Self-Supervised Pretraining with Meta-Learning for Few-Shot Intracranial Hemorrhage Segmentation

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Abstract

Accurate segmentation of intracranial hemorrhage in brain CT images is critical for timely diagnosis and treatment, yet the scarcity of annotated medical data poses significant challenges. This work presents a unified framework that combines self-supervised pretraining with meta-learning to enable few-shot intracranial hemorrhage segmentation. In the first stage, robust and domain-adapted feature representations are learned using contrastive learning and masked autoencoders on large unlabeled CT datasets, enhanced with medical image-specific augmentations. These pretrained encoders are then integrated into a meta-learning framework based on Model-Agnostic Meta-Learning (MAML) and Prototypical Networks, trained via episode-based sampling to facilitate rapid adaptation to new hemorrhage segmentation tasks. A U-Net-based segmentation architecture, enhanced with feature pyramid networks and attention mechanisms, serves as the backbone throughout. The proposed pipeline involves pretraining the encoder with self-supervised objectives, meta-training on limited annotated examples, and fine-tuning for few-shot adaptation. Evaluation using metrics such as the Dice Coefficient, Intersection over Union (IoU), sensitivity, and specificity demonstrates that our approach achieves state-of-the-art performance in few-shot settings, delivering both robust generalization and fast adaptation with minimal labeled data.

Keywords: **few-shot segmentation; self-supervised learning; meta-learning; intracranial hemorrhage; brain CT; U-Net**

1. INTRODUCTION

Intracranial hemorrhage (ICH) is a life-threatening condition characterized by bleeding within the cranial vault and requires rapid, accurate localization for effective clinical management. Non-contrast computed tomography (CT) is the gold standard for initial ICH detection due to its speed and widespread availability [1]. However, manual annotation of hemorrhagic regions is laborious and subject to inter-observer variability, leading to limited availability of high-quality labeled datasets [1]. The resulting data scarcity and the inherent variability in hemorrhage appearance pose significant challenges for fully supervised deep learning approaches.

Self-supervised learning (SSL) has emerged as a promising solution to mitigate labeling constraints by leveraging large corpora of unlabeled data to learn transferable feature representations [3], [4]. In medical imaging, contrastive learning—where an encoder is trained to distinguish between augmented views of the same image versus different images—has been shown to outperform conventional ImageNet pretraining on various tasks, including chest X-ray classification and dermatology image analysis [3], [4], [8]. Masked autoencoders (MAE), which learn to reconstruct deliberately masked regions, have further demonstrated efficacy in capturing global and local context, improving downstream segmentation performance in natural and medical domains alike [9]. Moreover, domain-specific augmentations such as intensity scaling and elastic deformations tailored to CT imaging characteristics enhance the robustness of the learned representations [3].

While SSL builds a strong backbone, the clinical reality of limited annotated examples necessitates models that can adapt rapidly—enter meta-learning. Gradient-based methods like Model-Agnostic Meta-Learning (MAML) train models on a distribution of tasks such that a small number of gradient steps on a new (few-shot) task yields significant performance gains [5]. Metric-based approaches, notably Prototypical Networks, learn a metric space where classification is performed by computing distances to class "prototypes" derived from support examples [6]. Episode-based training—sampling many small "support–query" tasks during training—further stabilizes learning and mirrors the few-shot evaluation scenario [7].

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Fig. 2. Visualization of Few-Shot Intracranial Hemorrhage Segmentation Pipeline and Results

Figure 2 shows example segmentation outputs. The proposed method yields sharper boundaries and more accurate detection of hemorrhagic regions compared to the baselines.

Conclusion and Future Work

Conclusion

In this work, we proposed a hybrid framework that integrates self-supervised learning and meta-learning for few-shot brain hemorrhage segmentation in CT images. The framework leverages large amounts of unlabeled data through contrastive and masked image modeling (SimCLR and MAE), and employs meta-learning strategies such as MAML and Prototypical Networks to enable rapid adaptation to new hemorrhage types with minimal labeled data.

Our results demonstrate significant improvements over baseline methods including supervised learning, ImageNet-pretrained models, and models using only self-supervision or only meta-learning. The proposed method achieved the highest Dice, IoU, sensitivity, and specificity scores across multiple few-shot scenarios, highlighting its robustness in low-data regimes.

Ablation studies confirm the critical role played by each component — particularly MAE, attention-enhanced U-Net, and Prototypical Networks — in improving segmentation accuracy. Qualitative results further validate the ability of the model to localize hemorrhagic regions with sharper boundaries and higher precision.

Overall, this work underscores the potential of combining self-supervised representation learning with meta-learning to tackle data scarcity challenges in medical image analysis, paving the way for more accessible and scalable clinical decision support systems.

Future Work

While the proposed approach shows promise, several avenues remain open for future investigation:

- **Cross-domain Generalization:** Future work can focus on evaluating the generalizability of the model across different modalities (e.g., MRI) or institutions with varying imaging protocols.
- **Model Efficiency:** While effective, the current framework can be computationally intensive. Exploring lighter backbone architectures or knowledge distillation strategies could make it more suitable for deployment in low-resource clinical settings.
- **Interactive Learning:** Incorporating user feedback into the few-shot learning loop could enhance adaptability and trust in real-time clinical workflows.
- **Multi-class Segmentation:** Extending the method to support multi-class segmentation of various hemorrhage types (e.g., epidural,

subarachnoid) in a single model would improve clinical usability.

- **Explainability:** Integrating explainable AI (XAI) techniques could enhance transparency and assist radiologists in interpreting model predictions, particularly for high-stakes medical applications.

By addressing these directions, the proposed hybrid framework can be further improved and adapted to serve as a robust, scalable solution for medical image segmentation in diverse real-world scenarios.

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