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# 半监督医学图像分割方法综述

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**摘　要**:半监督学习为缓解医学图像分割中高质量标注数据稀缺的难题提供了重要途径。近年来,伪标签生成、一致性正则化与协同训练等技术在充分挖掘未标注数据潜力、提升模型泛化能力方面取得显著进展。本文系统综述了半监督医学图像分割的关键方法,重点回顾了基于伪标签的方法在高置信度伪监督信号生成、边界感知增强等方面的技术创新;探讨了一致性方法在多域异构性与复杂解剖结构下的改进策略,如多层次特征对齐和不确定性对抗训练;分析了协同训练方法通过多模型协作提升分割稳健性的研究进展。随后,本文深入讨论了当前面临的核心挑战,包括伪标签质量控制、类别不平衡以及数据隐私保护,并展望了未来结合医学知识驱动、自适应阈值策略与隐私保护机器学习的新方向。通过全面梳理现有研究,本文旨在为半监督医学图像分割的持续发展提供系统性参考和研究启示。

**关键词**:半监督学习;医学图像分割;伪标签;一致性正则化;协同训练

# A review of semi-supervised medical image segmentation methods

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**Abstract**: Semi-supervised learning (SSL) has rapidly evolved into a cornerstone paradigm for medical image segmentation, offering a pragmatic resolution to the chronic scarcity of high-quality annotated data in clinical environments. Unlike fully supervised approaches that demand exhaustive pixel-level labeling, SSL frameworks leverage vast repositories of unlabeled images alongside limited annotated counterparts to achieve competitive, and often near-fully-supervised, segmentation performance. This survey presents a systematic and multidimensional review of semi-supervised medical image segmentation, covering methodological taxonomies, quantitative benchmarking, persistent challenges, and transformative research frontiers. We begin by establishing a hierarchical taxonomy that categorizes existing SSL segmentation methods into three principal streams: pseudo-labeling, consistency regularization, and co-training. For each category, we dissect representative models published at leading conferences and journals—including CVPR, ECCV, ICCV, MICCAI, TMI, MIA, and TPAMI—with an emphasis on their theoretical underpinnings, architectural innovations, and optimization strategies. In the pseudo-labeling domain, we analyze advances in high-confidence pseudo-signal generation, boundary-aware refinement, uncertainty-guided filtering, and label correction via generative diffusion models. For consistency-based methods, we explore how recent studies address multi-domain heterogeneity and complex anatomical structures through multi-level feature alignment, frequency-space consistency, task-affinity regularization, and adversarial perturbation training. In co-training, we examine multi-model collaboration mechanisms, including diverse architecture design, disagreement-based uncertainty estimation, dynamic fusion strategies, and cross-modal synergy. Beyond technical exposition, we pro-

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vide a granular assessment of the strengths, limitations, and suitable application scenarios associated with each methodological branch. A distinguishing contribution of this review lies in its extensive empirical benchmarking. We compile and evaluate 34 state-of-the-art semi-supervised segmentation models published between 2022 and 2025 across three publicly accessible medical imaging datasets: ACDC, Pancreas-NIH, and LA. Quantitative comparisons are conducted using three widely adopted metrics—Dice, IoU, and 95HD—providing a multi-faceted view of model performance in terms of volumetric overlap, boundary fidelity, and robustness to structural variability. This side-by-side comparison enables identification of performance leaders such as SDCL, FedSemiDG, CMMT-Net, and CV-SSL-MIS, and facilitates analysis of architectural commonalities underpinning their success, including discrepancy-aware correction, domain generalization in federated settings, cross-head mutual learning, and dual-contrastive transformer backbones. Through this analysis, we illuminate the evolving performance landscape and reveal persistent gaps in cross-modal generalization and small-object segmentation. We further consolidate and characterize ten commonly adopted datasets in the field—including ACDC, PROMISE12, M&Ms, BUSI, GlaS, MoNuSeg, LA, Pancreas-NIH, NCI-ISBI13, and I2CVB—detailing their imaging modalities, annotation protocols, dataset scales, and resolution characteristics. This resource-oriented summary provides practical guidance for researchers selecting appropriate benchmarks for method validation or domain transfer experiments. Despite considerable progress, semi-supervised medical image segmentation remains confronted by several systemic challenges. We critically examine four core dilemmas. First, pseudo-label quality control remains precarious; noisy, overconfident, or anatomically implausible pseudo-labels can propagate errors and destabilize training. We review mitigation strategies including uncertainty-based filtering, temporal ensembling, cooperative rectification networks, and diffusion-based label refinement. Second, class imbalance—particularly pronounced for small lesions, organs with low volumetric occupancy, or rare pathological patterns—is exacerbated in SSL settings due to biased pseudo-labeling toward majority classes. We discuss class-sensitive loss functions, re-sampling strategies, generative augmentation, and balanced confidence calibration as emerging countermeasures. Third, data privacy and regulatory constraints hinder the aggregation of distributed medical data, challenging traditional centralized SSL paradigms. We examine privacy-preserving alternatives, with particular attention to federated semi-supervised learning, differential privacy, and their intersection with domain generalization and communication-efficient optimization. Fourth, we identify cross-domain and cross-modal generalization as a fundamental bottleneck, especially when training and testing distributions diverge due to differences in scanner protocols, patient populations, or imaging modalities. We summarize recent efforts in domain adaptation, modality-collaborative learning, and invariant feature disentanglement. Looking forward, we articulate five forward-looking research directions poised to redefine the landscape of semi-supervised medical image segmentation. 1) Medical knowledge-driven segmentation seeks to transcend purely data-driven representations by embedding explicit anatomical priors, geometric constraints, or radiological semantics into SSL pipelines. We review emerging paradigms that encode shape priors via adversarial learning, distill textbook knowledge via vision-language pretraining, and employ large language models to generate dynamic prompts or pseudo-labels. However, we also caution against over-rigid knowledge injection that may conflict with image evidence, advocating for adaptive fusion mechanisms and retrieval-augmented frameworks. 2) Visual foundation models, particularly the Segment Anything Model (SAM) and its medical adaptations (e. g. , MedSAM, SAM2), present unprecedented opportunities for zero-shot and few-shot segmentation. We analyze how SAM can be integrated into SSL frameworks through parameter-efficient fine-tuning, automated prompt generation via multimodal LLMs, video-inspired volumetric segmentation, and teacher-student co-training. Critical open issues—domain gaps between natural and medical images, computational overhead, and knowledge conflict—are examined with proposed mitigation pathways. 3) Partial annotation in 3D volumetric segmentation is gaining urgency as fully labeling 3D medical scans remains prohibitively labor-intensive. We highlight recent advances leveraging sparsely labeled slices, orthogonal plane annotations, or scribble-based supervision, combined with multi-level consistency, signed distance function constraints, and pseudo-3D to true-3D progressive learning. Adaptive annotation selection via active learning and uncertainty sampling is identified as a promising synergy. 4) Federated semi-supervised learning offers a privacy-compliant framework for multi-institutional collaboration without centralized data sharing. We analyze recent contributions in dynamic client weighting, semi-centralized training paradigms, and frequency-space domain generalization. We further identify underexplored areas including incentive mechanisms via blockchain, neu-

ral architecture search for heterogeneous client capabilities, and personalized federated tuning. 5) Lightweight and efficient models are imperative for clinical deployment on edge devices, intraoperative systems, and low-resource settings. We survey recent breakthroughs in state-space models (e. g., Mamba-based architectures), multi-scale dynamic feature fusion, and hardware-aware neural architecture search that substantially reduce parameter counts while preserving segmentation fidelity. Challenges in maintaining cross-modal robustness and achieving real-time inference are critically assessed. In summary, this review provides a comprehensive, empirically grounded, and forward-looking synthesis of semi-supervised medical image segmentation. By bridging methodological innovation, rigorous benchmarking, dataset characterization, challenge dissection, and future roadmap, we aim to equip researchers and practitioners with both a holistic understanding of the current landscape and actionable insights for advancing the field toward greater accuracy, generalizability, privacy compliance, and clinical translatability.

**Key words**: Semi-supervised learning; Medical image segmentation; Pseudo-labeling; Consistency regularization; Co-training

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## 0 引　言

医学图像分割是计算机视觉领域的重要研究方向，广泛应用于临床诊断、治疗规划及疾病监测等场景。然而，医学图像往往对分割结果的精确性、边界细节和结构一致性提出极高要求，而获取充分且高质量的人工标注数据成本昂贵、耗时且依赖专业知识。因此，如何在有限标注样本条件下有效利用大量未标注数据，成为提升分割性能和泛化能力的关键问题。

近年来，半监督学习(Semi-Supervised Learning, SSL)因其能够结合少量标注数据与大量未标注数据进行高效训练，逐渐成为医学图像分割研究的热点。不同于完全监督学习，半监督方法通过构建伪标签、一致性约束或多模型协同机制，引导模型从未标注样本中挖掘潜在信息，以提升预测准确性与鲁棒性。Prior-Aware(Chen 等，2024)提出了一种先验感知伪标签方法，用于半监督超声图像分割。该方法基于编码器-双解码器网络架构，并利用对抗学习引入形状先验约束，通过判别器对伪标签进行校正以提升预测的解剖合理性。实验结果表明，该方法在两个超声图像基准数据集上实现了最先进的性能，显著优于传统伪标签策略。然而，由于该方法依赖对抗训练过程中的稳定性，仍可能面临训练不收敛或先验过拟合等问题。AHDC(Chen 等，2021)提出了一种自适应层次双重一致性框架，包含双向对抗推理模块(bidirectional adversarial inference，BAI)和层次双重一致性模块(hierarchical dual consistency，HDC)。其中，BAI 通过双向对抗映射网络实现跨域特征的互适应，有效消除了不同域之间的分布差异和样本失配问题；而 HDC 则构建双重建模网络，在域内通过一致性约束挖掘互补信息，在域间通过预测一致性融合跨域知识，从而实现跨域半监督左心房的精准分割。该方法显著提升了模型在多源数据条件下的泛化能力和分割精度，展示了强大的跨域适应性和稳健性。CMMT-Net(Li 等，2024)构建了一个多尺度协同训练框架，旨在通过多个子网络的协同学习提升半监督医学图像分割性能。该方法在两个子网络之间引入了通道和空间维度的调制机制，用以强化不同尺度下伪标签的语义传递。具体来说，调制机制增强了模型对关键解剖结构的感知能力，同时有效抑制了复杂背景的干扰，提高了分割的准确性和鲁棒性。实验结果显示，CMMT-Net 在小样本标注条件下表现优异，能够实现接近全监督学习的分割效果。

在本文中，我们对半监督医学图像分割领域的最新研究进展进行了系统而全面的调查。首先，重点回顾了三大主流方法：基于伪标签的方法，详细分析了伪标签生成策略、置信度筛选机制及边界增强技术；一致性正则化方法，探讨了多层次特征对齐、不确定性建模与对抗扰动训练等创新手段；以及协

同训练方法，介绍了多模型互助机制、视角融合及多任务协同优化的最新成果。其次，我们从分割精度、鲁棒性、跨域适应能力及计算效率等多个维度系统评估了上述方法在不同医学图像模态和数据规模上的表现，深入剖析各自优势、适用场景及存在的不足。最后，针对当前领域面临的关键挑战，如伪标签质量不稳定导致的噪声干扰、少数类目标的类别不平衡问题，以及医学数据隐私和多中心协作带来的安全隐患，本文进行了详细讨论。展望未来，本文提出结合医学专业知识驱动的结构约束、自适应阈值动态筛选伪标签和基于联邦学习及差分隐私的安全学习机制，作为推动半监督医学图像分割技术向更高精度、更强泛化能力和更广泛临床应用迈进的重要方向。

近年来，关于医学图像分割和半监督学习的综述性工作逐步增多。Hesamian 等人（2019）对深度学习医学图像分割方法进行了全面总结，系统回顾了基于卷积神经网络（convolutional neural network，CNN）、全卷积网络（fully convolutional network，FCN）和 U-Net 等架构的技术进展，重点分析了模型设计、损失函数、数据增强和评估指标等方面。然而，该综述主要聚焦于全监督学习范式，未涉及半监督策略。Cheplygina 等人（2019）系统回顾了弱监督和无监督医学图像分析方法，其中包含部分半监督分割的探讨，但对伪标签、一致性正则化和协同训练等关键技术仅作简要介绍。Mlynarski 等人（2019）重点讨论了混合监督策略在脑肿瘤分割中的应用，系统分析了将半监督学习与弱监督方法结合以利用有限标注与大量未标注数据的可行性和效果。该综述对深度学习在不同监督强度下的分割模型进行了归纳，但主要聚焦于特定解剖区域（脑部）和混合监督范式，对伪标签生成、一致性正则化及跨模态协同训练等通用半监督技术未作全面总结。Siddique 等人（2021）综述了深度学习医学图像分割的挑战与趋势，但仍以全监督方法为主，对多模态、跨域的半监督方法未作深入讨论。国内中文期刊中也已有相关综述工作关注医学图像分割方法的

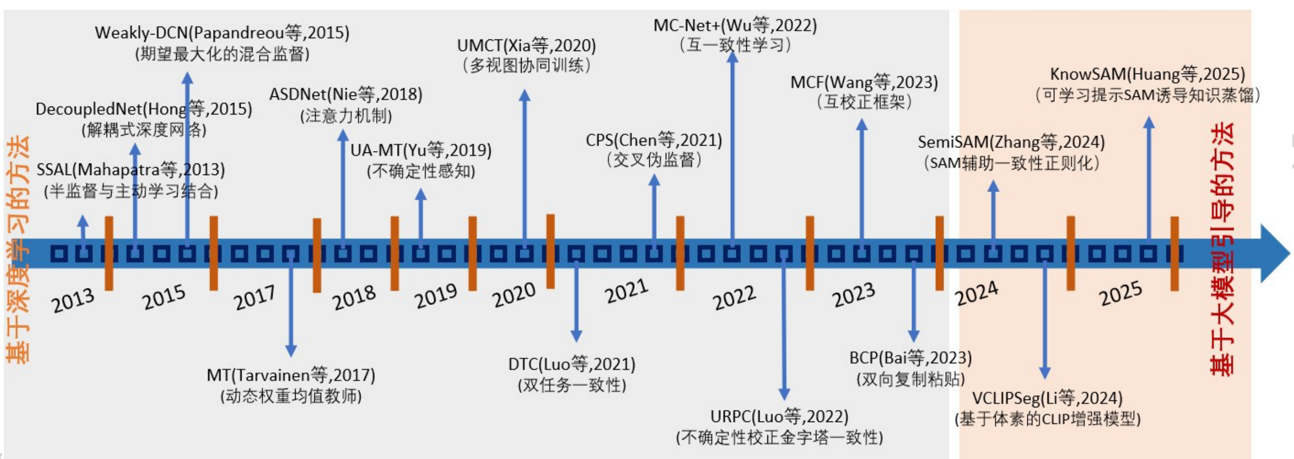
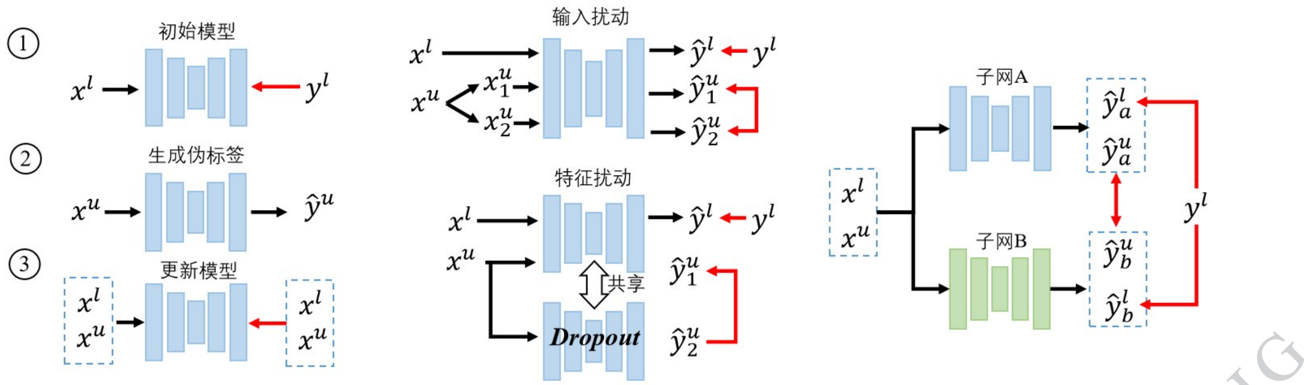



图 1　半监督医学图像分割的简要发展历程。2024 年之前的方法主要是非大模型的方法。自 2024 年以来，大模型的赋能极大地推动了深度学习技术在半监督医学图像分割领域的进步。更多细节可参见第 1 章节。

Fig. 1　A brief development history of semi-supervised medical image segmentation. Methods before 2024 were mainly non-large-model approaches. Since 2024, the empowerment of large models has greatly advanced deep learning technology in the field of semi-supervised medical image segmentation. For more details, see Chapter 1.

发展。杨鸿杰等人（2022）聚焦多模态医学影像分割，总结了深度学习方法在多模态信息融合与病灶区域分割中的研究进展；石军等人（2025）系统梳理了基于深度学习的医学图像分割方法，涵盖 U-Net、Transformer 及视觉基础模型等技术脉络。这些综述为医学图像分割领域提供了中文参考，但对半监督学习范式下伪标签、一致性正则化和协同训练等方法的系统梳理仍相对有限。

与上述综述相比，本文专注于半监督医学图像分割这一交叉领域，从伪标签生成、一致性正则化到协同训练的不同技术路径进行系统梳理，并重点分析了它们在高置信度伪标签生成、多域异构性建模




(a)伪标签法 (b) 一致性学习 (c)协同训练
((a) pseudo-labeling; (b) consistency; (c) co-training)

图2 典型的三种半监督医学图像分割框架

Fig. 2 Typical three semi-supervised medical image segmentation frameworks

及跨域适应等方面的最新进展。此外，本文还对类别不平衡、伪标签噪声传播及数据隐私保护等核心挑战进行了深入讨论，并展望了结合医学知识驱动、自适应筛选机制与隐私保护学习的新方向，旨在为相关研究人员提供更具针对性的参考和启示。

本文的主要贡献总结如下：

1)本文系统总结了近年来半监督医学图像分割的关键技术进展，重点围绕伪标签、一致性正则化与协同训练三大主流方法，详细剖析其理论基础、模型架构、优化策略及适用场景，为读者呈现了从基础方法到最新创新的完整技术脉络。

2)本文对多篇最新高影响力研究进行了对比分

**表1 半监督医学图像分割方法总结（2025年发表）**

**Table 1 Summary of Semi-Supervised Medical Image Segmentation Methods (Published in 2025)**

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 1 | 2025 | SKCDF(Zhang 等,2025) | CVPR | V-Net | 数据流解耦；语义互补；辅助平衡头 | link |
| 2 | 2025 | RD-Net(Li 等,2025) | CVPR | U-Net | 深度引导互学习；深度引导块增强 | link |
| 3 | 2025 | DyCON(Assefa 等,2025) | CVPR | 3D U-Net | 不确定性感知一致性；焦点熵感知对比 | link |
| 4 | 2025 | Enhanced SAM(Konwer 等,2025) | CVPR | SAM-Med2D | 高效提示；偏好优化 | N/A |
| 5 | 2025 | AmbiSSL(Kumari 和 Singh,2025) | CVPR | U-Net | 多解码器伪标签；交叉解码器监督 | N/A |
| 6 | 2025 | DiCo(Xu 等,2025) | CVPR | V-Net + UNETR | 动态师生切换；多视图集成；对抗监督 | link |
| 7 | 2025 | SynFoC(Ma 等.2025) | CVPR | U-Net + MedSAM | 基础模型协同训练；共识分歧一致性 | link |
| 8 | 2025 | ALHVR(Lei 等,2025) | ICCV | U-Net + V-Net | 高价值区域自适应学习；动态教师竞争教学 | link |
| 9 | 2025 | DVCL(Zhao 等,2025) | ICCV | 3D U-Net | 距离感知体素对比学习；邻居划分策略；查询异常检测 | N/A |
| 10 | 2025 | AdaMix(Shen 等,2025) | MIA | U-Net + V-Net | 自适应混合；自步调课程学习 | link |

表1续表

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 11 | 2025 | DSAIF(Gu等,2025) | MIA | V-Net | 双结构感知滤波;最大最小树滤波 | N/A |
| 12 | 2025 | SemiSAM+(Zhang等,2025) | MIA | 3D U-Net | 基础模型驱动半监督;专家-通才协同学习 | link |
| 13 | 2025 | w2sPC(Yang等,2025) | MIA | U-Net + 3D U-Net | 弱到强特征扰动一致性;边缘感知对比学习 | link |
| 14 | 2025 | AdvMIM(Zhu等,2025) | MICCAI | Swin-UNet + UNet | 对抗掩码图像建模;掩码域学习;域自适应 | link |
| 15 | 2025 | TextMoE(Zeng等,2025) | MICCAI | N/A | 文本增强混合专家;频率空间内容正则化 | link |
| 16 | 2025 | M3HL(Liu等,2025) | MICCAI | 3D V-Net + 2D U-Net | 互掩码混合;高低层特征一致性 | link |
| 17 | 2025 | SMMS(Meng等,2025) | MICCAI | N/A | 多阶段多模态融合;模态感知增强;对比互学习 | link |
| 18 | 2025 | STAR(Ma等,2025) | MICCAI | ResNet-50 | 空间聚合;空间交叉注意力;半监督主动学习 | link |
| 19 | 2025 | SGRS-Net(Wang等,2025) | MICCAI | V-Net | 协同引导区域监督;混合增强;分区损失评估 | link |
| 20 | 2025 | Text-SemiSeg(Huang等,2025) | MICCAI | V-Net | 文本驱动多平面交互;类别感知语义对齐;动态认知增强 | link |
| 21 | 2025 | AMVLM(Pan等,2025) | TMI | ViT-B/16 | 跨模态相似性监督;模态内对比学习;文本引导半监督 | link |
| 22 | 2025 | CGS(Wang等,2025) | TMI | U-Net | 通才-专家协同训练;头间错误检测;交叉分支一致性 | link |

注:“N/A”表示原文未明确说明相应主干网络或代码信息。

析,从分割精度、鲁棒性、跨域适应能力、计算效率等多个维度系统评估不同方法在超声、MRI和CT等多种医学影像模态下的应用表现,全面揭示了其优势与不足。

3)针对伪标签质量不稳定、类别不平衡、复杂解剖结构识别困难、以及医学数据隐私保护等关键问题,本文梳理了现有研究中的典型解决思路和存在的空白,进一步明确了亟突破的研究方向。

4)本文展望了结合医学知识驱动的解剖结构约束、自适应阈值动态筛选机制以及联邦学习与差分隐私融合的安全半监督框架等重要研究方向,旨在为未来提升分割精度、增强泛化能力和拓展临床应用提供指导和启示。

## 1 半监督医学图像分割方法

近年来,半监督学习在医学图像分割领域取得了显著进展,通过利用少量标注数据和大量未标注数据,有效缓解了医学图像标注成本高昂的问题。

**表2 半监督医学图像分割方法总结(2024年发表)**

**Table 2 Summary of Semi-Supervised Medical Image Segmentation Methods (Published in 2024)**

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 1 | 2024 | ABD(Chi等,2024) | CVPR | N/A | 双向位移;置信度调整 | link |

表2续表

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 2 | 2024 | MiDSS(Ma等,2024) | CVPR | U-Net | 中间域构建;对称引导训练 | link |
| 3 | 2024 | PH-Net(Jiang等,2024) | CVPR | ResNet-50 + U- Net | 自适应块增强;硬块对比学习;区域难度评估 | link |
| 4 | 2024 | AD-MT(Zhao等,2025) | ECCV | U-Net + V-Net | 随机周期交替更新;冲突对抗模块;交替多样教学 | link |
| 5 | 2024 | GA(Qi等,2024) | ECCV | 3D V-Net + 2D U-Net | 梯度感知损失;类别不平衡 | link |
| 6 | 2024 | TopoSemiSeg(Xu等,2025) | ECCV | UNet++ | 噪声感知拓扑一致性损失;信号拓扑一致性损失;噪声拓扑移除损失 | link |
| 7 | 2024 | PMT(Gao等.2025) | ECCV | V-Net | 渐进式均值教师;伪标签过滤;差异驱动对齐 | link |
| 8 | 2024 | SIAB(Qiu等,2025) | ECCV | U-Net | 统计个体分支;统计聚合分支;多级一致性正则化 | link |
| 9 | 2024 | AnatoSegUncertainty(Adiga等,2024) | MIA | V-Net | 解剖学感知表示;不确定性估计 | link |
| 10 | 2024 | CMMT-Net(Li等,2024) | MIA | V-Net + U-Net | 均值教师;交叉头协同训练;虚拟对抗训练 | link |
| 11 | 2024 | ReliablePseudoSeg(Su等,2024) | MIA | V-Net | 可靠伪标签;相互学习;类内相似性 | link |
| 12 | 2024 | SCL-Seg(Xu等,2024) | MIA | 2D U-Net | 分离协作学习;多站点学习 | N/A |
| 13 | 2024 | decoupledTrain(Das等,2024) | MICCAI | U-Net | 解耦训练;最坏情况感知 | link |
| 14 | 2024 | DiffRect(Liu等,2024) | MICCAI | U-Net | 潜在扩散;伪标签校正 | link |
| 15 | 2024 | FRCNet(He等,2024) | MICCAI | SegFormer-B4+AdaptFormer | 频率域一致性;多粒度区域相似性 | link |
| 16 | 2024 | MOST(Liu等,2024) | MICCAI | V-Net + U-Net | 多形态函数;软掩码 | link |
| 17 | 2024 | OMF(Liu等,2024) | MICCAI | V-Net | 学生-教师模型;知识蒸馏;形状感知 | link |
| 18 | 2024 | PSC(He等,2024) | MICCAI | U-Net | 配对混洗;一致性 | N/A |
| 19 | 2024 | CMC(Zhou等,2024) | MICCAI | N/A | 跨模态协作;对比一致性学习;特征融合 | link |
| 20 | 2024 | SDCL(Song等,2024) | MICCAI | 3D：VNet+ResVNet 2D：UNet+ResU-Net | 偏差纠正学习;学生-教师模型 | link |
| 21 | 2024 | Prior-Aware(Chen等,2024) | MICCAI | N/A | 通过对抗性学习的形状先验来正则化分割;编码器-双解码器网络 | link |
| 22 | 2024 | Textmatch(Li等,2024) | MICCAI | Mean Teacher structure | 文本提示;双边提示解码器;多视图一致性正则化;伪标签引导对比学习 | N/A |
| 23 | 2024 | VCLIPSeg(Li等,2024) | MICCAI | N/A | 体素智能提示;视觉文本一致性;动态标记 | N/A |
| 24 | 2024 | Boundary-Aware(Wang等,2024) | TIP | 改进的轻量级 U- Net | 基于边界感知原型;像素原型对比学习 | N/A |

表2续表

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 25 | 2024 | PPC(Yuan等,2024) | TMI | 3D V-Net + 2D U-Net | 解决数据不确定性问题;基于概率原型的分类器 | link |
| 26 | 2024 | COSST(Liu等,2024) | TMI | nnU-Net + 3D U-Net | 两阶段框架;将综合监督信号与自我训练相结合 | N/A |
| 27 | 2024 | LeFeD(Zeng等,2024) | TMI | N/A | 将反馈信号等信息馈送到编码器;从两个解码器获得特征级差异;通过训练差分解码器来扩大差异 | link |
| 28 | 2024 | DGARL(Xu等,2024) | TMI | N/A | 深度强化学习(DRL)域中的端到端半监督医学图像分割;整合DRL和GAN的管道 | N/A |
| 29 | 2024 | Inherent- onsistency (Huang等,2024) | TMI | U-Net+V-Net | 解剖结构分割;固有一致性 | N/A |
| 30 | 2024 | HSSF(Ma等,2024) | TMI | ResNet34 | 规则凝聚;规则融合;自我评估模块;伪标签生成模块 | N/A |
| 31 | 2024 | DDL(Zhou等,2024) | TMI | N/A | 掩码图像建模;多样联合任务学习;解耦学生学习 | link |
| 32 | 2024 | TraCoCo(Liu等,2024) | TMI | U-Net | 改变输入数据的空间输入上下文;干扰输入数据视图;置信区域交叉熵损失 | link |
| 33 | 2024 | MONA(You等,2024) | TPAMI | U-Net | 数据增强;最近邻;全局-局部对比 | link |

注:“N/A”表示原文未明确说明相应主干网络或代码信息。

为系统综述这些半监督分割算法,我们将现有的半监督医学图像分割方法主要可分为以下几类:

1)基于伪标签的方法:通过模型对未标注数据的预测生成伪标签,扩充原始标记数据集,从而提高训练的准确性并降低训练成本。这类方法的关键在于伪标签的质量优化和噪声过滤策略。其最大的缺点是可能会在训练数据中引入不准确的信息。

2)基于一致性的方法:基于扰动不应改变模型输出的假设,一致性学习旨在不同扰动下增强输入图像预测的不变性并将决策边界推送到低密度区域。这种方法由于其简单性而在半监督医学图像分割任务中广受欢迎。

3)基于协同训练的方法:利用多个模型或同一模型的不同视角进行协同训练,通过模型间的相互学习和监督,提高分割性能。这类方法通常结合差异最大化策略,以增强模型的多样性,尤其适用于较为复杂的场景。

图2为这三种方法的框架图。这些方法在减少标注依赖的同时,显著提升了医学图像分割的精度和稳定性,为临床辅助诊断提供了更高效的解决方案。

### 1.1 基于伪标签的方法

在半监督医学图像分割任务中,伪标签技术通过利用模型对未标注数据的预测生成“伪标记”,有效缓解了医学图像标注稀缺的问题。由于医学图像对分割结果的精确性和边缘细节要求极高,伪标签的质量直接影响模型的性能提升。因此,如何生成高置信度的伪标签,并减少错误标注带来的噪声干扰,成为了该领域的核心挑战。

近年来,研究者们从伪标签的生成策略、筛选机制、噪声校正、结构先验以及表示学习等多个维度出发,提出了一系列创新方法,显著提升了半监督医学图像分割的精度和鲁棒性。伪标签方法通常是其他半监督范式的基础监督信号,而不是孤立模块。例如部分一致性方法先用教师模型产生伪标签,再通过扰动一致性约束筛选可靠区域。因此,本文将此类方法归入伪标签分支时,主要依据其核心目标是提高伪标签质量或利用效率。以下我们将回顾几种

具有代表性的伪标签方法，重点分析其在医学图像分割中的关键技术与创新设计。

针对伪标签的可靠性评估与噪声抑制问题，部分工作致力于设计筛选或加权机制，以降低不可靠伪标签的负面影响。Su等人(2024)提出了ReliablePseudoSeg框架，使用双子网络相互学习，通过比较两个网络的预测置信度并利用类内相似性生成可靠性分数，以此作为权重减少不可靠伪标签的干扰。Mendel等人(2020)则引入辅助校正网络，不仅评估图像与分割结果的匹配程度，还提供修正建议作为未标记数据的代理标签，通过特定的损失函数与分割网络的预测结果相结合，自适应地调整其在训练过程中的贡献。为应对伪标签中存在的系统性错误与分布偏差，Liu等人(2024)引入潜在扩散标签校正模型，利用标签上下文校准模块(LCC)学习类别相关性，并借助潜在特征校正模块(LFR)通过扩散模型对潜在空间中的伪标签分布进行建模与对齐，实现从粗到细的连续分布转换，从而逐步

**表3 半监督医学图像分割方法总结（2023年发表）**

**Table 3 Summary of Semi-Supervised Medical Image Segmentation Methods (Published in 2023)**

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 1 | 2023 | BCP(BAI等, 2023) | CVPR | 3D V-Net | 双向复制粘贴；学生-教师模型 | link |
| 2 | 2023 | MagicNet(Chen等,2023) | CVPR | V-Net | 基于分割和恢复 N3 立方体；立方体伪标签混合；立方体位置推理 | link |
| 3 | 2023 | MCF(Wang等, 2023) | CVPR | 3D-ResVNet + V-Net | 对比差异审查; 动态竞争伪标签生成; | link |
| 4 | 2023 | PatchCL(Basak和Yin,2023) | CVPR | U-Net | 类感知补丁采样; 伪标签引导对比度损失; 伪标签生成与细化 | link |
| 5 | 2023 | MLB-Seg(Wei等,2023) | MICCAI | U-Net | 用于引导的元学习；基于一致性的伪标签增强；稳定元学习权重的平均教师； | link |
| 6 | 2023 | ACTION++ (You等,2023) | MICCAI | U-Net + V-Net | 自适应监督对比损失; 类特征自适应地匹配类中心; | link |
| 7 | 2023 | DCL(Basak和Yin,2023) | MICCAI | U-Net | 基于像素级特征一致性约束的内容解耦对比学习; 半监督微调 | link |
| 8 | 2023 | AC-MT(Xu等, 2023) | MIA | 3D V-Net/3D U-Net | 一致性目标选择；改进为模糊度共识均值-教师模型；从信息区域的扰动稳定性中学习 | link |
| 9 | 2023 | LCL-Pseudo (Chaitanya等, 2023) | MIA | UNet | 局部对比损失; 基于伪标签的自训练 | link |
| 10 | 2023 | semi-CML (Zhang等, 2023) | MIA | U-Net | 不同模态之间的跨模态信息和预测一致性进行对比互学习; 软伪标签重学习 | N/A |
| 11 | 2023 | TAC(Chen等, 2022) | TMI | 3D VNet + 2D UNet | 不成对一致性正则化损失; 基于特征映射中任务亲和一致性正则化; 结构亲和和上下文亲和 | link |
| 12 | 2023 | CV-SSL-MIS (Wang等,2023) | ICCV | CNN-based UNet +Swin ViT-based UNet | 3D ViT 对比一致性分割变换器；双对比学习策略和双一致性 | link |
| 13 | 2023 | CauSSL(Miao等,2023) | ICCV | 2D U-Net+3D V-Net+3D U-Net | 因果启发的 SSL 方法; 最小最大优化增强独立性 | link |

表3续表

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 14 | 2023 | ASE-Net(Lei 等,2022) | TMI | U-Net+U-Net++ + V-Net | 结合对抗性学习和一致性学习;基于动态卷积的双向注意力组件嵌入分割网络 | link |
| 15 | 2023 | SSRL-MVS (Chen 等,2023) | TMI | VGG13+ResNet | 18语义对比学习;受试者内和跨受试者切片预测机制 | link |
| 16 | 2023 | SASSL(Lyu 等,2022) | TMI | 2D U-Net | 伪标签引导图像合成;合成辅助交叉伪监督和合成辅助自训练 | link |
| 17 | 2023 | CS-CADA(Gu 等,2022) | TMI | U-Net | 跨解剖域自适应的对比半监督学习;域特定批归一化;集成到自嵌入均值教师框架 | link |
| 18 | 2023 | GCS(Chen 等,2022) | TMI | TRSF-Net | 生成一致;扰动数据的一致性 | link |
| 19 | 2023 | Graph Flow (Zou 等,2022) | TMI | U-Net | 基于教师网络和学生网络的特征流的知识提取;提取跨层图流知识和输出 | N/A |
| 20 | 2023 | SCANet(Shen 等,2022) | TMI | U-Net+ DeepLabV3 | 多尺度递归神经网络、一致性解码器和对抗学习 | N/A |
| 21 | 2023 | UDiCT(Qiao 等,2022) | TMI | U-Net | 不确定性的数据配对;混合样本数据增强;最小化监督损失和不可靠性稀释一致性损失 | N/A |
| 22 | 2023 | Cycle- Consistent(Zhang 等,2023) | TMI | RU-Net | 迭代循环一致性学习;自动上下文建模; | link |
| 23 | 2023 | SABR-Net (Chen 等,2023) | TMI | U-Net+ Attention U-Net + Deeplabv3 | 自适应掩码;基于边界细化的阴影感知网络 | N/A |
| 24 | 2023 | MMS(Lou 等,2023) | TMI | Res2Net | 双视图训练的对比学习;注重构建正负特征对 | link |
| 25 | 2023 | ComWin(Wu 等,2023) | TMI | 2D UNet + 3D VNet | 增强伪标签;竞争取胜策略;边界感知增强 | link |
| 26 | 2023 | CAT(Wang 等,2023) | TMI | ENet | 对抗性训练;不可微分约束的随机优化 | N/A |
| 27 | 2023 | DeSCO(Cai 等,2023) | TMI | V-Net | 密集伪标签学习,稀疏标签提升;标记一个体积的两个正交切片 | link |
| 28 | 2023 | DualRel(Mai 等,2023) | CVPR | ResNet50 | 线粒体分割;半监督语义分割;可靠的像素聚合、原型选择 | N/A |
| 29 | 2023 | SCP-Net (Zhang 等,2023) | MICCAI | U-Net | 自感知一致性学习;双损失重加权 | link |
| 30 | 2023 | CDMA(Zhong 等,2023) | MICCAI | ResNet50 | 多注意力三分支网络;交叉解码器知识蒸馏 | link |

注:“N/A”表示原文未明确说明相应主干网络或代码信息。

校正伪标签。Li等人(2020)则提出了SLU方法,采用自监督任务递归优化神经网络产生的自环不确定性作为伪标签,通过自监督任务递归优化网络。该伪标签可视为多个模型集成的不确定性估计的近似值,在减少推理时间的同时提升伪标签质量。

为了增强模型对解剖结构和形状先验的感知能

力，部分方法将形状约束或结构一致性引入伪标签生成过程。Chen 等人（2024）提出一种先验感知伪标签方法，采用编码器-双解码器网络架构，并引入对抗学习的形状先验作为隐式形状模型，仅惩罚解剖学上不合理的预测而不惩罚偏离真实标签的预测，从而在保持分割细节的同时提升结构合理性。Liu 等人（2022）提出的 SLC-Net 使用形状感知与形状不可知两个并行网络，通过跨模型伪监督相互提供伪标签，并借助形状感知和局部上下文约束生成解剖学上合理的预测结果。

跨域场景下的域偏移问题给伪标签的可靠性带来了额外挑战。针对此问题，Ma 等人（2024）提出混合域框架，通过统一复制粘贴（UCP）构建中间域样本缓解域偏移问题，并设计对称引导训练策略（SymGD）双向优化伪标签质量。并引入训练感知的随机幅度混合（TP-RAM）实现渐进式风格迁移，从而在跨域条件下提升分割性能。Lyu 等人（2022）另辟蹊径，不再直接改进伪标签质量，而是保留伪标签并合成与之匹配的新图像，为模型提供额外高质量训练数据，从数据增补角度缓解域差异问题。

对比学习因其在判别性特征学习中的优势，也逐渐被众多研究者引入伪标签框架中以提升分割性能。Basak 和 Yin（2023）利用伪标签为对比学习提供额外指导，同时借助对比学习中的类别信息反向优化伪标签质量，并设计了促进类间可分性与类内紧凑性的新型损失函数。Chaitanya 等人（2023）则提出局部对比损失，联合优化分割与对比损失，鼓励相同类别像素表示的相似性和不同类别像素表示的差异性，在有限标注下实现了高分割性能。

基于伪标签的方法也存在一定局限性。伪标签依赖模型早期预测质量，若初始模型偏差较大，错误伪标签会在迭代训练中被放大，尤其容易损害边

**表 4　半监督医学图像分割方法总结（2022 年发表）**

**Table 4　Summary of Semi-Supervised Medical Image Segmentation Methods（Published in 2022）**

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 1 | 2022 | ACPL(Liu 等,2022) | CVPR | DenseNet-121 | 交叉分布样本信息量；信息混合生成伪标签；锚定集纯化 | link |
| 2 | 2022 | BoostMIS(Zhang 等,2022) | CVPR | Wide ResNet50 | 自适应伪标记；信息主动注释；自动学习算法 | link |
| 3 | 2022 | CDCL(Wu 等,2022) | CVPR | DenseUNet | 对齐教师和学生网络的特征；一致性正则化；熵最小化 | linvk |
| 4 | 2022 | DSSML(Chai 等,2022) | CVPR | ResNet-101 | 学习度量空间；提案级别和原型级别双重对齐 | N/A |
| 5 | 2022 | GBDL(Wang 和 Lukasiewicz, 2022) | CVPR | 3D-UNet | 估计联合分布隐式；贝叶斯框架 | link |
| 6 | 2022 | SimMatch(Zheng 等,2022) | CVPR | ResNet-50 | 语义相似性；实例相似性；一致性正则化；展开和聚合操作 | N/A |
| 7 | 2022 | SDTL(Shi 等,2021) | TMI | CNN | 预先训练的结节识别模型；迭代特征匹配计算深度特征相似性 | N/A |
| 8 | 2022 | SSNS-Net(Huang 等,2022) | TMI | 3D ResUNet | 从受扰动的卷中重建原始卷进行与训练；像素级预测一致性 | link |
| 9 | 2022 | SimCVD(You 等,2022) | TMI | V-Net | 体素表示学习；无监督训练策略；蒸馏成对相似性来进行结构蒸馏 | N/A |
| 10 | 2022 | NRCF(Wu 等,2022) | MIA | U-Net | 自适应时空语义校准方法；利用时间信息来处理不规则和各向异性运动；平均教师半监督架构 | N/A |

表4续表

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 11 | 2022 | SDF+UWI+MTS(Wang等,2022) | MIA | U-Net | 利用辅助任务并考虑任务级别的一致性;施加形状约束的符号距离场;不确定性加权积分策略 | N/A |
| 12 | 2022 | DEP-Net+ECGSSL (Zhang等, 2022) | MIA | FCN-8 +ResNet-101 | 典型分割误差的特定掩码降级;针对未标记数据的双重纠错 | N/A |
| 13 | 2022 | SSA-Net(Wang等,2022) | MIA | ResNet34 | 自我注意机制;空间卷积;基于重新加权损失和高置信度选择预测值的半监督少样本迭代分割框架 | N/A |
| 14 | 2022 | MASS(Chen等,2022) | MIA | 3D U-Net | 利用从未配对的CT和MRI扫描获取独立知识;跨模态一致性;对比相似性损失来正则化两种模态 | link |
| 15 | 2022 | DC-MT(Huo等,2022) | MIA | Se-ResNeXt50 | 基于均值-教师分类模型;注意力损失函数;注意力一致性机制;聚合方法来集成切片级分类结果 | link |
| 16 | 2022 | URPC(Luo等,2022) | MIA | 3D-UNet | 一致性正则化;多尺度不确定性校正;不同尺度的分割预测 | link |
| 17 | 2022 | MC-Net+(Wu等,2022) | MIA | V-Net+U-Net | 多个不同的解码器;相互一致性约束;正则化 | link |
| 18 | 2022 | HCE+HC-loss(Jin等,2022) | MICCAI | DeepLabV3+ | 分层一致性执行;分层一致性损失 | N/A |
| 19 | 2022 | S5CL(Tran等,2022) | MICCAI | ResNet18 | 多种学习方式统一框架;反映距离关系层次结构 | link |
| 20 | 2022 | SSTAN(Zhao等,2022) | MICCAI | ResUnet | 时间局部上下文注意力模块;接近框架时空注意力模块;伪掩码 | link |
| 21 | 2022 | CVRL(You等,2022) | MICCAI | V-Net | 解剖信息;3D图像;双级对比优化 | N/A |
| 22 | 2022 | SS-Net(Wu等,2022) | MICCAI | U-Net+V-Net | 约束强扰动的像素的一致性;类级分离利用低熵正则化进行模型训练;探索像素级的平滑度和类间分离 | link |
| 23 | 2022 | TEAR(Yang等,2022) | MICCAI | AlexNet | 自适应放宽伪标签;迭代原型协调来鼓励模型以无监督的方式学习判别性表示 | link |
| 24 | 2022 | SLC-Net(Liu等,2022) | MICCAI | U-net | 跨模型伪监督;形状感知网络;形状无关网络 | link |
| 25 | 2022 | Labeling- Representations (Vasudeva等,2022) | MICCAI | V-net | 重建分割掩码;标记表示来估计像素级的不确定性 | link |

表4续表

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 26 | 2022 | SD-LayerNet(Fazekas等,2022) | MICCAI | U-net | 解剖先验;耦合;像素级结构化分割 | link |

注:"N/A"表示原文未明确说明相应主干网络或代码信息。

界模糊、小器官和少数病灶区域。置信度阈值、温度系数、类别重加权等超参数对结果影响明显,且不同数据集上的最优阈值难以迁移。扩散校正、对抗先验或多网络互教虽然能降低噪声,但会增加训练成本和实现复杂度;在临床部署中,还需要关注伪标签是否符合解剖常识以及是否会掩盖罕见病变。

总的来说,当前半监督医学图像分割中的伪标签技术已从单一的自训练范式发展为涵盖可靠性筛选、噪声校正、形状先验、跨域对齐、对比学习与图像合成等多条技术路径的多元化研究体系。这些方法分别从伪标签的生成、评估、校正、约束与增强等环节切入,有效提升了伪标签的置信度与稳定性,抑制了错误标注带来的噪声干扰,并在多个医学图像分割基准上取得了显著进展。未来,如何在保持高精度的同时进一步提升伪标签的边界细节感知能力与跨域泛化能力,仍将是该领域的重要研究方向。

### 1.2 基于一致性的方法

在半监督医学图像分割中,除了伪标签方法,研究人员还使用一致性正则化方法,通过约束模型对未标注数据不同扰动版本的预测一致性,在挖掘无标注数据分布特征方面发挥着至关重要的作用。医学图像多域异构性(如模态差异、成像噪声)及解剖结构复杂性,使传统约束易致模型泛化能力受限。近年来,研究者们从多层次特征对齐、解剖感知机制、不确定性对抗训练等方向展开了深入探索。一致性正则化常与伪标签和协同训练共同出现。均值教师框架中的教师预测可视为软伪标签,而扰动前后一致性用于约束其稳定性;双分支或多解码器方法则同时利用协同训练的模型差异与一致性损失。因而,一致性方法的边界主要体现在其优化目标是保持输入、特征或输出空间扰动下的预测不变,而不是单纯生成新标签。下文将梳理代表性方法,解析其技术突破与架构设计。

通过对输入数据施加扰动并约束预测一致性,是一致性方法中最简洁而有效的技术路线。He等人(2024)提出配对洗牌这一新型增强方法,将图像对拆分为块后随机重组以获得混合图像,通过利用随机图像进行训练有效挖掘补丁中的局部信息,再借助随机图像与非随机图像之间的一致性约束将局部信息与全局信息有效集成。Nguyen等人(2020)提出了一种依赖流形内与流形外样本的一致性正则化方法,结合插值一致性策略高效利用未标记数据,在显著减少标注需求的同时性能可媲美全监督方法。为了进一步丰富一致性正则化的约束形式,Xie等人(2021)提出基于对内-对间一致性的模型,通过构建跨图像的像素级注意力图以突显异图中同语义区域,再施加多图一致性约束过滤低置信区域,生成精炼注意力图并与原特征融合增强表征,同时设计对象级损失解决腺体接触导致的分割模糊问题。挖掘多幅图像之间的语义关联也能够进一步丰富一致性正则化的约束形式,Xie等人(2020)提出成对关系半监督模型,包含分割网络与无监督成对关系网络,其中成对关系网络通过挖掘图像对间的语义一致性增强特征表征,其学习成果反哺分割网络以提升性能,同时联合优化对象级Dice损失与交叉熵损失。针对三维医学影像中标注数据尤为稀缺的困境,Huang等人(2022)提出了SSNS-Net,包括两阶段半监督神经元分割方法:第一阶段设计自监督代理任务,通过重建受扰动的原始三维体数据预训练网络,隐式学习神经元结构特征;第二阶段利用未标记样本和扰动样本之间的像素级预测一致性来规范监督学习过程。在标签数量有限的情况下,提高了学习模型的泛化性。

面对不同成像模态及跨域场景带来的分布差异,一系列方法致力于通过特征解纠缠、知识迁移、对抗学习或跨模态协作等来实现域间对齐。Basak

**表5 半监督医学图像分割方法总结(2021年发表)**

**Table 5 Summary of Semi-Supervised Medical Image Segmentation Methods (Published in 2021)**

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 1 | 2021 | Semi-supervised Contrastive Learning(Hu 等,2021) | MICCAI | U-Net | 对比学习:结合了全局对比和局部对比 | link |
| 2 | 2021 | MC-Net(Wu 等,2021) | MICCAI | V-Net | 引入一种循环伪标签机制; | link |
| 3 | 2021 | Duo-SegNet(Zhong 等,2020) | MICCAI | U-Net | 双分支架构;特征融合;多尺度学习 | link |
| 4 | 2021 | Self-Supervised Correction Learning (Zhang 等,2021) | MICCAI | ResNet34UNet | 粗到精的策略;双任务网络;自监督学习;特征融合模块 | link |
| 5 | 2021 | DGNet(Liu 等,2021) | MICCAI | U-Net | 表示解耦;结合元学习;自监督学习与约束机制;领域泛化目标 | link |
| 6 | 2021 | task-driven data augmentation(Chaitanya 等,2021) | MIA | U-Net | 任务驱动的数据增强;双变换建模;端到端优化 | link |
| 7 | 2021 | self-paced and self-consistent co-training(Wang 等,2021) | MIA | ResNet | 自步学习策略;不确定性正则化;自集成损失;联合训练框架 | N/A |
| 8 | 2021 | ATSO(Huo 等,2021) | CVPR | FCN8s ×2 | 异步教师-学生优化;数据分割与交替训练;强化伪标签的动态性 | N/A |
| 9 | 2021 | collaborative andadversarial learning (Huang 等,2021) | ICCV | U-Net | 多模块特征提取; 对抗性训练框架; 一致性正则化; 辅助对抗学习 | link |
| 10 | 2021 | Graph-BAS3Net(Huang 等, 2021) | ICCV | GAN-based SSL+boundary-aware task | 边界检测任务; 基于图的跨任务模块; 边界感知的半监督学习 | N/A |
| 11 | 2021 | SCO-SSL(Xu 等,2021) | TMI | U-Net | 针对阴影伪影的设计; 通过 Shadow-AUG 和 Shadow-DROP, 与未标注数据协同使用 | link |
| 12 | 2021 | I2CS(Xie 等,2021) | TIP | EfficientNet | 双重一致性模块: 像素级关系建模, 一致性约束, 特征增强 | N/A |
| 13 | 2021 | CoraNet(Shi 等,2021) | TMI | U-Net | 基于不确定性估计的创新方法; 保守-激进模块; 确定区域分割网络; 不确定区域分割网络; 交替训练策略 | link |
| 15 | 2021 | RLSSS(Zeng 等,2021) | MICCAI | V-Net | 教师学生模型,互惠学习机制;独立于具体的 CNN 架构 | link |
| 16 | 2021 | AHDC(Chen 等,2021) | TMI | U-Net | 双向对抗推理模块;分层双一致性模块:层次一致性学习,域内学习,跨域 学习 | link |
| 17 | 2021 | CVRL(You 等,2022) | MICCAI | V-Net | 引入体素级对比学习; 双层对比优化 | N/A |
| 18 | 2021 | Semi-Weakly Super- vised Segmentation Algorithm(Reiß 等,2021) | MICCAI | U-Net | 多标签深度监督;学生-教师模型 | N/A |
| 19 | 2021 | IAG-Net(Wang 等,2021) | TMI | U-Net | 全局 MIL 中的注意力;局部 MIL 中的注意力; | N/A |

表5续表

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 20 | 2021 | Triple-Uncertainty Guided-Mean Teacher (Wang等, 2021) | MICCAI | U-Net | SDF 预测任务；任务级一致性；三任务不确定性；不确定性加权整合 (UWI)s | link |
| 21 | 2021 | 3D Graph-S2Net(Huang等, 2021) | MICCAI | MT+SDM | SDM 预测任务；任务间一致性； | N/A |
| 22 | 2021 | SSUMML(Zhu等,2021) | MICCAI | DeepCo-Training Framework（深度协同训练框架） | 多模态分割网络；图像翻译模块；语义一致性约束；类别均衡的伪标签生成 | link |

注："N/A"表示原文未明确说明相应主干网络或代码信息。

和Yin(2023)设计了两阶段分割框架，第一阶段通过域内容解纠缠对比学习提取域不变全局语义特征，结合像素级特征一致性约束增强局部空间敏感性，实现编码器自监督预训练。第二阶段采用半监督策略微调解码器完成下游分割任务。Chen等人(2022)提出一种类特定表征迁移方法，其核心是任务亲和性模块，将特征图分解为关注局部细节的视图和捕捉结构信息的视图，融合生成多尺度类表征。基于此构建亲和一致性损失，强制标记与未标记图像在类表征空间对齐，实现结构化知识迁移。为了进一步实现无配对多模态数据下的跨模态分割，Chen等人(2022)利用非配对的CT和MRI数据，通过使用跨模态一致性来规范语义和解剖空间方面的深度分割模型，学习模态内和模态间的对应关系，以扭曲地图集的标签以进行预测。还提出了一种对比相似性损失来规范两种模态的潜在空间，以便学习广义和鲁棒的模态无关表示。Zhou等人(2024)提出了一种新的多模态分割框架CMC，该框架协同结合了跨模态协作和对比一致性学习策略，在通道语义一致性损失的约束下确保不同模态之间与模态无关的信息得以对齐，同时整合对比一致性学习来调节解剖结构预测，有效促进了多模态场景中未标注数据的解剖学预测对齐。针对跨域场景中更为复杂的分布差异与样本失配问题，Chen等人(2021)提出自适应层次双重一致性框架，包含双对抗推理模块(BAI)和层次双重一致性模块(HDC)。通过双对抗推理模块实现跨域特征的互适应以消除域间分布差异与样本失配，再借助层次双重一致性模块在域内和域间分别施加一致性约束，实现了跨域半监督场景下的左心房精准分割。

提升类内特征的紧凑性与类间特征的可分离性也是一致性正则化的重要目标。Zhang等人(2023)提出了一种自我感知与跨样本原型学习方法，通过自我感知的一致性学习利用未标记数据提高每个类别中伪标签的紧凑性，同时在跨样本原型一致性学习中集成了双重损失重加权方法，有效提升了模型的可靠性与稳定性。Wu等人(2022)提出跨补丁密集对比学习模块，通过对齐教师网络与学生网络的特征，从补丁级和像素级的跨图像中采样，加强了特征的类内紧凑性与类间可分离性，同时设计了一种结合一致性正则化与熵最小化技术的新型优化框架，在缓解梯度消失方面表现出良好特性。

此外，为了充分保留医学图像中至关重要的结构信息，Xu等人(2025)引入噪声感知拓扑一致性损失，通过对齐教师模型与学生模型的表示，将预测的拓扑分解为信号拓扑与噪声拓扑两部分，从而确保模型学习真实的拓扑信号并增强对成像噪声的鲁棒性。

在局限性方面，一致性方法建立在"合理扰动不改变语义标签"的假设上，但医学图像中的强噪声、器官形变等差异可能使扰动后的图像偏离真实临床分布，导致一致性约束反而强化错误预测。此类方法对扰动强度、教师更新动量、无监督损失权重和训练阶段调度较敏感；多尺度或多域一致性还会增加显存与训练时间开销。对于边界极细或拓扑结构复杂的组织，仅依赖像素级一致性可能不足以保证解剖结构正确。

总的来说，当前半监督医学图像分割中的一致

**表6　半监督医学图像分割方法总结（2020年发表）**

**Table 6 Summary of Semi-Supervised Medical Image Segmentation Methods (Published in 2020)**

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 1 | 2020 | SLU(Li等,2020) | MICCAI | ResUNet-18 | 自环不确定性生成伪标签;Jigsaw 拼图任务;不确定性引导损失 | N/A |
| 2 | 2020 | FocalMix(Wang等,2020) | CVPR | 3D CNN | 软目标焦点损失;多次增强与集成;MixUp 增强;无标注数据利用 | N/A |
| 3 | 2020 | SRC(Liu等,2020) | TMI | DenseNet | 半监督自集成框架;样本关系一致性(SRC)范式;自集成教师模型 | N/A |
| 4 | 2020 | V-Net(Li等,2020) | MICCAI | V-Net | 符号距离图(SDM),生成精细的边界图; | link |
| 5 | 2020 | DMNet(Fang等,2020) | MICCAI | ResNet-34 | 低熵掩码生成;采用对抗训练策略,提高模型性能 | N/A |
| 6 | 2020 | DAFNet(Chartsias等,2020) | TMI | U-Net | 解耦图像中的解剖信息和模态特定的强度信息;STN 处理多模态图像之间的配准 | link |
| 7 | 2020 | AlexNet(Gyawali等,2020) | MICCAI | AlexNet | 输入和潜在空间的混合;标签猜测机制; | link |
| 8 | 2020 | ResNet101(Ouyang等,2020) | ECCV | ResNet101 | 自监督学习;通过局部池化窗口提取支持图像中的局部原型特征;基于相似度的分类器; | link |
| 9 | 2020 | 3DU-Net(Pérez-García等,2020) | MICCAI | 3D U-Net | 通过自生成的标签进行训练;模拟扰动生成切除空腔的掩模标签 | link |
| 10 | 2020 | S-Net(Xie等,2020) | MICCAI | DeepLabv3+ | 对偶一致性学习;通过图像扰动的一致性假设来提升模型鲁棒性;基于图像对的无监督学习模块; | N/A |
| 11 | 2020 | UATE(Cao等,2020) | TMI | Dense U-Net | 伪标签生成与不确定性映射;不确定性感知时间集成模型 | N/A |
| 12 | 2020 | CycleGAN(Wang等,2020) | TMI | U-Net | 生成对抗网络 CycleGAN 架构;判别器引导生成器通道校准(DGCC);基于变分自编码器(VAE)的判别器;噪声鲁棒学习过程 | N/A |
| 13 | 2020 | DeepLabv3+(Ibrahim等,2020) | CVPR | DeepLabv3+ | 辅助模型通过边界框注释提供弱标签;自我修正机制(线性自我修正、卷积自我修正) | N/A |
| 14 | 2020 | MMT-PSM(Zhou等,2020) | MICCAI | Mask R-CNN | 使用教师模型和学生模型的均值教师算法;选择具有高扰动敏感度的样本来进行蒸馏;通过语义分割掩膜引导特征蒸馏 | link |
| 15 | 2020 | ATSO(Huo等,2020) | CVPR | ResNet-18 | 异步教师-学生优化,关闭持续学习,避免重复使用无标签数据;迁移学习 | N/A |

表6续表

| # | 年份 | 方法 | 发表期刊或会议 | 主干网络 | 描述 | 代码 |
|---|---|---|---|---|---|---|
| 16 | 2020 | U-Net(Chen等,2020) | MICCAI | U-Net | 对抗性偏置场(bias field)模拟和虚拟对抗训练(VAT),通过对抗性训练不断优化;强度不均匀性建模 | N/A |
| 17 | 2020 | Dual-UNet(Yang等,2020) | MICCAI | Dual-UNet | 对抗学习;深度Q学习作为预定位;不确定性约束 | N/A |
| 18 | 2020 | NoTeacher(Unnikrishnan等,2020) | MICCAI | DenseNet121 | 伪标签;虚拟对抗训练;移除了教师模型的EMA更新,学生和教师模型完全独立 | N/A |
| 19 | 2020 | Error- Correcting (Mendel等,2020) | ECCV | DeepLabv3+ | 错误修正机制;伪标签生成 | N/A |
| 20 | 2020 | U-Net(Li等,2020) | MICCAI | U-Net | 结合同一领域(intra-domain)和跨领域(inter-domain)教师模型来高效利用标注数据、无标注数据以及跨模态数据; | N/A |
| 21 | 2020 | Semixup(Nguyen等,2020) | TMI | Siamese 网络 | 内外流形一致性正则化;两个共享权重的子网络 | N/A |
| 22 | 2020 | MCPM(Wang等,2020) | MICCAI | U-Net | MCPM基于元学习的框架来挖掘并减小标签腐化(噪声标签)对训练的影响;元掩膜网络;医学图像分割中的标签腐化仿真 | N/A |
| 23 | 2020 | ARL-GAN(Chen等,2020) | TMI | ARL-GAN | 解剖结构正则化;生成对抗网络(GAN)来实现源模态到目标模态的图像转换;转换保持正则化;循环一致性损失 | link |

注:“N/A”表示原文未明确说明相应主干网络或代码信息。

性正则化方法正在向数据增强、特征对齐与结构感知等多元技术路径发展。这些方法从数据空间、特征空间与输出空间等不同层面施加一致性约束,有效提升了模型对未标注数据的利用效率与泛化能力。未来,如何在保持计算效率的同时进一步增强一致性约束对医学图像中复杂解剖结构的感知能力,以及如何在更广泛的多模态、多中心数据场景下保持方法的鲁棒性,仍将是该领域的重要研究方向。

### 1.3 基于协同训练的方法

在半监督医学图像分割任务中,协同训练方法作为另一类重要技术路径,近年来受到越来越多关注。不同于一致性正则化直接约束模型对扰动数据的响应,协同训练通过引入多个模型或判别视角,使它们在未标注样本上相互指导、逐步提升各自的预测能力。这种策略尤其适用于医学图像中的复杂场景,如多模态融合或结构差异显著的区域分割,在提高模型稳健性和泛化性方面展现出独特优势。协同训练并不排斥伪标签或一致性机制,而是通过模型差异提供互补监督。例如部分不确定性感知协同训练会把置信度筛选作为伪标签质量控制环节。因此,协同训练的核心边界在于多模型、多分支或多视角之间的互教关系。接下来将围绕协同训练的典型方法展开分析,并探讨其在架构设计和训练机制上的关键创新。

为了提升协同训练中伪标签的质量与稳定性,一系列方法致力于优化双模型或多模型之间的交互机制。Zhao等人(2025)提出的AD-MT通过引入动态融合机制对两个模型的预测结果进行加权整合,从而提升伪标签的质量与稳定性。该方法还引入了交替多样性约束以防止模型间的收敛一致性陷阱。此方法展现出优于传统一致性监督的性能,尤其在

数据稀缺条件下更具优势。Li 等人(2024)提出的 CMMT-Net 构建了一个多尺度协同训练框架,在两个子网络之间引入通道和空间维度的调制机制,使得伪标签在不同尺度下能有效传递语义信息。该方法不同点在于通过调制机制增强了模型对关键结构的感知能力,同时抑制了背景干扰。与上述方法不同,Shi 等人(2021)提出的 CoraNet 引入保守预测和激进预测的双分支结构,利用预测结果之间的不一致性来估计不确定性,并指导伪标签生成。CoraNet 包含三个主要组件:保守-激进模块(CRM)、确定区域分割网络(C-SN)和不确定区域分割网络(UC-SN)。在训练过程中,C-SN 和 UC-SN 交替训练,分别处理确定区域和不确定区域的分割任务。这种协同训练策略使得模型能够更有效地利用未标注数据,提升分割性能。

不确定性感知是提升协同训练鲁棒性的另一重要技术路线。Qiao 等人(2022)提出不确定性感知的深度协同训练框架,利用不确定性信息选择高置信度的伪标签,从而提高伪标签质量并增强模型的泛化能力。Luo 等人(2022)在 URPC 中进一步提出不确定性感知的协同训练策略,分别以两个模型的预测不确定性为依据进行伪标签过滤和软增强,通过引入概率引导机制提升伪标签质量并抑制模型一致性陷阱。

在多模态场景下,协同训练通过多分支网络的相互指导实现跨模态知识迁移。Zhu 等人(2021)提出的 SSUMML 引入了两个独立的分支网络,分别处理不同模态的数据。通过交叉伪标签生成和一致性约束,这两个网络在训练过程中相互指导,从而实现协同学习。具体而言,每个网络利用自身对未标注数据的预测结果,生成伪标签供另一个网络学习。此外,SSUMML 还引入了对抗性训练机制,以增强模型对不同模态之间分布差异的适应能力。这种协同训练策略不仅提高了模型在未标注数据上的学习效率,还增强了其对多模态数据的泛化能力。

对于标注极为稀疏的场景,部分方法通过协同训练框架来显著减轻人工标注负担。Cai 等人(2023)提出密集-稀疏协同训练框架,仅在标注体积中标注两个正交切片,通过配准获得稀疏标注体积的初始伪标签,随后引入未标注体积并采用双网络范式,利用早期阶段的密集伪标签和后期阶段的稀疏标签同时强制两个网络输出一致。Vasudeva 等人(2022)提出语义引导的三元组协同训练框架,通过仅注释少量体积样本的三个正交切片减轻标注负担,并引入基于预训练 CLIP 模型的语义引导辅助学习机制,实现语义感知和细粒度的分割。

通过引入异构网络结构或样本关系约束,协同训练方法进一步增强了伪标签的多样性与特征表示的稳定性。Xu 等人(2023)提出的 AC-MT 构建了异构结构(3D UNet 与 3D VNet)间的协同训练框架,设计了不对称的一致性损失函数以强化模型间信息补偿,利用模型结构差异化促进伪标签多样性、减少过拟合风险,在多个 3D 器官分割任务中表现出强鲁棒性和泛化能力。Liu 等人(2020)提出基于样本关系一致性的半监督框架,采用 DenseNet 架构并训练多个自集成的教师模型以提供稳定伪标签,其核心在于保持有标注和无标注样本在特征空间中的相对关系一致,在训练过程中迭代更新教师和学生网络,通过最大化无标签样本间相似性的保持提升对未见样本结构的建模能力。

协同训练方法也有一定局限性,比如其依赖模型间差异提供互补信息,但差异过小会导致模型快速同质化,差异过大又可能互相传播噪声。异构网络或多分支解码器通常带来更高计算与显存开销,训练过程也更依赖更新频率、交叉监督权重和伪标签筛选策略。对于多中心或多模态数据,协同模型可能学习到站点特异性偏差;在临床场景中,还需评估额外模型复杂度是否与推理效率、可解释性和维护成本相匹配。

总的来说,当前半监督医学图像分割中的协同训练方法已从简单的双模型相互指导发展为交互机制优化、极弱标注协同、不确定性感知筛选、多模态交叉指导以及异构网络协同等多个技术方向。这些方法通过优化模型间的交互策略、降低对密集标注的依赖、提升伪标签的可靠性与多样性,以及拓展跨模态与复杂场景下的泛化能力等方法,有效推动了协同训练方法在医学图像分割中的应用。未来如何平衡模型异构性与训练稳定性,以及进一步提升协同训练在复杂临床场景下的泛化效率,仍是该领域面临的重要挑战。

## 2 数据集汇总与介绍

1)ACDC(Bernard 等,2018)是一个用于心脏

MRI图像分析和自动诊断的挑战数据集。它包含了150个病例的心脏MRI图像，每个病例包括不同的心脏阶段（如舒张期和收缩期）的图像。

2）PROMISE12（Litjens 等，2014）是医学图像分割领域的经典数据集，作为 MICCAI 2012 挑战赛的一部分，提供了50例前列腺MRI图像及其对应的分割标注。

3）M&Ms（Martín-Isla 等，2023）一个专注于在多中心、多设备、多疾病下进行心脏磁共振（CMR）图像中心脏分割的数据集，包括375 名患者，其中有多种病理的患者以及健康受试者。训练集包含150张已标注图像，以及25张未标注图像。测试集包含200个测试案例，包括来自训练集中每个供应商的50个新研究，以及来自第四个未见过的供应商的额外50个研究。

4）BUSI（Al-Dhabyani 等，2020）是一个包含乳腺超声图像的分类和分割数据集。该数据集包括了2018年收集的乳腺超声波图像，涵盖了25至75岁的 600名女性患者。数据集由780张图像组成，每张图像的平均大小为500*500像素。这些图像被划分为三类：正常、良性和恶性。

5）Pancreas-NIH（Roth 等，2016）是一个全面的数据集，包含几所有可用于胰腺癌发病率和死亡率分析的 PLCO 研究数据。该数据集包含 PLCO 试验中大约155,000名参与者的一条记录。

6）GlaS challenge（Sirinukunwattana 等，2015）由165幅图像组成，这些图像自16个经 H&E 染色的T3期或T42期结直肠腺癌的组织切片，组织切片数字化扫描后分辨率为0.465微米。数据集在染色分布和组织结构方面都表现出很高的受试者间变异性和组织结构方面都存在很大差异。

7）MoNuSeg（Kumar 等，2019）是一个用于细胞核分割的医疗图像数据集，由 TCGA 档案中的 H&E 染色组织图像创建。数据集包含38张训练图像和15张测试图像，每张图像都有对应的标注文件，可用于开发和评估细胞核分割技术。

8）LA Challenge 2018（Xiong 等，2021）该数据集一共有154例包心房颤动的3D MRI图像。MRI灰度分布在［0，255］，空间分辨率为0.625* 0.625* 0.625 mm³，切片尺寸因人而异，Z 轴包含88个切片，分为训练集和测试集。

9）NCI-ISBI13（Bloch 等，2015）60例前列腺MRI 3D 系列。训练由医学数字成像和通信（DICOM）图像组成，这些图像具有匹配的NRRD标记，可定义组织 CG 和 PZ，可通过癌症成像档案（TCIA）从 NCI 获取。

10）I2CVB（Lemaître 等，2015）提供多参数磁共振成像数据集，帮助开发计算机辅助检测和诊断（CAD）系统。

**表8　半监督分割模型在选定医疗数据集上的基准测试结果，评估指标包括Dice，IoU和95HD。**

**Table 8　Benchmarking results of semi-supervised segmentation models on selected medical datasets, with evaluation metrics including Dice, IoU, and 95HD.**

| 方法 | 发表刊物及时间 | ACDC | | | Pancreas-NIH | | | LA | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Dice | IoU | 95HD | Dice | IoU | 95HD | Dice | IoU | 95HD |
| CAD(Xiao 等,2025) | CVPR 2025 | .904 | .829 | 1.24 | / | / | / | / | / | / |
| BCP(Zhou 等,2025) | CVPR 2025 | .904 | .830 | 1.63 | / | / | / | .902 | .823 | 6.27 |
| PCCS(Li 等,2025) | CVPR 2025 | .864 | / | 5.57 | / | / | / | / | / | / |
| FedSemiDG(Deng 等,2025) | CVPR 2025 | / | / | / | .848 | .739 | .541 | .928 | .862 | 4.20 |
| CRLN(Wang 等,2025) | MIA 2025 | / | / | / | .835 | .720 | 4.70 | .920 | .852 | 4.33 |
| w2sPC(Yang 等,2025) | MIA 2025 | .902 | .812 | 4.01 | / | / | / | .911 | .835 | 5.94 |
| DSAIF(Gu 等,2025) | MIA 2025 | / | / | / | .829 | .708 | 6.43 | .921 | .853 | 4.68 |
| VerSemi(Zeng 等,2025) | TMI 2025 | / | / | / | .833 | .717 | 5.33 | .909 | .835 | 5.38 |
| SFR(Li 等,2025) | TMI 2025 | / | / | / | / | / | / | .910 | .835 | 6.13 |
| CvDd-Net(Zhong 等,2025) | MIA 2025 | / | / | / | .853 | .746 | 4.22 | / | / | / |
| ABD(Chi 等,2024) | CVPR 2024 | .890 | .807 | 1.57 | / | / | / | / | / | / |

表8续表

| 方法 | 发表刊物及时间 | ACDC | | | Pancreas-NIH | | | LA | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Dice | IoU | 95HD | Dice | IoU | 95HD | Dice | IoU | 95HD |
| AD-MT(Zhao等,2025) | ECCV 2024 | .888 | .804 | 1.48 | .802 | .675 | 7.18 | .896 | .813 | 6.56 |
| CMMT-Net(Li等,2024) | MIA 2024 | .911 | .841 | 1.17 | .835 | .714 | 5.36 | .918 | .850 | 4.95 |
| DiffRect(Liu等,2024) | MICCAI 2024 | .893 | .811 | 3.85 | / | / | / | / | / | / |
| Inherent-Consistency(Huang 等, 2024) | TMI 2024 | .895 | .815 | 1.42 | .812 | .687 | 6.17 | .893 | .807 | 6.96 |
| LeFeD(Zeng等,2024) | TMI 2024 | / | / | / | .822 | .712 | 5.25 | .914 | .842 | 6.15 |
| MOST(Liu等,2024) | MICCAI 2024 | .893 | .812 | 3.28 | .838 | .724 | / | .912 | .839 | 5.63 |
| PMT(Gao等,2025) | ECCV 2024 | / | / | / | .832 | .715 | 7.60 | .908 | .832 | 5.61 |
| ReliablePseudoSeg(Su等,2024) | MIA 2024 | / | / | / | .815 | .694 | 6.81 | .910 | .836 | 5.78 |
| SDCL(Song和Wang,2024) | MICCAI 2024 | .909 | .838 | 1.29 | .850 | .742 | 5.22 | .924 | .858 | / |
| TraCoCo(Liu等,2024) | TMI 2024 | .912 | .843 | 1.29 | .834 | .717 | / | .915 | .844 | 5.63 |
| BCP(Bai等,2023) | CVPR 2023 | .888 | .806 | 3.98 | .829 | .710 | / | .896 | .813 | 6.881 |
| PatchCL(Basak和Yin,2023) | CVPR 2023 | .923 | / | 3.66 | / | / | / | / | / | / |
| ACTION++(You等,2023) | MICCAI 2023 | .904 | / | / | / | / | / | .899 | / | / |
| CauSSL(Miao等,2023) | ICCV 2023 | .900 | .823 | 3.60 | .809 | .636 | 8.11 | / | / | / |
| CV-SSL-MIS(Wang和Ma,2023) | ICCV 2023 | .930 | .872 | / | / | / | / | / | / | / |
| MCF(Wang等,2023) | CVPR 2023 | / | / | / | .750 | .613 | 11.59 | .887 | .804 | 6.32 |
| ComWin(Wu等,2023) | TMI 2023 | .836 | / | 11.15 | .740 | .597 | 9.10 | / | / | / |
| SDF+UWI+MTS(Wang等,2022) | MIA 2022 | .914 | .849 | / | / | / | / | / | / | / |
| MC-Net+(Wu等,2022) | MIA 2022 | .885 | .802 | 5.35 | .806 | .681 | 6.47 | .911 | .837 | 5.84 |
| SS-Net(Wu等,2022) | MICCAI 2022 | .868 | .777 | 6.07 | / | / | / | .886 | .796 | 7.49 |
| URPC(Luo等,2022) | MIA 2022 | / | / | / | .803 | / | 6.58 | / | / | / |
| CVRL(You等,2022) | MICCAI 2022 | / | / | / | .767 | .612 | 8.24 | .905 | .830 | / |
| SimCVD(You等,2022) | TMI 2022 | / | / | / | .754 | .616 | / | .890 | .803 | 2.59 |

注:“/”表示对应论文未报告该数据集或该指标的结果。

11)FUGC(Bai等,2026)是ISBI 2025挑战赛发布的宫颈经阴道超声图像半监督分割基准数据集。该数据集包含890张TVS图像,划分为训练集、验证集和测试集,用于评估低标注条件下宫颈区域自动分割算法的性能,并采用DSC、HD和运行时间等指标进行综合评价。

12)AbdomenAtlas 1.1(Li等,2025)是面向腹部CT多器官分割的大规模三维医学图像数据集,包含9262例三维CT体数据,提供25类解剖结构的体素级标注,并包含7类肿瘤的伪标注。该数据集主要用于研究大规模有监督预训练和跨任务迁移能力,为腹部多器官分割模型训练和评估提供了重要资源。

13)PancreasDG(Zhang等,2025)是面向胰腺MRI分割和域泛化研究的多中心三维数据集,包含来自6家机构的563例MRI扫描,并覆盖静脉期和反相位等不同序列。该数据集提供像素级胰腺标注,可用于评估模型在跨中心、跨序列场景下的泛化能力,弥补了现有公开数据集中胰腺MRI分割资源不足的问题。

表7　根据年份、发表期刊、数据集大小以及分辨率，对数据集进行统计分析。有关每个数据集的更多详细信息，请参见第2章节。

Table 7　Perform statistical analysis on the datasets based on year, published journals, dataset size, and resolution. For more detailed information on each dataset, refer to Chapter 2.

| # | 数据集 | 年份 | 发表期刊 | 大小 | 分辨率 |
|---|---|---|---|---|---|
| 1 | ACDC(Bernard等,2018) | 2017 | TMI | 150 | [0.7 ~1.9]mm × [0.7 ~1.9]mm |
| 2 | PROMISE12(Litjens等,2014) | 2012 | MIA | 100 | [0.25 ~0.625]mm × [0.25 ~0.625]mm |
| 3 | M&Ms(Martín-Isla等,2023) | 2020 | JBHI | 375 | N/A |
| 4 | BUSI(Al-Dhabyani等,2020) | 2018 | Data in brief | 780 | 500 × 500 |
| 5 | Pancreas-NIH(Roth等,2016) | 2016 | TCIA | 82 | N/A |
| 6 | GlaS challenge(Sirinukunwattana等,2015) | 2015 | TMI | 16 | 1512 × 1516 |
| 7 | MoNuSeg(Kumar等,2019) | 2018 | TMI | 44 | 1000 × 1000 |
| 8 | LA Challenge 2018(Xiong等,2021) | 2018 | MIA | 154 | 0.625 × 0.625 × 0.625mm$^3$ |
| 9 | NCI-ISBI13(Bloch等,2015) | 2013 | TCIA | 80 | N/A |
| 10 | I2CVB(Lemaître等,2015) | 2015 | CIBM | N/A | [308 ~368] × [384 ~448] |
| 11 | FUGC(Bai等,2026) | 2026 | ISBI 2025/arXiv | 890 | N/A |
| 12 | AbdomenAtlas 1.1(Li等,2025) | 2025 | arXiv | 9262 | N/A |
| 13 | PancreasDG(Zhang等,2025) | 2025 | arXiv | 563 | N/A |

注：“N/A”表示相应公开资料未提供数据集大小的信息。

## 3　模型结果评估与分析

### 3.1　评估指标

我们简要回顾息肉分割任务中常用的三个关键评估指标：Dice相似系数（Dice Similarity Coefficient，DSC）、交并比（Intersection over Union，IoU）和95% Hausdorff距离（95% Hausdorff Distance，95HD）。

首先，我们介绍一些参数。真阳性（True Positive，TP）表示模型正确预测为正的正样本数（即正确分割的息肉像素数）。假阳性（False Positive，FP）表示模型错误地预测为正的负样本数（即背景像素被错误分割为息肉）。假阴性（False Negative，FN）表示模型错误地预测为负的正样本数（即息肉像素未被分割出来）。

1）IoU。交并比（也称为Jaccard系数）直接测量预测分割区域与真实目标区域之间的重叠程度。它计算两者交集面积与并集面积的比值。IoU同样对类别不平衡（如小息肉与大背景）具有鲁棒性。其计算公式为：

$$IoU = \frac{TP}{TP + FP + FN} \tag{1}$$

2）Dice。Dice系数衡量预测分割结果与真实标注之间的相似性，尤其关注分割区域的体积重叠精度。它对假阴性（FN）和假阳性（FP）同样敏感，是医学图像分割中广泛使用的核心指标。其计算公式为：

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

3）95HD。95% Hausdorff距离用于量化预测分割边界与真实分割边界之间的形状差异。其计算公式为：

$$95HD = \max\left(percentile_{95}\left(d_{A \to B}\right), percentile_{95}\left(d_{B \to A}\right)\right) \tag{3}$$

其中 $d_{A \to B} = \left\{\min_{b_j \in B} \|a_i - b_j\| \mid i = 1, \cdots, m\right\}$，

$$d_{B\rightarrow A}=\left\{\min_{a_i\in A}\|b_j-a_i\|\,|j=1,\cdots,n\right\},$$

A=预测边界点集，B=真实边界点集。

95HD 相较于最大 Hausdorff 距离（HD）对分割轮廓上的局部小错误（如小突起或凹陷）更不敏感，能更稳健地反映整体边界匹配度，单位为毫米（mm）。

### 3.2 性能比较和分析

为了量化不同模型的性能，我们对34个具有代表性的息肉分割模型进行了综合评估，时间跨度从2022年至2025年，包括模型：CAD（Xiao 等，2025），BCP（Zhou 等，2025），PCCS（Li 等，2025），FedSemiDG（Deng 等，2025），CRLN（Wang 等，2025），w2sPC（Yang等，2025），DSAIF（Gu 等，2025），VerSemi（Zeng等，2025），SFR（Li 等，2025），CvDd-Net（Zhong 等，2025），ABD（Chi 等，2024），AD-MT（Zhao 等，2025），CMMT-Net（Li 等，2024），DiffRect（Liu 等，2024），Inherent-Consistency（Huang 等，2024），LeFeD（Zeng等，2024），MOST（Liu 等，2024），PMT（Gao 等，2025），ReliablePseudoSeg（Su 等，2024），SDCL（Song 等，2024），TraCoCo（Liu 等，2024），BCP（Bai 等，2023），PatchCL（Basak 和 Yin，2023），AC-TION++（You 等，2023），CauSSL（Miao 等，2023），CV-SSL-MIS（Wang等，2023），MCF（Wang 等，2023），ComWin（Wu 等，2023），SDF+UWI+MTS（Wang 等，2022），MC-Net+（Wu 等，2022），SS-Net（Wu 等，2022），URPC（Luo 等，2022），CVRL（You 等，2022），SimCVD（You 等，2022）。

我们在三个公开数据集 ACDC（Bernard 等，2018），Pancreas- NIH（Roth 等，2015），LA（Xiong 等，2021）上，针对 Dice 系数、IoU 交并比、95HD 三项指标，对上述 34 种模型进行了独立评估。评估结果详见表7。

1）深度模型的对比：在基于深度学习的模型中，FedSemiDG（Deng 等，2025），SDCL（Song 等，2024），CvDd-Net（Zhong 等，2025），CRLN（Wang 等，2025），DSAIF（Gu 等，2025），CV-SSL-MIS（Wang 等，2023）有更好的性能。为了更深入地理解性能更优的模型，我们在以下内容中讨论这六个模型的主要特性。

2）CvDd-Net（Zhong 等，2025）通过利用形态差异和切片先验和视图依赖模块，高效融合多视图信息，尤其在数据有限场景下，提升了三维医学图像分割的精度和鲁棒性。

3）DSAIF（Gu 等，2025）通过结构感知滤波增强医学图像外观样性并保持拓扑结构，结合互监督网络缓解伪标签噪声，显著提升半监督分割性能，增强外观多样性同时保持结构一致性，有效提升了半监督医学分割的鲁棒性。

4）SDCL（Song 等，2024）采用双学生单教师架构，通过差异掩码和双损失机制提升分割精度，通过差异感知的迭代校正有效缓解了伪标签导致的认知偏差，显著提升分割精度。

5）FedSemiDG（Deng 等，2025）提出首个联邦半监督医学分割框架，通过动态调整聚合权重、本地双教师伪标签优化和通道丢弃等特征扰动强制模型学习域不变特征机制提升域泛化能力，有效解决多中心协作中的域偏移与标注稀缺问题。

6）CRLN（Wang 等，2025）通过多原型校正与动态交互模块提升伪标签质量，通过外部知识先验，原型与多分辨率特征的成对交互和跨类聚合和对比学习优化不确定区域的表征，显著提高了伪标签可靠性和分割精度。

7）BDG-Net（Qiu 等，2022）通过双对比学习、结合图像扰动与网络扰动的双一致性学习和双 Transformer架构解决医学图像标注数据稀缺问题。

需要说明的是，汇总结果主要依据各原始论文报告的公开数据集实验，部分方法的标注比例、数据集划分、预处理、和评价脚本等并不完全一致。因此，跨文献横向比较非严格统一实验条件下的性能排序，仅用于观察不同方法在常用基准上的大致性能区间和趋势。对于同一数据集下的严格比较，仍需结合原论文设置或在统一代码、统一数据划分下复现实验。

## 4 挑战与未来研究方向

尽管半监督医学图像分割方法已经取得了相对较好的性能，但存在的方法仍然面对一些挑战以及一些开放性问题有待未来研究。在本节中，本文概述了其中一些挑战和可能的未来方向，如下所述。

### 4.1 挑战

1）伪标签质量：在半监督医学图像分割任务中，伪标签的质量在很大程度上决定了模型训练的效果与稳定性。其本质挑战在于：模型缺乏外部验证来

判断自身预测是否可靠,高置信度未必准确,而低置信度区域(如病灶边界)却可能蕴含关键信息。为提升伪标签质量,现有方法包括基于不确定性估计的过滤策略、一致性正则化、多尺度特征融合、自适应阈值、时间一致性累计策略以及学生-教师框架等。但这些方法大多仍停留在“筛选可靠伪标签”的层面。未来研究应突破这一思路,从“筛选可靠伪标签”转向“构建可质疑的伪标签利用机制”,例如将伪标签机制与主动学习相结合,通过人机协同实现高价值样本的筛选,或引入外部先验知识进行交互验证,以推动半监督医学图像分割向更高精度发展。

2)类别不平衡问题:医学图像分割中普遍存在类别分布不均的问题,尤其在肿瘤、微小病灶等区域占比较小时更为突出。该挑战在半监督场景下更为显著:伪标签倾向于主导类别的高置信预测,易造成对少数类的关注不足。更深层的问题是,少数类因初始置信度低而被持续排除在伪标签训练之外,判别能力难以提升。为缓解此类偏差,现有方法从多个维度进行优化,包括加权 Dice、Focal loss 等类别敏感损失函数,基于稀有类别的重采样与数据增强,以及在伪标签生成中引入类别平衡约束或置信度调节策略。未来研究的关键在于从不平衡的“补偿”思路转向对潜在少数类的“主动发现”,而非仅依赖已知分布下的重加权策略。

3)数据隐私问题:医学图像数据高度敏感,受限于隐私保护法规及伦理审查,其获取与共享在跨机构协作中受到较大限制。这种分布式数据环境对传统半监督学习范式构成挑战。其核心矛盾在于:半监督学习依赖数据的集中式利用以充分挖掘未标注样本的信息,而隐私保护法规及伦理审查要求原始数据不得出域,两者之间存在冲突。针对上述问题,联邦学习通过在数据本地完成训练、仅交换模型参数,能够在不暴露原始数据的前提下实现多机构协同训练,结合差分隐私机制可进一步增强隐私保障。未来的研究可在通信效率提升、异构数据分布建模以及跨域知识迁移等方面进行优化,但从根本上看,应从“保护数据不出域”转向“在分布不可知条件下的有效知识共享”,以解决异构节点间的负迁移与联合建模问题。

### 4.2 未来研究方向

1)医学知识驱动:医学知识驱动的核心在于将解剖学先验(如形态规则、空间约束)融入半监督学习,以弥补标注不足导致的语义缺失。现有方法可分为两类:一是将知识编码为数学约束,如 Jones 等人(2022)提出的形状程序推断方法、Zhao 等人(2024)结合知识蒸馏与对抗扰动的半监督框架;二是利用自然语言描述对齐视觉特征,如 Li 等人(2023)的语言-视觉 Transformer、Pan 等人(2025)的对齐多重性感知视觉语言模型。然而,知识表达的准确性是主要瓶颈——过于严格则难以适应数据多样性,过于宽松则指导有限,如 Yu 等人(2025)通过对抗类自知识蒸馏框架实现知识权重的自适应平衡。未来研究可从两个方向突破:一是结合大语言模型自动提炼可计算的知识规则;二是设计分层融合机制,在底层注入几何约束、在高层引入拓扑约束。总体而言,知识驱动与数据驱动需动态权衡,构建可解释、可干预的分割系统是该领域的长期目标。

2)视觉基础大模型:视觉基础大模型(如 SAM)为半监督医学分割带来了零样本泛化和提示驱动的新范式。当前面临两大瓶颈:医学与自然图像的领域差异导致零样本性能有限,以及提示生成仍依赖专家知识。近期研究通过多模态大模型自动生成提示,如 Konwer 等人(2025)融合 BiomedCLIP、Med-VInT 和 GPT-4 自动生成视觉与文本提示,Jiang 等人(2024)提出的 TV-SAM 通过 GPT-4 生成描述性提示、GLIP 生成检测框、SAM 完成分割的三阶段流程。针对三维数据,Zhu 等人(2024)提出的 MedSAM-2 将 3D 图像视为视频序列,实现单次提示跨切片分割。在师生框架融合方面,Liang 等人(2025)提出的 STAR 框架将 SAM 融入均值教师架构,Li 等人(2025)提出的 SFR 框架在仅 1 个标注样本下实现显著改进。未来研究应聚焦三个方向:领域自适应预训练以缩小模态鸿沟;模型压缩以降低部署成本;以及当基础模型先验与医学证据冲突时的动态权衡机制。总体而言,多模态基础模型协同与终身学习框架是实现临床落地的关键路径。

3)3D 数据的部分标注:3D 医学图像分割的核心挑战在于利用稀疏标注提取全局结构信息。现有方法通过多级一致性约束、时序一致性增强或三任务互学习等方式挖掘 3D 数据的空间连续性,如 Sun 等人(2023)提出的多级一致性框架、Wen 等人(2024)利用动态特征提取和时间一致性约束、Chen 等人(2024)提出的三任务互一致性学习。未来研究可从三个方向推进:一是自适应标注策略,结合主动

学习动态选择信息量最大的切片进行标注;二是伪3D到真3D的渐进学习,通过轴向注意力或记忆增强网络建模长程依赖;三是解剖学先验引导,利用形状约束损失增强分割的拓扑正确性。此外,多模态协同标注也值得关注,如利用2D标注生成3D伪标签,或结合文本报告自动生成弱监督信号。总体而言,如何以最小标注代价获得完整的三维结构感知能力,是该领域的核心命题。

4)联邦半监督:联邦半监督学习的核心挑战在于客户端间的数据异质性及标注资源的非均衡分布。现有方法在模型聚合策略和客户端协作机制方面取得进展,如Wang等人(2024)提出的FedDUS框架通过动态权重聚合算法调整模型参数贡献度,Li等人(2023)开发的3SC-FL采用半集中式训练范式。在跨域泛化方面,Liu等人(2021)提出的FedDG-ELCFS通过频率空间插值技术编码多源域分布信息。未来研究应重点关注:基于强化学习的动态客户端选择以优化通信效率;元学习与隐空间解耦技术以增强跨域泛化;以及隐私-性能的帕累托前沿突破。此外,联邦神经架构搜索、基于区块链的激励机制、轻量级个性化微调技术等也是值得探索的方向。总体而言,联邦半监督学习有望成为多中心医学图像分析的基础范式。

5)轻量化模型:轻量化模型的核心目标是推动医学图像分割向临床实时化、移动化发展。当前技术路线主要包括三类:基于状态空间模型(state space models,SSM)的轻量化架构、多尺度动态特征融合网络、以及训练策略与部署的协同优化。在SSM架构方面,Wu等人(2024)提出的UltraLight VM-UNet通过并行视觉Mamba层压缩参数量,Liao等人(2024)提出的LightM-UNet采用纯Mamba架构的残差视觉Mamba层。在多尺度动态融合方面,Dong等人(2024)提出的MDSNet-Light通过动态调整感受野实现自适应尺度融合,Kassem等人(2024)开发的LW-MHFI-Net采用分层特征集成模块,参数量仅9.3M。未来研究需解决Mamba在深层网络的收敛难题,探索可微分神经架构搜索与解剖学先验结合的自动化设计,以及端侧异构计算单元的编译优化。总体而言,轻量化医学分割模型将加速向基层医疗、术中导航等场景渗透,最终实现“模型即医疗器械”的临床闭环。

## 5 结 论

本文系统性地综述了半监督医学图像分割领域的发展历程与评估体系,我们首先将现有方法划分为基于伪标签、基于一致性和基于协同训练的三大类别,继而从多维度深入剖析当前主流分割模型的算法特征。随后,本文汇总了常用的半监督医学图像分割数据集,并详细阐述了各数据集的关键信息。在此基础上,我们对34种具有代表性的分割模型进行了综合评估与性能分析。此外,本文探讨了当前研究面临的挑战,并指明了未来可能的突破方向。

通过系统梳理可以发现,三类方法呈现出互补关系:基于伪标签的方法在标注数据质量较高时优势明显,但需解决错误累积问题;基于一致性的方法对噪声和标注稀缺更具鲁棒性,适合低质量标注场景;基于协同训练的方法能够整合多模态信息,但计算成本较高。从整体发展趋势来看,半监督医学图像分割正逐步从依赖单一学习范式走向多范式融合,从仅关注分割精度走向精度、鲁棒性与隐私保护的协同优化。在此基础上,未来研究应优先关注以下三个方向:一是面向临床落地的算法轻量化与实时性优化,二是跨病种、跨模态的泛化能力增强,三是大模型与半监督学习的深度融合路径探索。

尽管过去几十年半监督医学图像分割领域已取得显著进展,但仍有较大提升空间。我们希望本综述能够为相关领域的研究者提供有价值的参考,并推动半监督医学图像分割技术的进一步发展。

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