Self-supervised Assisted Active Learning for Skin Lesion Segmentation

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Abstract—Label scarcity has been a long-standing issue for biomedical image segmentation, due to high annotation costs and professional requirements. Recently, active learning (AL) strategies strive to reduce annotation costs by querying a small portion of data for annotation, receiving much traction in the field of medical imaging. However, most of the existing AL methods have to initialize models with some randomly selected samples followed by active selection based on various criteria, such as uncertainty and diversity. Such random-start initialization methods inevitably introduce under-value redundant samples and unnecessary annotation costs. For the purpose of addressing the issue, we propose a novel self-supervised assisted active learning framework in the cold-start setting, in which the segmentation model is first warmed up with self-supervised learning (SSL), and then SSL features are used for sample selection via latent feature clustering without accessing labels. We assess our proposed methodology on skin lesions segmentation task. Extensive experiments demonstrate that our approach is capable of achieving promising performance with substantial improvements over existing baselines.

Clinical relevance—The proposed method can smartly select samples to annotate without requiring labels for model initialization, which can save annotation costs in clinical practice.

I. INTRODUCTION

Segmenting lesions and pathological structures from medical images has received great attention in clinical practice. Recently, deep learning has set up an incredibly high standard in semantic segmentation tasks \cite{1,2,3}. However, such success of deep neural networks always comes with the price of massive amounts of high-accuracy annotations. Additionally, obtaining labeled large-scale datasets at pixel-level is time-consuming, labor-intensive and expensive, requiring extensive clinical experience.

Common label scarcity scenarios encourage research into alleviating the annotation burden under limited supervision, including semi-supervised learning (SSL) \cite{4,5,6}, self-supervised learning \cite{7,8}, transfer learning (TL) \cite{9,10,11,12} and active learning (AL) \cite{13,14,15}. More recently, deep active learning receives much attention, since it can reduce annotation costs while maintaining model performance. AL is developed to judiciously query valuable samples for annotation based on various criteria and then update the current model in an iterative manner \cite{16}. To obtain an initially trained segmentation model, AL requires a minimal set of base annotations for initialization, while most existing AL methods randomly select samples from the unlabeled pool with cold-start \cite{17,18,19}, followed by active selection based on different criteria, including entropy \cite{13}, diversity \cite{20} and representation \cite{21}. However, such cold-start/random-start initialization may introduce under-value labels, leading to annotation redundancy. Moreover, suboptimal initial models may affect the quality of the following AL selection, especially for model-based methods \cite{13,14}. By enforcing transformation consistency between similar unlabeled samples, self-supervised learning (SSL) methods can learn transferable representations for downstream tasks \cite{8,21,22}, which motivates us to explore the robust representation ability of SSL for model initialization and sample selection.

In this work, we introduce a novel warm-start active learning method, in which we first train a self-supervised model to learn deep features in the latent space, and leverage distance-based clustering to build an initial representative set for annotation, thereby reducing annotation costs and minimizing the redundancy. To validate our proposed methods, extensive experiments are conducted on ISIC 2017 skin lesion dataset \cite{23}. Quantitative results indicate that our approach exceeds various baselines by large margins, with the proposed sample selection for AL initialization.

II. RELATED WORK

In active learning, the model is fine-tuned iteratively with newly-annotated samples by selecting unlabeled samples for annotation using various AL strategies based on uncertainty and diversity \cite{16}. With the great progress of deep learning, deep active learning (DAL) has emerged \cite{5,13,20,24}. For instance, Zhou et al \cite{20} proposed an AIFT framework, in which, the model is continuously fine-tuned, and valuable samples are selected based on model uncertainty and diversity for gradually improving model performance. CEAL \cite{13} adopts a complementary sample selection strategy for skin lesion segmentation by assigning pseudo labels to samples with low prediction confidence and querying annotations for those samples with high uncertainty iteratively. Despite the great success of these methods, most existing DAL methods focus on sample selection using model-based criteria and highly rely on the initial model performance trained with randomly-annotated labels, ignoring the validity and feasibility of initial labels. Zheng et al \cite{25} developed representative annotation (RA), a one-shot active learning method for fast selecting representative samples through extracted features from an unsupervised network.

Recently, self-supervised learning has witnessed the significant potential for learning visual representations, achieving promising performance for a wide range of computer vision
applications [26]. In self-supervised learning, pretext tasks with unlabeled data are designed for visual representation
learning and model initialization. For medical imaging, Zhou et al [8] devised a self-supervised learning framework, i.e., ModelGenesis, in which, reconstruction loss is constructed with various transformation techniques to improve self-supervised performance for downstream tasks. We are inspired to advance SSL into AL for model warm-up and representative sample selection.

III. METHODOLOGY

Fig. 1 illustrates the proposed active learning architecture, in which, a self-supervised learning framework is firstly built to explore features from unlabeled dataset as well as warm up the segmentation model. Then, based on clustering results of latent features extracted from SSL, we develop a criterion to select representative samples from unlabeled data, forming the initial dataset for training with warm-start. In this self-supervised manner, we make full use of robust representation learning of SSL from both aspects of the model and features for model initialization and sample selection.

A. Self-Supervised Learning Model

In our framework, U-Net [2], a well-known encoder-decoder architecture, serves as the backbone segmentation network in our system and is also utilized for self-supervised learning. To learn robust features from unlabeled data, we follow ModelGenesis [8] to perform a series of deformation operations and enforce reconstruction consistency between original images and responding transformed ones. Specially, we denote the training dataset as \( \mathcal{X} = \{(x_i)\}_{i=1}^{N} \), where \( x_i \) is the input 2D medical image, and \( N \) is the number of samples. The model is optimized by minimizing the reconstruction loss between original images and recovered images as:

\[
\min_{\theta} \sum_{i=1}^{N} l(f(D(x_i); \theta), x_i),
\]

where \( l \) is the reconstruction loss, \( f(\cdot) \) is the self-supervised neural network, \( D(\cdot) \) is the deformation operations, and \( \theta \) denotes the model weights. We adopted \( L_2 \) distance to measure the reconstruction loss, and deformation operations including nonlinear changes, local pixel perturbation out/in-painting were adopted to learn visual features, e.g., surfaces and texture via self-supervised learning.

B. Embedded Feature Clustering

The latent features of the last encoder are always transferred for downstream tasks, such as classification. Following the paradigm of SSL, similar images should have similar latent features. In other words, the neighbors in latent space to the inferred cluster centroids should be more representative. To cluster SSL features in a compact space, we first adopt adaptive average pooling (AAP) [27] to downsample the SSL features extracted from the last encoder layer for reducing dimensions and filtering some redundant information. Then, we apply \( K \)-means [28], [29] for clustering, and its objective can be expressed as:

\[
\arg \min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \| \phi(x_i) - \mu_i \|^2,
\]

where \( k \) is the number of clusters, and \( S_i \) is the cluster subset, \( \mu_i \) is the mean of all points in \( S_i \). The centroids can be regarded as the representative of the cluster, and then we select the centroids and their \( N_{C_i} \) neighbors based on \( L_2 \) distance to form our initial dataset. The number of selected samples in cluster \( C_i \) is defined as \( N_{C_i} = \lfloor C \times N_i / N \rfloor \), where \( C \) is the number of candidates for annotation to build the initial training dataset, \( N_i \) is the number of samples in cluster \( C_i \), and the total number of samples is denoted by \( N \) in the dataset. In this manner, the representative samples were selected to warm up the model.
C. Segmentation Model

Prior to the AL procedure, the pre-trained weights from the self-supervised learning model are adopted to initialize the segmentation model. The segmentation loss in our model is formatted as

\[ L_{seg} = L_{ce} + L_{dice}, \]

where \( L_{ce} \) is the cross-entropy loss, and \( L_{dice} \) is the Dice loss, which is widely used in various segmentation tasks [30]. Similar to other AL methods, our model is further finetuned with the enlarged labeled dataset iteratively based on our representative criterion. Alternatively, our model can be trained with the initially labeled dataset in a one-stop manner.

TABLE I

| Select Criteria | Random | Pre-trained weights |
|-----------------|--------|---------------------|
|                 | W/o    | W/                  |
| Dataset         |        |                     |
| ISIC 2017       |        |                     |
| Pre-trained weights |        |                     |
|                  |        |                     |

IV. EXPERIMENTS

A. Dataset and Experimental Settings

The ISIC 2017 dataset [23], which contains 2000 RGB dermoscopy images manually annotated by medical specialists, was chosen for our experimental assessment. For preprocessing, the dermoscopy images were resized to 256 \times 256 and transformed to grayscale, followed by min-max normalization. We formed the unlabeled pool of 1,600 unlabeled images for representative selection and another 400 for testing. The most common segmentation metric, Dice coefficient [5] was used to evaluate the segmentation performance, which calculates the overlap ratio between ground truth labels and predicted segmentation masks. Thus, a higher Dice would mean better segmentation performance.

According to the representative rank-based selective criteria via clustering, 300 samples were selected for annotation and formed as the base training set. Following [13], we set initial training epochs as 10, the number of iteration \( T = 9 \), and at each iteration \( t \), 35 labeled samples were added to the training set for training 2 epochs. In our method, Adaptive Average Pooling (AAP) was used to reduce dimensionality to process the SSL features from a dimension of 512 \times 16 \times 16 to 512 \times 2 \times 2, obtaining 2048-dimensional features after flattening. The number of clusters here was set to 10.

B. Results and Discussions

To corroborate the efficiency of our initial sample selection strategy, we first compare the proposed approach with a random query strategy on base set initialization and following a few iterations. Table II summarizes the experimental results. We can observe that initialization with samples based on random query achieved 58% in Dice, while our AL criteria can achieve much better performance, which demonstrates that it is feasible to select representative samples based on SSL features for annotation. We further implemented both the random query strategy and our method with pre-trained SSL weights, and observe that pre-trained SSL weights can boost the segmentation performance. Through the first few iterations, the training set was enlarged to 580. A considerable improvement in segmentation performance over the baseline random query method. It is noted that the pre-trained weights may decrease performance slightly for the initial few iterations, especially for random queries, which possibly because the pre-trained SSL features take the dominant of the model training with only few training epochs. Along with the iterations increase, more task-related features are learned, boosting the segmentation performance.

To further evaluate the effectiveness of the proposed method for AL, we compared our approach with representative AL counterparts, including ensemble-S (ens-S) [17], [18], ensemble-JS (ens-JS) [19], MC Dropout (MCD) [31], CEAL [13], and DSAL [5] on the same AL scenario [5]. The final results after 9 iterations are shown in Fig. 2. It can be observed that the proposed method achieved comparable performance among different AL methods, which demonstrates that our method can not only help initial set selection but also serve as an AL criterion for iterative training.

To investigate the influence of cluster number and dimensionality, we squeeze features from a dimension of 512 \times 16 \times 16 to 512 \times 2 \times 2 or 512 \times 1 \times 1, obtaining 2048-dimensional or 512-dimensional features after flattening, while the numbers of clusters were set to 10 or 5 as shown in Table II. We observe that increasing the feature dimensions and the number of clusters can help improve the model performance, since higher dimensions of features can preserve more important spatial information, while more clustering centroids can help reduce information redundancy and extract more representative samples in the feature space.

V. CONCLUSIONS

This paper presents a deep feature selection strategy based on self-supervised learning by projecting into the hidden space to query representative samples, and the initialization
strategy of AL with pre-trained weights from self-supervised learning. According to extensive experiments, the proposed AL scheme successfully boosts the baseline performance by a significant margin. Furthermore, experiments with different clusters and feature dimensions have been conducted to verify the efficiency of the various components of our framework. In the future, combinations with other selection criteria could be explored, and we could implement our framework for more medical segmentation datasets to evaluate the generalization ability.

### Table II

**Segmentation Results of Different Methods on ISIC 2017 Dataset Without Initial Pre-trained Weights.**

| Iter | Random | Cluster 5 AAP 312 | AAP 2048 | Cluster 10 AAP 512 | AAP 2048 |
|------|--------|------------------|---------|-------------------|---------|
| Base | 0.580  | 0.714            | 0.734   | 0.739             | 0.744   |
| t = 1 | 0.614  | 0.676            | 0.690   | 0.667             | 0.647   |
| t = 2 | 0.657  | 0.723            | 0.720   | 0.699             | 0.716   |
| t = 3 | 0.717  | 0.737            | 0.719   | 0.736             | 0.743   |
| t = 4 | 0.708  | 0.749            | 0.753   | 0.741             | 0.750   |
| t = 5 | 0.772  | 0.767            | 0.776   | 0.747             | 0.767   |
| t = 6 | 0.776  | 0.786            | 0.784   | 0.779             | 0.797   |
| t = 7 | 0.776  | 0.783            | 0.784   | 0.776             | 0.800   |

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