# Federated Active Learning for Multicenter Collaborative Disease Diagnosis

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Current computer-aided diagnosis system with deep learning method plays an important role in the field of medical imaging. However, it is difficult to construct large labeled datasets since the labeling of medical images is time-consuming, labor-intensive, and medical expertise demanded. In addition, centralized learning systems have shortcomings in privacy protection and model generalization. To meet these challenges, we propose two federated active learning methods for multicenter collaborative diagnosis of diseases: the Labeling Efficient Federated Active Learning (LEFAL) and the Training Efficient Federated Active Learning (TEFAL). The proposed LEFAL adopts a hybrid sampling strategy that simultaneously considers sample diversity and predicted loss, which can improve data utility. The hybrid sampling strategy adopted by LEFAL builds on our previous research, in which we propose a hybrid active learning framework HAL for efficient annotation in the medical field that combines active learning with deep learning to reduce the cost of manual annotation and take full advantage of deep neural networks. On the Hyper-Kvasir dataset, HAL achieved 95% of the performance of deep learning methods trained on the entire dataset using only 10% of the labels. The quantitative and qualitative analysis proves that HAL can greatly reduce the number of labels needed for training a deep neural network, which is robust to address efficient labeling problems even with imbalanced data distribution. Moreover, the proposed TEFAL uses discriminators to evaluate customer value to accelerate model convergence. The effectiveness and efficiency of the LEFAL and TEFAL are verified on two medical image datasets. On the Hyper-Kvasir dataset for gastrointestinal disease diagnosis, using only 65% of labeled data, LEFAL achieved 95% performance on the segmentation task for the entire labeled data. On the CC-CCII COVID-19 diagnostic dataset, with only 50 iterations, the accuracy and F1-score of TEFAL on the classification task were 0.90 and 0.95, respectively. A large number of experimental results show that the proposed federated active learning methods is superior to the most advanced methods in the segmentation and classification tasks of multi-center collaborative disease diagnosis.

目前，基于深度学习方法的计算机辅助诊断系统在医学影像领域发挥着重要作用。然而，由于医学图像的标记耗时，劳动密集，并且需要医学专业知识，因此很难构建大型标记数据集。此外，集中式学习系统在隐私保护和模型泛化方面存在不足。为了应对这些挑战，我们提出了两种用于疾病多中心协同诊断的联邦主动学习方法:标记高效联邦主动学习(LEFAL)和训练高效联邦主动学习(TEFAL)。该算法采用混合采样策略，同时考虑了样本多样性和预测损失，提高了数据利用率。LEFAL 采用的混合采样策略是基于我们之前的研究，我们提出了一种混合主动学习框架 HAL，用于医学领域的高效标注，将主动学习与深度学习相结合，降低人工标注的成本，充分利用深度神经网络。在 Hyper-Kvasir 数据集上，HAL 仅使用 10%的标签就实现了在整个数据集上训练的深度学习方法的 95%

的性能。定量和定性分析证明，HAL 可以大大减少训练深度神经网络所需的标签数量，即使在数据分布不平衡的情况下也能鲁棒地解决高效标注问题。此外，提出的 TEFAL 使用鉴别器来评估客户价值，以加速模型收敛。在两个医学图像数据集上验证了 LEFAL 和 TEFAL 的有效性和效率。在用于胃肠道疾病诊断的 Hyper-Kvasir 数据集上，仅使用 65%的标记数据，LEFAL 在整个标记数据的分割任务上取得了 95%的性能。在 CC-CCII COVID-19 诊断数据集上，仅迭代 50 次，TEFAL 在分类任务上的准确率和 f1 分分别为 0.90 和 0.95。大量实验结果表明，在多中心协同疾病诊断的分割和分类任务中，所提出的联邦主动学习方法优于目前最先进的方法。