Project 2

Segment Anything Model (SAM) under Occluded Medical Imaging Conditions

Project Overview

Foundation segmentation models such as the **Segment Anything Model (SAM)** and its medical variants (e.g., **MedSAM**, **SAM2**) have shown strong generalization capabilities across medical imaging datasets. However, in real clinical environments, anatomical regions of interest are frequently **partially occluded** due to surgical tools, imaging probes, catheters, markers, implants, or overlapping anatomical structures.

This project aims to **systematically evaluate the robustness and failure modes of SAM-based models under controlled occlusion scenarios in 2D medical images**, using synthetic but clinically motivated occlusion strategies such as **Cutout**, **CutMix**, and **copy–paste of surgical tools**. The ultimate goal is to establish a **standardized occlusion robustness benchmark** for medical segmentation, suitable for **CVPR workshop submission** and later extension to a **Q1 journal paper**.

Research Objectives

1. **Occlusion Robustness Evaluation**
   Quantify how segmentation performance degrades when clinically relevant image regions are partially or fully occluded.
2. **Occlusion Strategy Comparison**
   Study different occlusion mechanisms and their impact:
   - Random occlusion (Cutout)
   - Structured occlusion (CutMix)
   - Realistic tool-based occlusion (copy–paste of surgical instruments)
3. **Model Generalization Analysis**
   Compare robustness across:
   - SAM
   - SAM2
   - Medical-domain adaptations (e.g., MedSAM)
4. **Failure Mode Characterization**
   Identify where and how SAM-based models fail under occlusion, particularly at anatomical boundaries and small structures.
5. **Research Dissemination**
   Deliver:
   - A **CVPR workshop paper** focused on occlusion robustness
   - An extended **Q1 journal article** with broader datasets, models, and analyses

Methodology

1. Dataset Selection

- Choose **2D medical imaging datasets** (e.g., endoscopy, X-ray, ultrasound, fundus, CT/MRI slices).
- In the first phase, focus on **a single imaging modality** to ensure controlled comparison.

2. Occlusion Simulation Strategies

Occlusions are injected at the preprocessing stage to simulate realistic clinical scenarios:

(a) Cutout

- Randomly mask rectangular or irregular regions of the image.
- Control occlusion size, location, and percentage of coverage.

(b) CutMix

- Replace selected regions with patches from other images.
- Simulates overlapping anatomy or foreign objects in the field of view.

(c) Surgical Tool Copy–Paste

- Extract surgical tools (e.g., forceps, scalpels, probes) from annotated datasets or public tool segmentation benchmarks.
- Paste tools into target images with controlled scale, rotation, and placement.
- Mimics real intraoperative occlusion.

Occlusion severity will be systematically varied to enable fine-grained robustness analysis.

3. SAM-Based Model Benchmarking

- Apply SAM-based models using consistent prompting strategies.
- Evaluate both **automatic segmentation** and **prompt-guided segmentation** where applicable.
  Maintain uniform inference settings across all occlusion types.

4. Evaluation Metrics

- Dice coefficient
- Intersection-over-Union (IoU)
  Boundary metrics (Hausdorff Distance, ASSD)
- Occlusion sensitivity curves (performance vs. occlusion ratio)
- Stability metrics across occlusion types

5. Visualization & Analysis

- Qualitative comparisons across occlusion methods
- Failure case visualization (missed anatomy, hallucinated boundaries)
- Robustness heatmaps and degradation plots

Timeline (6 Months Total)

Phase 1: CVPR Workshop Target (Months 1–3)

Scope:

- 2 datasets
- Same imaging modality
- 2–3 occlusion strategies
- 2–3 SAM-based models

Deliverables:

- Controlled occlusion benchmark
- Quantitative and qualitative results
- **CVPR workshop paper submission**

Compute Resources:

- Google Colab
- Kaggle

Phase 2: Q1 Journal Target (Months 4–6)

Scope Expansion:

- 4–5 datasets (potentially multi-modal)
- Additional SAM variants
- More occlusion types and severity levels
- Deeper analysis on clinical relevance and generalization

Deliverables:

- Extended benchmark and ablation studies
- Comprehensive discussion and limitations
- **Q1 journal submission**

Compute Resources:

- AIVN GPU cluster
- Private server GPUs