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CSE 584: Machine Learning – Tools and Algorithms
Homework – 1

Paper 1: Cost-Sensitive Active Learning for Intracranial Hemorrhage Detection
https://arxiv.org/pdf/1809.02882

1. **The problem this paper tries to solve (motivation):**
   - This paper aims to address the high cost and time-consuming nature of labeling large medical imaging datasets for deep learning applications, focusing on intracranial hemorrhage detection and segmentation on head CT scans.
   - The authors observed that the time needed for pixel-wise labeling of intracranial hemorrhages can vary by up to three orders of magnitude between different cases. This wide variation in labeling time adds another layer of complexity to the data collection process.
   - The motivation is to develop a cost-sensitive method to expand labeled datasets while maintaining high-performance standards required for clinical applications and favorable with the state-of-the-art methods using less memory and running faster.

2. **How it solves the problem:**
   - Uses an ensemble of PatchFCN models to generate uncertainty measures for unlabeled data. This architecture has the advantage that the network has to make its predictions based on the local morphology and hence is less prone to overfit into the global context, which results in better test time accuracy than standard FCNs.
   - Employs a Query-by-Committee (QBC) approach, using multiple models to estimate uncertainty with Jensen-Shannon (JS) divergence as the uncertainty measure, which was found to perform best among various tested measures. Calculates uncertainty at the patch level and aggregates to the stack level by averaging the top K uncertain patches.
   - Predicts labeling time for each example based on features like mask boundary length and number of connected components.
   - Employs a 0-1 Knapsack algorithm to select the most informative examples for labeling within a given time budget.
   - Validates the approach on a substantially larger dataset (29,095 frames) compared to standard medical segmentation datasets
   - Demonstrates effectiveness in both core-set selection and expanding datasets with unlabeled data.

3. **List of novelties/contributions:**
   - A cost-sensitive active learning approach that considers both informativeness and labeling time.
   - A PatchFCN architecture that outperforms whole image baselines for hemorrhage detection.
   - A method to predict labeling time based on image features.
   - Validation of the active learning approach on a large dataset (29,095 frames), which is significantly larger than standard medical segmentation datasets.

- Demonstration of the system's effectiveness in both core-set selection and expanding datasets with unlabeled data.

4. **Potential downsides of the work:**
   - The system's performance may be limited when the ratio of unlabeled to labeled data becomes small, as indicated by the leveling off of performance after the initial round of selection.
   - The approach requires an initial large seed set to be effective, which may not always be available in all medical imaging contexts.
   - The labeling time prediction model, while effective, may not generalize well to other types of medical imaging tasks or datasets.
   - The system's effectiveness is primarily demonstrated on intracranial hemorrhage detection, and its applicability to other medical imaging tasks is not fully explored.

Paper 2: Breast cancer diagnosis through active learning in content-based image retrieval
https://www.sciencedirect.com/science/article/abs/pii/S092523121930726X

1. **The problem this paper tries to solve (motivation):**

- The MARRow approach integrates active learning strategies to identify images that balance similarity, diversity, and uncertainty, enhancing the retrieval process in medical image diagnosis.
- The approach significantly reduces the need for extensive expert annotations by presenting a smaller, curated set of informative images for validation, thus streamlining the expert's role in the learning process.
- By continuously refining the classifier model with the most informative images, MARRow enhances the precision of image retrieval, leading to more accurate and efficient medical decision-making.
- The method addresses shortcomings of traditional relevance feedback by fully utilizing expert input across multiple iterations and incorporating active learning to optimize the selection of informative samples throughout the learning process.

2. **How it solves the problem:**

- The approach integrates content-based image retrieval (CBIR) with active learning strategies to enhance the effectiveness of medical image diagnosis, particularly for breast cancer.
- It selects informative images by employing criteria that consider similarity, diversity, and uncertainty, ensuring that the most relevant images are chosen for training the classifier.
- The method utilizes relevant feedback from experts to iteratively refine image queries, allowing for continuous improvement based on expert input and enhancing the learning process.
- A classifier model is trained using the selected informative images, which helps improve the accuracy of the retrieval process over time as more relevant images are incorporated.
- An active learning strategy is implemented that balances similarity to the query image with diversity and uncertainty, optimizing the selection of images that contribute most to the classifier's learning.
- The approach minimizes expert involvement by presenting pre-labeled images for validation and correction, streamlining the annotation process, and reducing the time required from medical experts.

3. **List of novelties/contributions:**

- The MARRow approach introduces a novel active learning strategy specifically designed for medical content-based image retrieval (CBIR), which balances similarity, diversity, and uncertainty to enhance the effectiveness of image selection in breast cancer diagnosis.
- This method minimizes the involvement of medical experts by presenting pre-labeled images for validation and correction, allowing experts to focus on the most informative cases rather than extensive manual annotation, thereby streamlining the annotation process.
- The integration of active learning with relevant feedback allows the system to continuously refine the image retrieval process, utilizing expert input to improve the accuracy of subsequent queries and ensuring that expert knowledge is effectively incorporated into the learning model.

- The approach includes a systematic method for selecting the most effective feature extractor and distance function tailored to the specific characteristics of medical image datasets, ensuring optimal performance in the retrieval process.
- An iterative learning process is employed, where the classifier model is continuously updated with newly annotated images, leading to progressive improvements in its performance and the overall accuracy of the image retrieval system.
- The selection strategy considers not only the similarity of images to the query but also prioritizes informative samples located at class boundaries, which are crucial for refining the classifier's decision-making and improving the overall learning process.

4.Potential downsides of the work:

- Initial setup and tuning may be required for different medical image datasets, as the optimal feature extractor and distance function can vary significantly based on dataset characteristics. This necessitates a tailored approach for each dataset to achieve the best performance.
- The effectiveness of the MARRow approach might depend on the quality and consistency of expert feedback, as inconsistent or erroneous annotations can negatively impact the model's learning. Variations in expert interpretations could lead to discrepancies in the relevance feedback process.
- The computational complexity for processing very large datasets is not thoroughly discussed in the paper, raising questions about the scalability of the approach. As dataset sizes increase, the time and resources required for clustering and classification may become substantial.
- Performance on rare or underrepresented medical conditions is not explicitly addressed, which could limit the approach's effectiveness in identifying fewer common cases. The focus on more prevalent conditions might overlook critical insights from rare medical images.
- The approach may require a certain minimum amount of initial labeled data to be effective, as insufficient labeled samples could hinder the initial training of the classifier. The paper does not specify the minimum data requirements, which could be crucial for practical implementation.

Paper 3: Enhancing Retinal Disease Classification from OCTA Images via Active Learning Techniques
https://arxiv.org/pdf/2407.15293v1

1. What problem does this paper try to solve, i.e., its motivation?

- The motivation stems from the limited availability of labeled data and the imbalanced nature of existing datasets, which hinder the performance of standard deep-learning models.
- Given the prevalence of eye diseases that can lead to vision loss, improving classification accuracy through effective data utilization is crucial for timely diagnosis and treatment.

2. How does it solve the problem?

- The authors use active learning strategies to improve deep learning model training.
- Despite the limits of labeled data, the model can achieve improved generalization by choosing the most informative subsets of data for training.
- In terms of F1 assessment metrics, the study shows that active learning procedures perform noticeably better than conventional techniques such as inverse frequency class weighting and random sampling.
- To further enhance model performance on unbalanced datasets, the authors investigate several data engineering techniques, such as subject-based sampling and data augmentation.

3. A list of novelties/contributions:

- The paper introduces active learning as a method to select the most valuable data points for training deep learning models, thereby improving classification performance on imbalanced datasets.
- It utilizes the OCTA500 dataset, which is characterized by a high degree of imbalance among classes, demonstrating the effectiveness of active learning in this context.
- The study compares active learning strategies with conventional methods (inverse frequency class weighting, random under sampling, and oversampling), showing significant performance improvements.
- The authors analyze different uncertainty metrics (Least Confidence, Margin, Ratio, and Entropy Sampling) to determine their effectiveness in selecting data for active learning.
- The implementation of subject-based sampling helps prevent data leakage and improves the model's robustness by ensuring that samples from the same subject do not appear in both training and validation sets.

4. What do you think are the downsides of the work?

- Without additional validation, the results might be limited to the OCTA500 dataset and might not translate well to other datasets or imaging modalities.
- The initial labeled dataset's representativeness and quality have a major impact on how well active learning works. A poorly chosen first set of data could result in less-than-ideal performance.
- Because it necessitates repeated training and uncertainty evaluation rounds, active learning can be computationally demanding and may not be practical in all clinical settings.
- Implementing active learning strategies adds complexity to the training process, which may require additional expertise and resources compared to standard deep learning approaches.