# Think Twice Before Selection: Federated Evidential Active Learning for Medical Image Analysis with Domain Shifts

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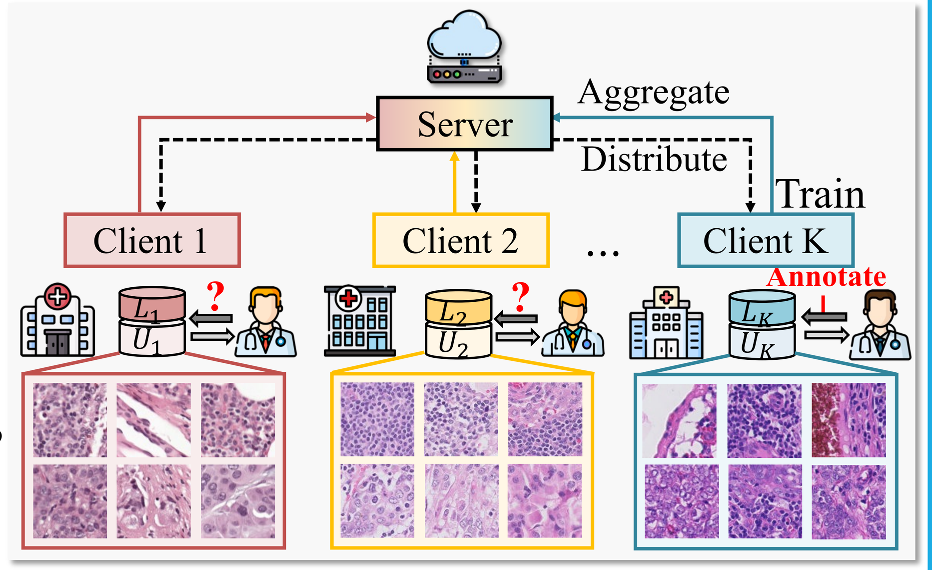
CVPR SEATTLE, WA JUNE 17-21, 2024

## Challenge

- **Annotation cost**
  Labeled data scale is constrained by the available expertise, time, and budget for data annotation.




- **Overconfidence**
  Existing methods evaluate data uncertainty based on softmax prediction, which are easily miscalibrated on data with domain shifts.
- **Limited uncertainty representation**

$$\textit{Uncertainty}\begin{cases}\textit{Aleatoric uncertainty } (\surd)\\ \textit{Epistemic uncertainty } (\times)\end{cases}$$

  The softmax prediction fails to capture epistemic uncertainty, resulting in incomplete evaluation.

## Motivation

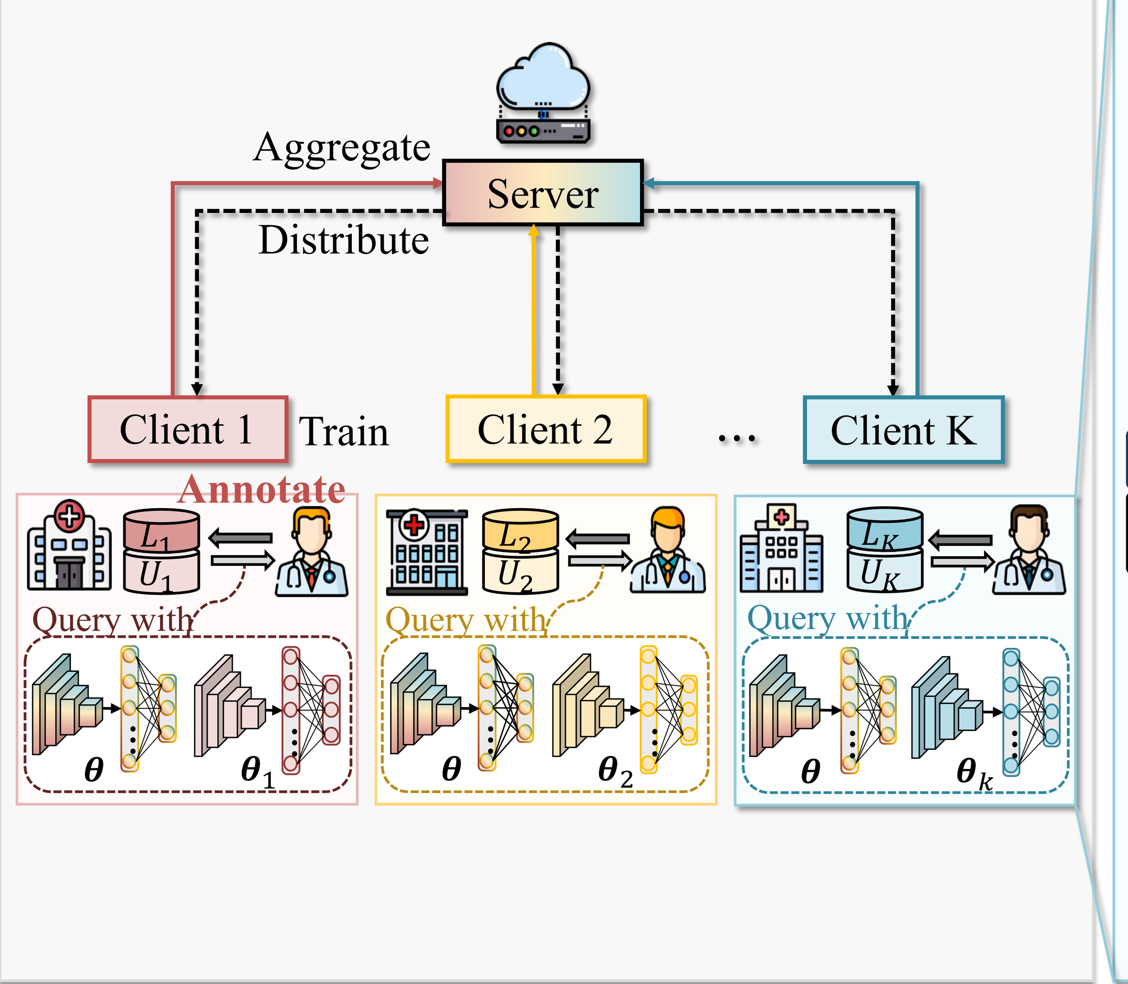
- We employ **Federated Active Learning (FAL)** to identify and annotate informative data, thereby reducing annotation costs.
- We utilize the **Dirichlet-based evidential model** to treat the categorical prediction of a sample as following a distribution, allowing multiple potential predictions for a sample.
- We evaluate data uncertainty by considering epistemic uncertainty in the global model and aleatoric uncertainty in both global and local models for **comprehensive uncertainty representation**.

## Contribution

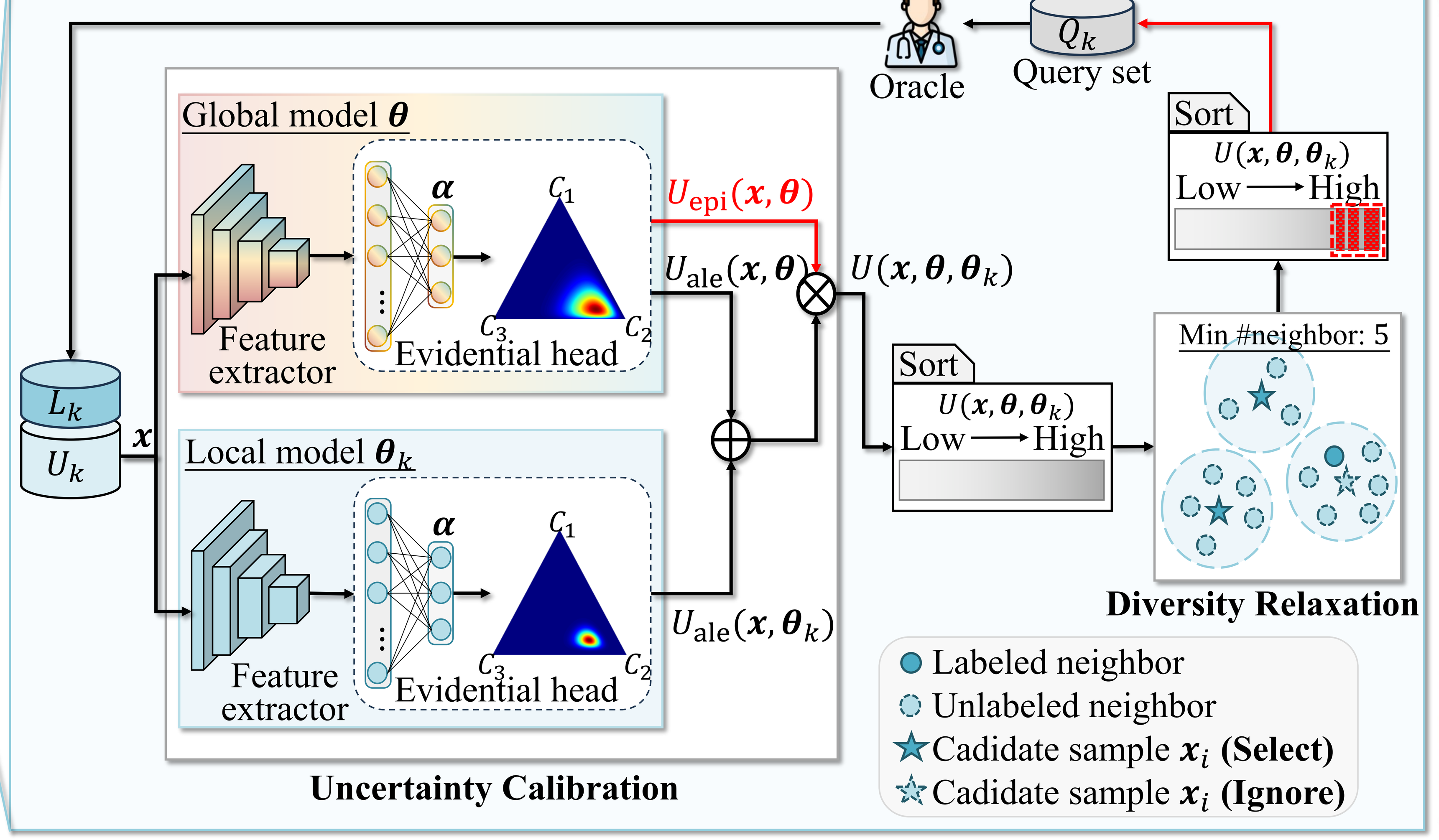
- We explore a rarely studied problem, **FAL with domain shifts**.
- We propose the **Federated Evidential Active Learning (FEAL)** method, with a sampling strategy CES and a local training scheme EML, to tackle the challenges in FAL with domain shifts.
- We conducted extensive experiments and analysis on **five real multi-center medical image datasets** to verify the effectiveness of the proposed method.

## Method

**(a) Federated Evidential Active Learning (FEAL)**




**(b) Calibrated Evidential Sampling (CES)**

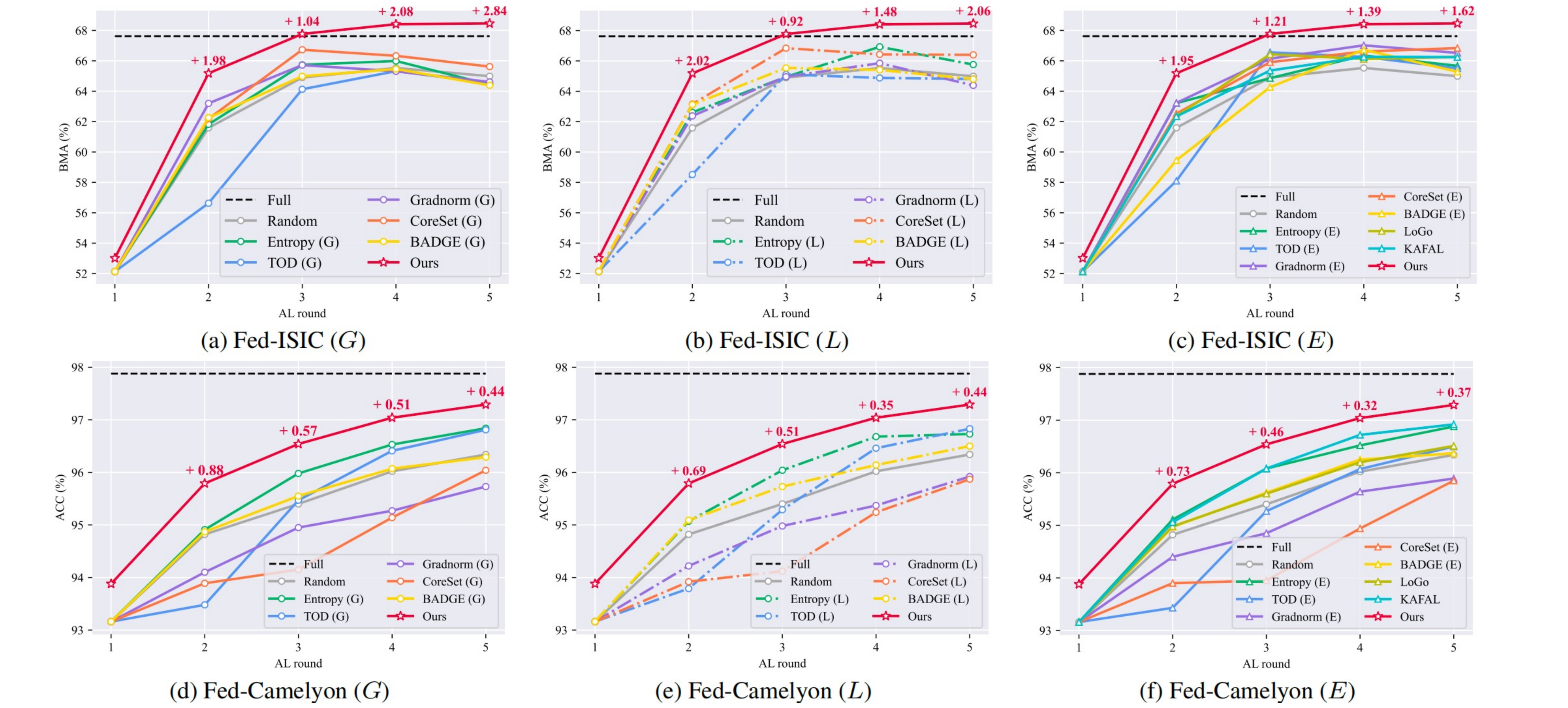



**Algorithm 1** Diversity Relaxation for Local Client $k$

**Input:** unlabeled set $U_k^{r-1}$, local model $\boldsymbol{\theta}_k$, annotation budget $B_k$, similarity threshold $\tau$, minimum neighbor size $n$
**Output:** query set $Q_k^r$
Sort $U_k^{r-1}$ by descending calibrated uncertainty.
Initialize index $i=1$ and query set $Q_k^r=\emptyset$.
**while** $|Q_k^r|<B_k$ **and** $i\le|U_k^{r-1}|$ **do**
  Select a candidate sample $\boldsymbol{x}_i$ from $U_k^{r-1}$.
  Compute feature similarity $s(\boldsymbol{x}_i,\boldsymbol{x}_j)$ using $\boldsymbol{\theta}_k$, where $\boldsymbol{x}_j\in U_k^{r-1}\setminus\boldsymbol{x}_i$.
  Form neighbor set $N(\boldsymbol{x}_i)$, including $\boldsymbol{x}_j$ with $s(\boldsymbol{x}_i,\boldsymbol{x}_j)\ge\tau$.
  **if** $|N(\boldsymbol{x}_i)|<n$ **or** $N(\boldsymbol{x}_i)\cap Q_k^r=\emptyset$ **then**
    Add $\boldsymbol{x}_i$ to $Q_k^r$.
  **end if**
  Increment $i$.
**end while**
**return** $Q_k^r$

## Experiments & Analysis

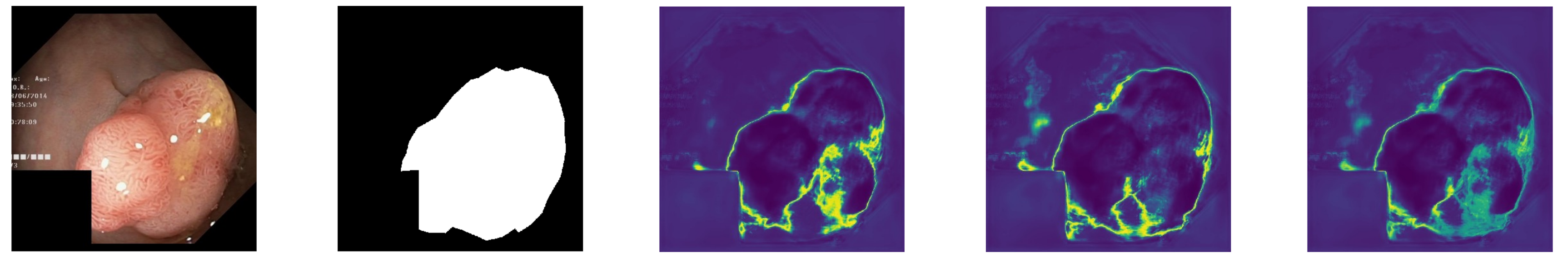
- **Experimental results on medical image classification** (Fed-ISIC & Fed-Camelyon)



(a) Fed-ISIC ($G$) (b) Fed-ISIC ($L$) (c) Fed-ISIC ($E$)
(d) Fed-Camelyon ($G$) (e) Fed-Camelyon ($L$) (f) Fed-Camelyon ($E$)

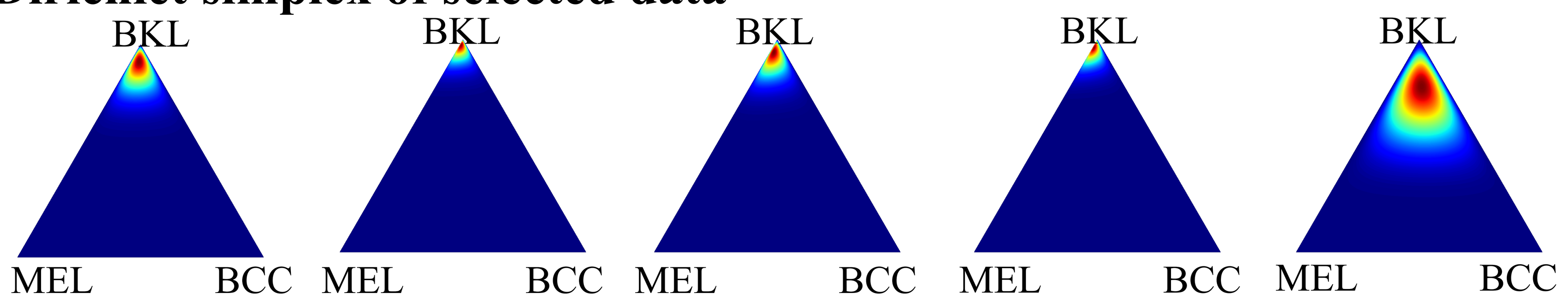
- Experimental results on medical image segmentation (Fed-Polyp, Fed-Prostate, Fed-Fundus) and ablation studies are provided in the paper.

- **Visualization of aleatoric uncertainty**



Input Ground truth $U_{ale}^G$ $U_{ale}^L$ $U_{ale}^G + U_{ale}^L$

- **Dirichlet simplex of selected data**




Entropy CoreSet LoGo KAFAL FEAL (Ours)

Red region $\begin{cases}\text{Spread: more concentrated} \rightarrow \text{less epistemic uncertainty } (U_{epi})\\ \text{Location: closer to corner} \rightarrow \text{less aleatoric uncertainty } (U_{ale})\end{cases}$

**FEAL identifies samples with higher uncertainty!**