Few-shot Medical Classification: Methods, Challenges and Future Directions

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Abstract: In the context of medical imaging, due to the high cost and time-consuming nature of expert annotation, the scarcity of available annotated data often leads to overfitting during network construction. Few-shot learning offers a promising solution to this issue and has attracted significant research attention in recent years. This survey provides a comprehensive review of the most advanced techniques in few-shot learning-based medical image classification. Depending on the underlying deep learning mechanisms, existing methods are categorized into four groups: transfer learning-based, meta-learning-based, data augmentation-based, and multi-modal-based methods. This article also systematically summarizes publicly available few-shot medical image datasets and outlines prospective research directions.

Keywords: few-shot learning, few-shot medical image classification, transfer learning, meta-learning, data augmentation, multi-modal

1. Introduction

Medical images, such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and histopathology images, play a pivotal role in modern clinical practice for disease diagnosis, treatment planning, and prognostic assessment[1]. The integration of artificial intelligence into medical image analysis has significantly enhanced diagnostic accuracy and efficiency. However, AI models typically require large-scale annotated datasets for training, and conventional supervised learning models often suffer from overfitting and poor generalization when applied to data-scarce medical tasks. Few-shot learning (FSL) aims to learn rapidly from limited annotated examples, thus Its potential value in clinical applications, especially in resource-limited environments or in cases of emerging diseases, has led to a significant increase in the research community's interest in it. While several surveys discuss AI in medical imaging [2][3], and some touch upon learning with limited data[4], they often lack a dedicated and comprehensive focus on few- shot classification across the full spectrum of medical modalities.

2. Few-shot medical image classification methods

2.1 Transfer Learning-based Methods

2.1.1 Feature embedding-based Methods

Feature embedding-based methods aim to construct a latent feature space where inter-class separability is maximized and intra-class consistency is maintained. As is well known, Matching Networks [5] and Prototypical Networks [6] project both support and query images into a shared embedding space and classify queries by computing distances to support prototypes. These architectures have been widely adapted to medical tasks [7][8]. Besides, recent works enhance embeddings through domain adaptation [9][10]. After, attention mechanisms have also been integrated into embeddings [11]. Beyond CNNs, transformer-based embeddings have recently been investigated[12][13]. Overall, feature embedding-based methods in FSMIC highlight the importance of constructing task-agnostic but domain-relevant representations. By combining metric learning, attention, generative augmentation, and uncertainty modeling, embedding-based strategies provide a strong foundation for reliable few-shot classification in medical imaging.

2.1.2 Fine tuning-based Methods

Fine-tuning-based methods adapt pre-trained models to novel medical imaging task with few samples. Unlike embedding methods that focus on metric spaces, fine-tuning directly optimizes model parameters (partially or fully) to improve classification. Classical methods adopt full or partial fine-tuning of CNNs [14]. After, parameter-efficient fine-tuning methods were proposed[15]. With the development of the large vision-language models (VLMs) [16] such as CLIP. In addition, domain-specific fine-tuning has also been explored[17][18].

2.2 Meta-Learning-based Methods

2.2.1 Optimization-based Methods

Optimization-based meta-learning methods focus on learning initialization parameters or update rules that enable rapid task-specific adaptation. A prominent example is Model Agnostic Meta-Learning (MAML) [19], which optimizes for a shared initialization across tasks that can be fine-tuned with only a few gradient steps. MAML and its extensions[20][21] have inspired numerous FSMIC applications[22]. In FSMIC, MAML-based strategies are often combinedwith domain-specific augmentations to address variability in medical modalities[23]. Besides, several works integrate optimization met-learning with transfer learning[24]. Optimization-based FSMIC has also benefited from regularization enhancements [25] introduced taskspecific adaptive regularizers, preventing overfitting when adapting to small cohorts. Other methods leverage Bayesian meta-learning to estimate uncertainty during adaptation, improving safety in clinical decision-making [26].

2.2.2 Model-based Methods

Model-based meta-learning incorporate inductive biases through memory, gating, or modular structures, such as memory-augmented neural networks (MANNs), which can rapidly store and retrieve task-specific information. Recently, MANNs have been adapted for histopathological image analysis, enabling fast learning of rare cancer subtypes[9]. Besides, FSMIC studies integrate attention gates into CNNs for endoscopic image classification, allowing networks to dynamically adjust representations [11]. Afer, multi-modal module are proposed, combining image encoders with text-based memory retrieval for few-shot radiology classification.

2.3 Data Augmentation-based Methods

2.3.1 Transformation-based Methods

Transformation-based augmentation includes techniques such as rotation, flipping, scaling, cropping, and intensity modification [7]. Shorten and Khoshgoftaar's survey[27] outlined classical augmentation strategies and their applications in medical imaging. Moreover, patch-based augmentation methods, such as Cutoutand Mixup, have been adapted to FSMIC [28]. Besides, domain-specific transformations have also been developed[29]. In ultrasound imaging, speckle noise simulation has been applied to increase robustness [30]. While traditional augmentation is simple and effective, its capacity is limited because transformations are predefined and may not cover the full complexity of real medical variability. Nevertheless, it remains a necessary component of FSMIC pipelines, often used in conjunction with meta-learning or transfer learning frameworks. Its ease of implementation and computational efficiency ensure its continued importance in clinical applications.

2.3.2 Generative Models-based Methods

Generative models-based augmentation has gained significant traction in FSMIC, as it can synthesize entirely new, diverse samples that approximate the true data distribution. For example, Frid-Adar et al. [31] showed that GAN-generated liver lesion images improved CNN performance in limited-data scenarios. For few-shot classification, Guo et al. [10] proposed MedMFG, a plug-and-play feature generation approach where GAN-like modules generate synthetic embeddings that augment support sets. This strategy directly increases intra-class diversity and reduces prototype bias[9]. By sampling from latent distributions, VAEs provide smoother and less mode-collapsed augmentations than GANs, which can be advantageous in FSMIC with noisy medical labels. More recently, diffusion models have been explored for medical augmentation [32]. After, hybrid generative augmentation has also emerged.

2.4 multi-modal Methods

Unlike single-modal methods, which rely solely on visual information, multi-modal methods leverage another modal information to improve representation quality and enhance generalization in low-data regimes. The most influential framework is CLIP. Further advancements incorporate hierarchical contrastive alignment[16]. Another line of work explores domain-specific prompts. More complex multi-modal setups integrate structured clinical data[33]. Challenges remain: multi-modal FSMIC requires careful alignment of heterogeneous data, suffers from missing modality issues, and raises concerns about privacy when combining EHR and imaging data.

3. Conclusions

This paper provides a systematic review of few-shot learning for medical image classification, systematically categorizing and analyzing the four predominant methodological paradigms: transfer learning, meta-learning, data augmentation, and multi-modal learning. The reviewed literature demonstrates that while these methods have achieved significant progress in improving model generalization from limited examples, no single approach is a panacea. The most promising future

direction lies in the development of robust hybrid frameworks that synergistically combine the strengths of these paradigms. Future research must therefore not only pursue incremental performance gains on standardized datasets but also prioritize practical aspects such as domain generalization, computational efficiency, and integration into clinical workflows.

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