Core-set based batch-mode active learning for intelligent training of optical coherence tomography (OCT) based retinal pathologies detection models

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Poster #2393 – C0456

PURPOSE

- The bottleneck of developing modern advanced deep learning models is the lack of sufficient annotated training data.
- We used a core-set active learning (AL) approach to effectively select unlabeled samples based on informativeness and representativeness to effectively query for labels from the expert annotators.
- We show the benefit of such sampling strategy on pathology detection for OCT images.

METHODS

- The retrospective study data includes 68,992 B-scans (539 OCT cubes) acquired from CIRRUS™ HD-OCT 4000/5000 (ZEISS, Dublin, CA) [1, 2].
- Training, validation and testing set contain B-Scans from 54784, 7808, and 6400 B-scans, corresponding to 428, 61, 50 OCT cubes respectively.
- Each B-scan was labeled by two experts for retinal pathologies with derived binary labels [2].
- Initially, 500 B-scans from the training set were randomly selected and labeled.
- In one AL iteration:
  - A SqueezeNet pre-trained on ImageNet is trained using the labeled samples
  - Model evaluation on the validation and testing dataset
  - Feed the unlabeled samples from the training set into the model, using the final layer embeddings to select a batch of unlabeled samples to query for labels using the core-set active learning
  - A total of 100 samples are selected and queried for labels
  - Update the training set by adding the 100 newly labeled samples
- Performance is compared against baseline methods, including random sampling and uncertainty sampling, using classification accuracy.

CONCLUSIONS

Core-set AL is an efficient approach to minimize the cost and efforts of labeling medical data. By only selecting the most informative subset to train the DL model on, the process is accelerated, and competitive performance is achieved. Core-set AL also showed potential compared to other methods when combined with CNN models where batch sampling is needed to avoid longer training times.

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Disclosures: ML (E), AE (E), KP (E), AE (E): Carl Zeiss Meditec AG; AS (E): Carl Zeiss Meditec, Inc.

RESULTS

As shown in Fig 1, to achieve the same accuracy, core-set AL queries fewer labeling data compared to random sampling and uncertainty sampling. Uncertainty sampling behaves worse than random sampling in some cases due to the batch-mode setting. Furthermore, by only labeling 3,000 B-Scans using core-set AL, we achieved the accuracy of 92%, while a fully supervised model trained on 54,784 labeled B-scans achieved the accuracy of 94% on the test set.

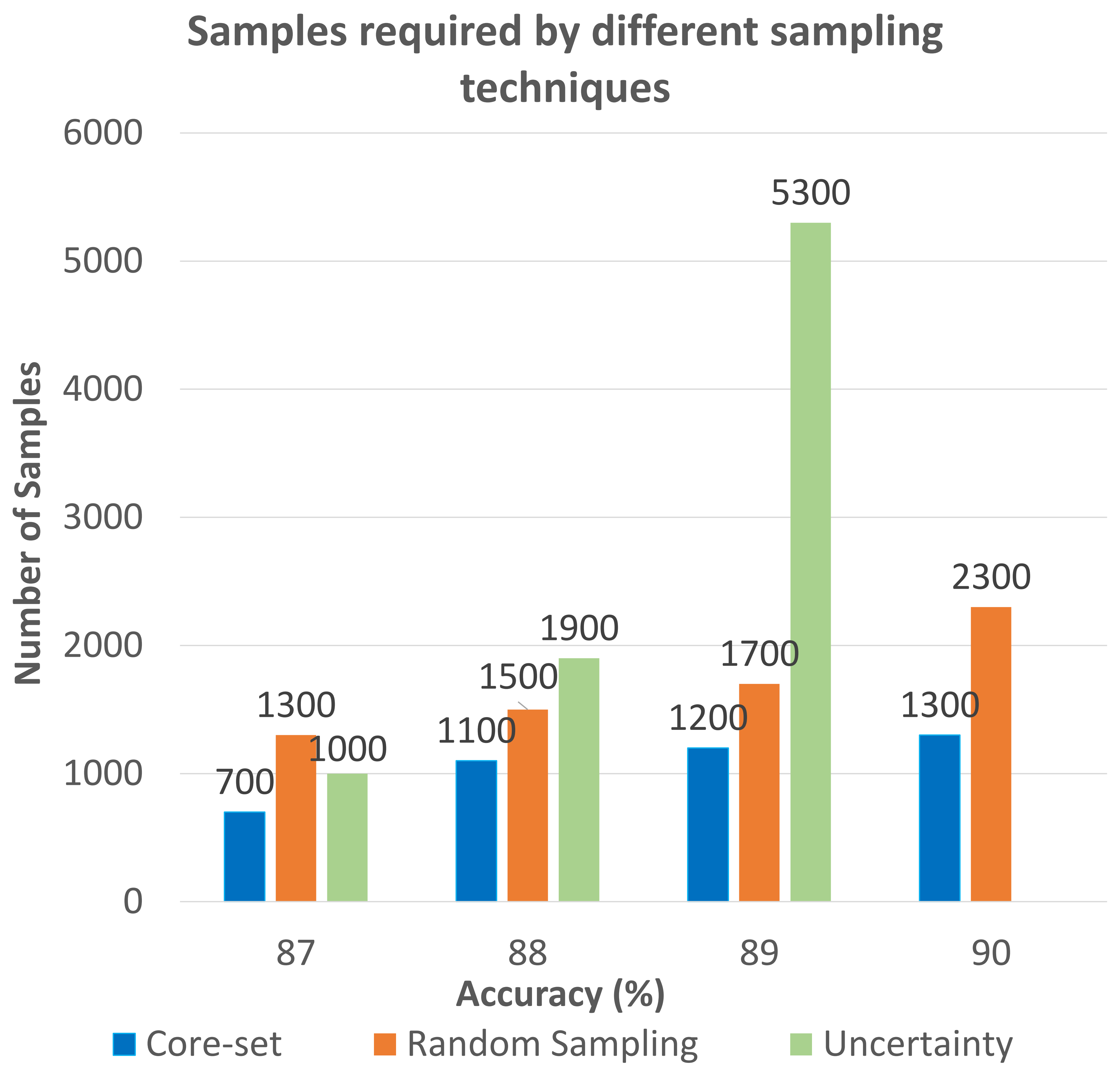

Figure 1: Number of samples required to achieve target levels of accuracy

REFERENCES

[1] Yu et al. *IOVS* 2020; 61(9): PB0085
[2] Ren et al. *IOVS* 2020; 61(7): 1635