Project Proposal

Title: *Exploring the Role of Optimizers and Architectures in Active Learning*

Members:

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Introduction:

Deep learning models have achieved remarkable success in image classification tasks, but this success often comes at the cost of requiring large volumes of labeled data. In real-world scenarios, labeling such data can be expensive, time-consuming, and in some domains—such as medical imaging or satellite imagery—requires expert annotators. Active Learning (AL) offers a compelling solution to this problem by selecting the most informative or uncertain samples from a large pool of unlabeled data for annotation. Instead of randomly choosing data points, AL prioritizes instances that are expected to improve model performance the most when labeled. A key AL strategy is uncertainty sampling [1], where the model queries data points it is least confident about, such as those with ambiguous class probabilities or high entropy. This approach helps the model refine its decision boundaries, especially during the early stages of training.

In this research, we aim to explore how different choices of optimizers (SGD, Adam, AdamW, RMSProp) and model architectures (ResNet18, ResNet34, ResNet50) [5] affect the performance and efficiency of an active learning pipeline using uncertainty sampling. Using the widely adopted CIFAR-10 dataset, we will simulate a real-world budget-constrained labeling scenario by incrementally increasing the labeled dataset over 10 active learning cycles. Through systematic experimentation, we intend to uncover insights into how these fundamental design decisions influence not just model accuracy but also sample efficiency and computational cost—key considerations for deploying image classification systems in practical, resource-constrained environments.

Research Objectives:

- To assess the effectiveness of various optimizers (SGD, Adam, AdamW, RMSProp) in the context of active learning using uncertainty sampling.
- To evaluate how different ResNet architectures (ResNet18, ResNet34, ResNet50) impact the performance of active learning on CIFAR-10 dataset.
- To compare the overall performance (accuracy, sample efficiency, and computational cost) of these models and optimizers under a fixed labeling budget.

Methodology:

This research adopts an iterative **active learning** framework based on uncertainty sampling, designed to evaluate how different model architectures and optimizers impact learning efficiency and performance. The study uses two benchmark image classification datasets: **CIFAR-10** [6]. For model architectures, three variants of ResNet—**ResNet18**, **ResNet34**, and **ResNet50**—will be trained using four optimizers: **SGD** [3], **Adam** [2], **AdamW** [4], and **RMSProp** [3]. In each experiment, the active learning process begins with no initially labeled data. Instead, in the first cycle, 1,000 samples will be selected and labeled based on uncertainty sampling. In each subsequent cycle, the model selects an additional 1,000 most uncertain samples from the unlabeled pool and adds them to the labeled training set. This continues over **10 cycles**, resulting in a total labeling budget of **10,000 samples** per run. After each cycle, the model is trained using the updated labeled set to ensure a consistent evaluation of the evolving dataset. The model's performance is evaluated after every cycle using several key metrics: accuracy on a held-out test set, sample efficiency, computational efficiency, and the F1-score to better capture the balance between precision and recall. This methodology will be applied systematically across all model-optimizer combinations on both datasets, allowing for a detailed comparison of how these factors influence the effectiveness of active learning.

Conclusion:

This research aims to provide a comprehensive understanding of how model architectures and optimization strategies influence the effectiveness of active learning when using uncertainty sampling. By systematically evaluating combinations of ResNet architectures and optimizers across CIFAR-10 dataset under a fixed labeling budget, the study will uncover how different design choices affect learning efficiency, model performance, and computational cost. The findings are expected to highlight which optimizer-model pairs are most suitable for active learning scenarios where labeled data is limited but model accuracy is critical.

Milestone:

- Week 1–2 (Oct 1–Oct 13): Project Setup and Literature Review
- Week 3 (Oct 14–Oct 20): Model and Optimizer Implementation
- Week 4 (Oct 21–Oct 27): Active Learning Framework Implementation
- Week 5 (Oct 28–Nov 2): Progress Report and Preliminary Results
- Week 6–7 (Nov 3–Nov 17): Full Experimental Evaluation
- Week 8–9 (Nov 18–Nov 30): Analysis, Interpretation and Report

Bibliography:

[1] Y. Yang and M. Loog, "Active learning using uncertainty information," in *2016 23rd International Conference on Pattern Recognition (ICPR)*, Cancun: IEEE, Dec. 2016, pp. 2646–2651. doi: 10.1109/ICPR.2016.7900034.

[2] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," 2014, *arXiv*. doi: 10.48550/ARXIV.1412.6980.

[3] S. Ruder, "An overview of gradient descent optimization algorithms," June 15, 2017, *arXiv*: arXiv:1609.04747. doi: 10.48550/arXiv.1609.04747.

[4] I. Loshchilov and F. Hutter, "Decoupled Weight Decay Regularization," 2017, *arXiv*. doi: 10.48550/ARXIV.1711.05101.

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Dec. 10, 2015, *arXiv*: arXiv:1512.03385. doi: 10.48550/arXiv.1512.03385.

[6] A. Krizhevsky, "Learning multiple layers of features from tiny images," Tech. Rep., University of Toronto, 2009.