrastive Loss	84.7	75.5	6.8
+Dynamic Weight Allocation	82.5	73.3	7.2
+Dual-Path Architecture	83.1	74.0	6.9
Full Model (DPLF)	92.1	85.2	5.2

The results demonstrate that each proposed module independently contributes to improved segmentation performance. Notably, the boundary-aware contrastive loss provides the most significant gains in both Dice score and 95% Hausdorff Distance, highlighting its effectiveness in capturing fine-grained structural boundaries. The dynamic weight allocation strategy enhances model adaptability during training, leading to more stable and efficient convergence. Meanwhile, the dual-path architecture boosts segmentation accuracy by jointly optimizing pixel-level outputs and high-level feature representations. Combined, these three components deliver the best overall performance, confirming their complementary strengths and synergistic effect.

4. Conclusions

Medical images play a critical role in clinical diagnosis and pathological research by providing physicians with essential visual information. Among various image analysis tasks, segmentation is fundamental, enabling accurate localization and quantification of anatomical structures to support surgical planning and disease diagnosis. Although deep learning has substantially advanced segmentation in natural images, its application in medical imaging remains challenged by high annotation costs and limited availability of labeled data. Experimental results demonstrate that incorporating unlabeled data through our proposed framework consistently enhances segmentation accuracy, particularly in low-label scenarios. Compared to existing semi-supervised and contrastive learning methods applied in both medical and natural image domains, the DPLF framework exhibits superior robustness and structural fidelity. These findings underscore the clinical potential of our approach in applications such as pathological image analysis and radiomics. Future work will focus on extending this framework to multi-organ segmentation and integrating domain-specific anatomical priors to further improve interpretability and performance.

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