Project 3
Brain Image Segmentation under Annotation Scarcity

Project Overview

Accurate brain image segmentation is a foundational task in medical image analysis, supporting applications such as disease diagnosis, treatment planning, and longitudinal analysis. While deep learning–based segmentation models have achieved strong performance, they typically rely on fully annotated datasets, which are expensive and time-consuming to obtain in clinical practice.

This project investigates how segmentation performance degrades under limited annotation availability, and how different model architectures cope with varying proportions of labeled data. By systematically reducing the percentage of labeled samples in a standard brain imaging dataset, this study aims to benchmark classical and advanced segmentation models and establish a clear performance–annotation trade-off. The project will first target an international conference and then be extended toward a Q2 journal publication with more advanced learning paradigms.

Research Objectives

- Quantify segmentation performance under different proportions of labeled data (e.g., 1%, 5%, 10%, 25%, 50%, 100%).
- Benchmark segmentation models including U-Net, U-Net++, DeepLabV3, TransUNet, and nnU-Net.
- Study model generalization as annotation availability decreases.
- Provide qualitative and quantitative analysis of failure cases under sparse supervision.
- Produce a conference paper and an extended Q2 journal submission.

Methodology

1. Dataset Preparation:
- Use a fully annotated brain imaging dataset (e.g., MRI slices).
- Construct multiple training subsets by sampling different proportions of labeled data.
- Keep validation and test sets fixed to ensure fair comparison.

2. Limited Annotation Simulation:
- Systematically vary the proportion of labeled data used for training.
- Maintain consistent preprocessing and data splits.

3. Model Benchmarking:
- Train CNN- and Transformer-based segmentation architectures.
- Include nnU-Net as a strong automated baseline.

4. Evaluation Metrics:
- Dice, IoU, Hausdorff Distance, Average Surface Distance.

5. Visualization and Analysis:
- Qualitative segmentation overlays across annotation levels.
- Failure case analysis under extreme label scarcity.
- Architecture sensitivity comparison.

Timeline (6 Months)

Phase 1 (Months 1–3): Conference Target
- 1 brain imaging dataset
- Fully supervised training with varying annotation ratios
- Conference submission (ICISN, CITA, MAPR)
- Compute: Google Colab, Kaggle

Phase 2 (Months 4–6): Journal Target
- Extend to 2 brain datasets
- Apply semi-supervised, self-supervised, and few-shot learning
- Q2 journal submission
- Compute: AIVN GPUs, Private servers