Information Gain Sampling for Active Learning in Medical Image Classification

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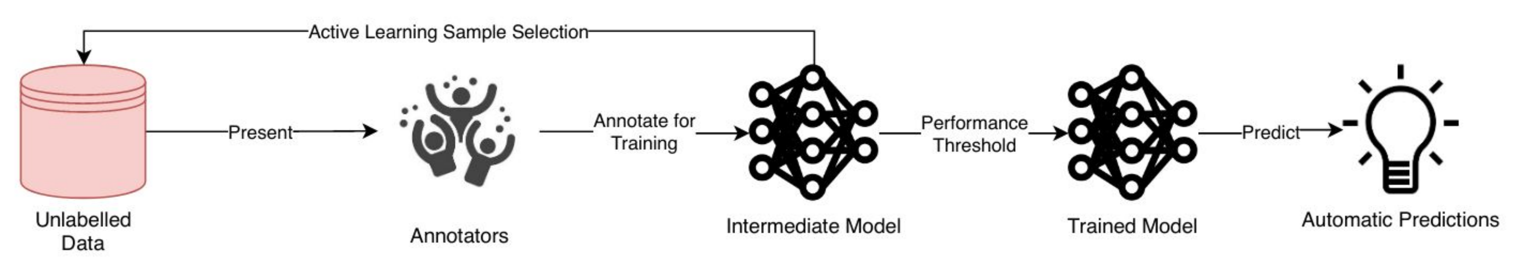
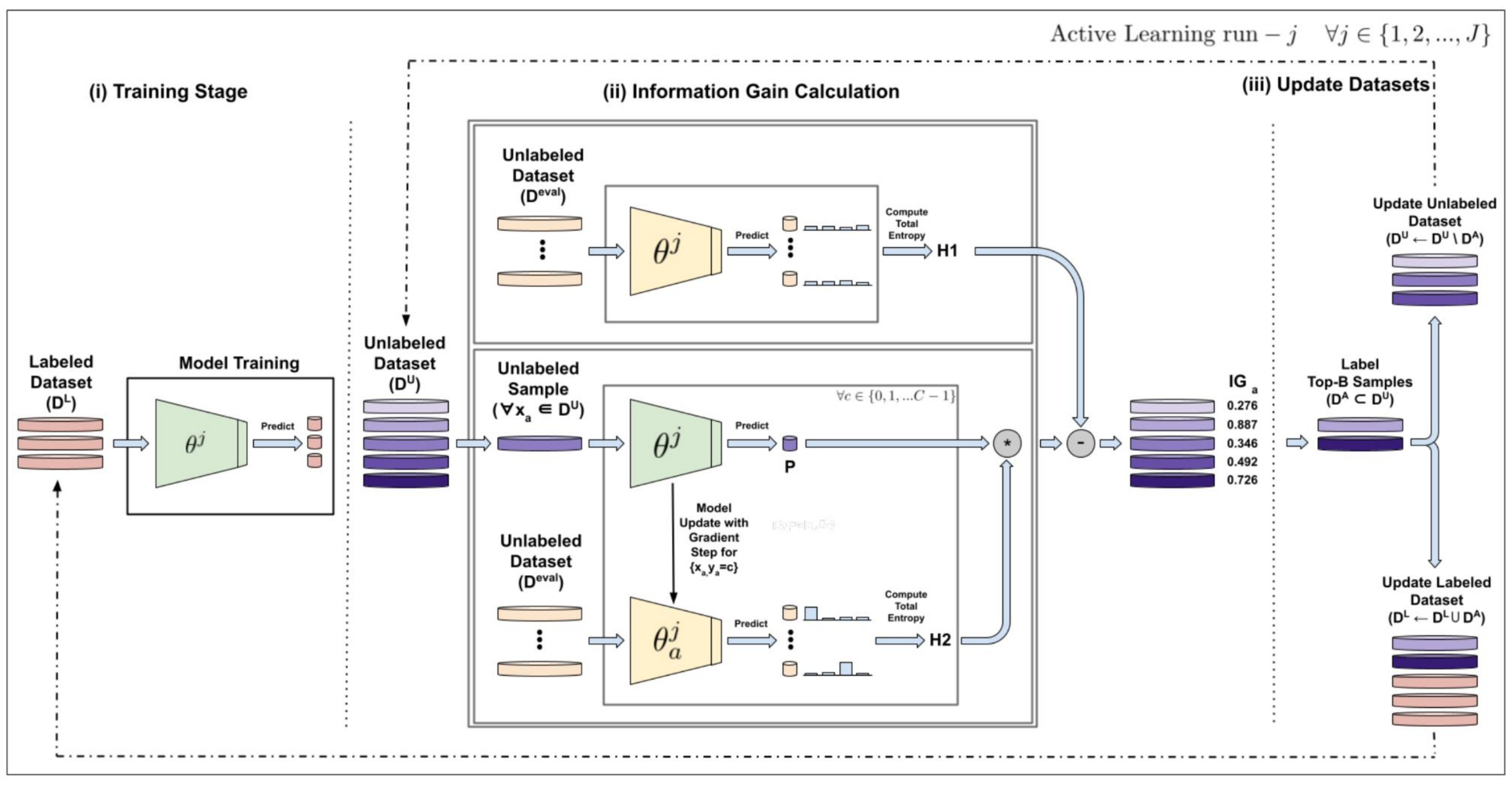
(1) Introduction

- ❖ Active Learning methods provide a way to select optimal images to label from a large set of unlabeled dataset
- ❖ **Goal**: **Select samples** from the unlabeled pool which **maximizes the Expected Information Gain** (EIG) on an unseen evaluation dataset



(2) Proposed Framework



$$\mathrm{EIG}(Y^{\text{eval}}; y_a | x_a, X^{\text{eval}}, D^L)$$
$$= \mathbf{H}[Y^{\text{eval}} | X^{\text{eval}}, D^L] - \mathbf{H}[Y^{\text{eval}} | y_a, x_a, X^{\text{eval}}, D^L]$$
$$= \underbrace{\mathbf{H}[Y^{\text{eval}} | X^{\text{eval}}, D^L]}_{\mathbf{H1}} - \underbrace{\sum_{c=0}^{C-1} p(y_a = c | x_a, D^L)\, \mathbf{H}[Y^{\text{eval}} | y_a = c, x_a, X^{\text{eval}}, D^L]}_{\mathbf{H2}}$$
$$= \underbrace{\sum_{j=0}^{K} \mathbf{H}[y_j^{\text{eval}} | x_j^{\text{eval}}, D^L]}_{\mathbf{H1}} - \underbrace{\sum_{c=0}^{C-1} p(y_a = c | x_a, D^L) \left(\sum_{j=0}^{K} \mathbf{H}[y_j^{\text{eval}} | y_a = c, x_a, x_j^{\text{eval}}, D^L] \right)}_{\mathbf{H2}}$$

- ❖ For high-class imbalance case like medical image classification, the predicted **softmax probability (P)** of the training model is **adjusted with the class frequencies of the evaluation set**

$$\mathrm{AEIG}(Y^{\text{eval}}; y_a | x_a, X^{\text{eval}}, D^L) \; = \mathbf{H1} - \underbrace{p(y_a = c | x_a, D^L) \frac{|y_{\text{eval}} = c|}{\sum_{j=0}^{C-1} |y_{\text{eval}} = j|}}_{\mathbf{P}} \mathbf{H2}$$

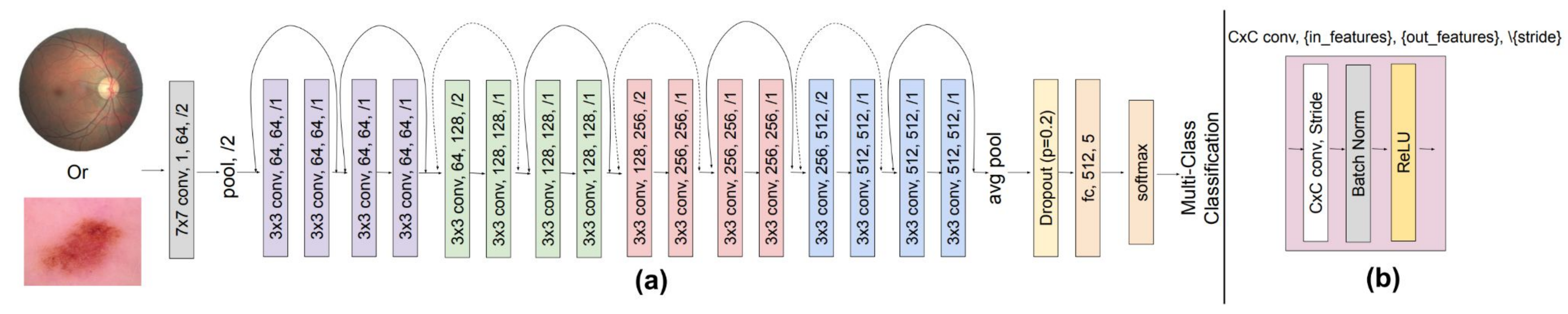
❖ **Practical Considerations**

- ➢ EIG calculation requires model update for each image (N) in the unlabeled set and for each possible labels (C)
- ➢ Total N*C model updates
- ➢ Calculation of evaluation set entropy after each of these updates
- ➢ Too much computational overhead

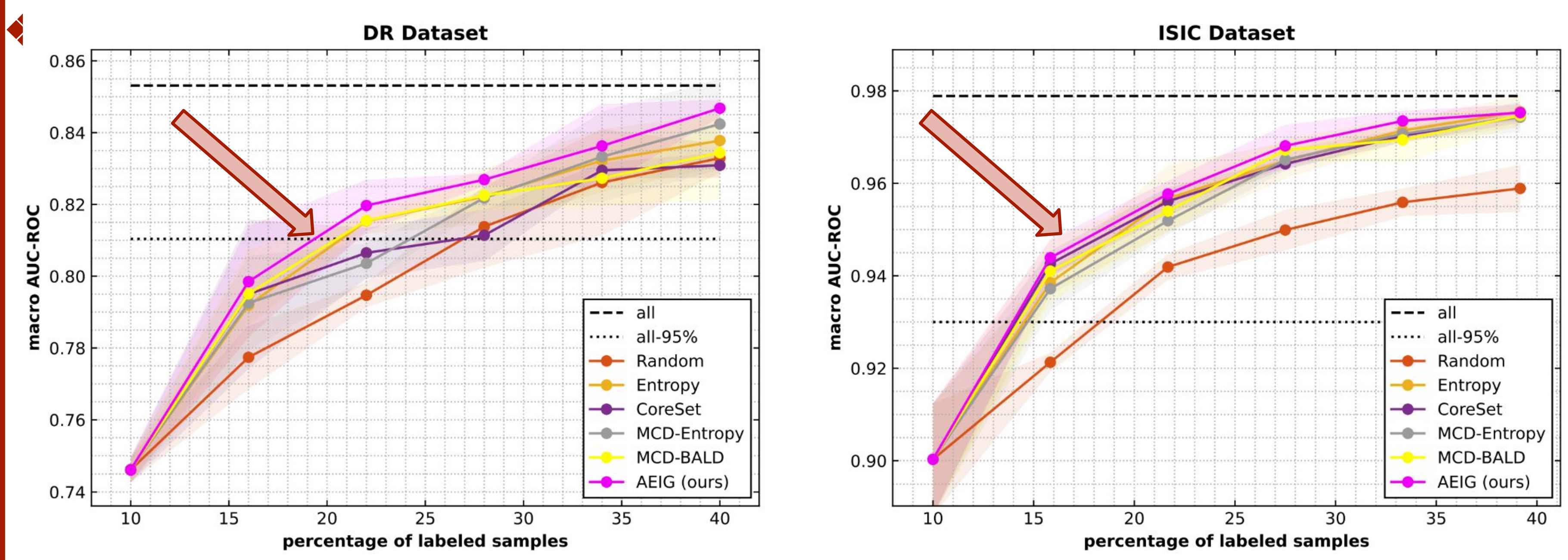
❖ **Design choices**

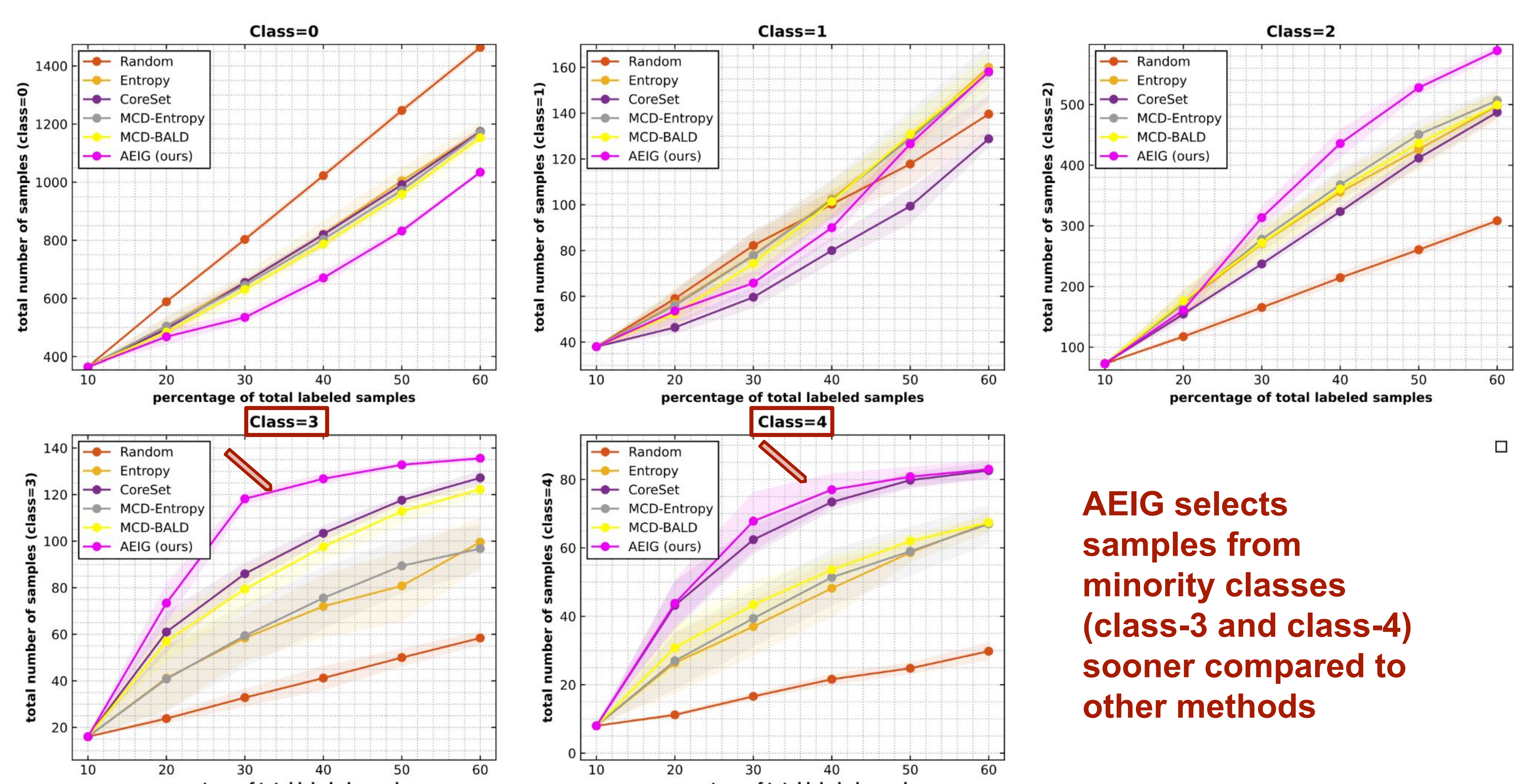
- ➢ Model update using only a **single gradient step**
- ➢ Deep Learning models have two parts
  - ▪ Convolutional Layers: feature extraction
  - ▪ Multi-Layer Perceptron: classification
- ➢ **Only update classification layer** parameters during EIG calculation
- ➢ Use Validation set as evaluation set

(3) Experiments and Results



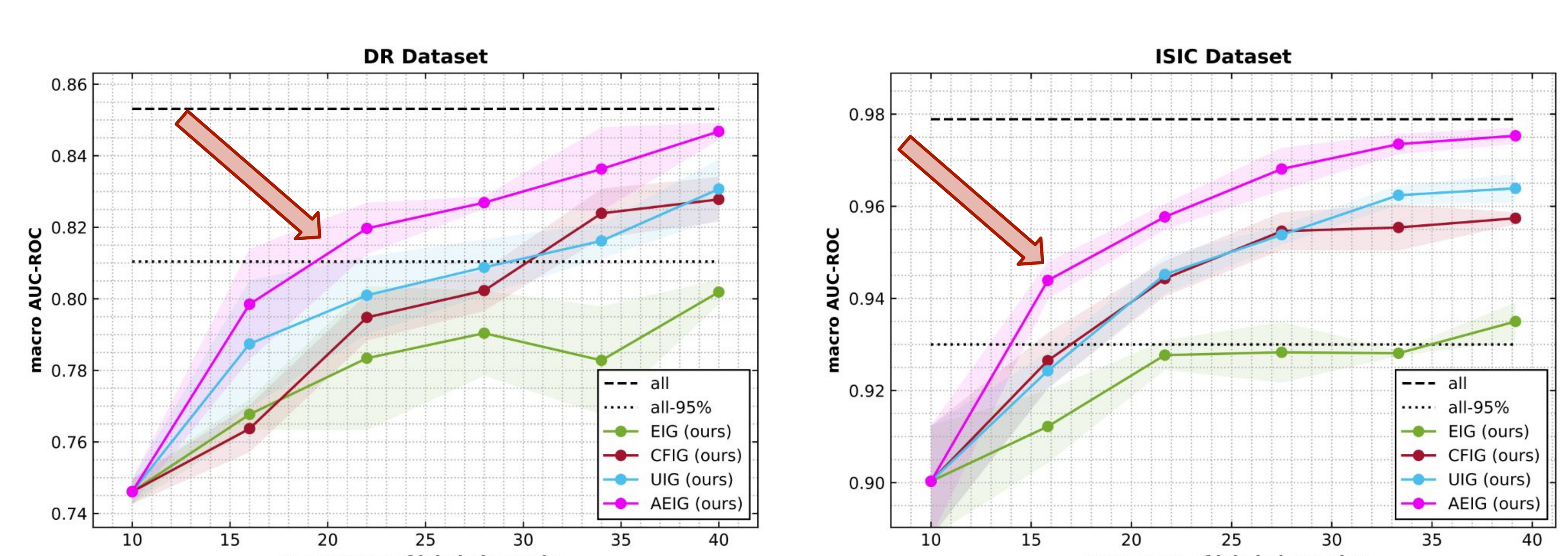
- ❖ **Datasets**: Multi-class Diabetic Retinopathy (DR) disease stage classification and multi-class ISIC Skin lesion classification with high class imbalance
- ❖ **Evaluation Metric**: 'macro' Area Under the Receiver Operating Characteristic Curve (ROC AUC) for one-vs-rest classifier
- ❖ **Active learning Implementation Details:**
  - ➢ Total Active Learning runs (J): 6
  - ➢ Labeled Set (D^L): 600 for ISIC, 500 for DR
  - ➢ Unlabeled Set (D^U): 5400 for ISIC, 4500 for DR
  - ➢ Selected Set (D^A): 350 for ISIC, 300 for DR
  - ➢ 5 repetition for both dataset





AEIG selects samples from minority classes (class-3 and class-4) sooner compared to other methods

❖ **Comparison of different Information Gain sampling methods**



(4) Conclusion

- ❖ Proposed an **information theoretic active learning** samples selection approach
- ❖ With **careful design choices,** method can be **easily integrated into existing deep learning classifiers**
- ❖ **The proposed method** achieves **95% of overall performance** with **only 19% of the training data,** while other active learning approaches require around 25%.
- ❖ The proposed method **selects more samples from the least representative classes**
- ❖ Useful for medical imaging context with high class imbalance
- ❖ Future work will explore effect of Information Gain sampling for medical image segmentation tasks

Reference:

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