MIAS-SAM: Medical Image Anomaly Segmentation without thresholding

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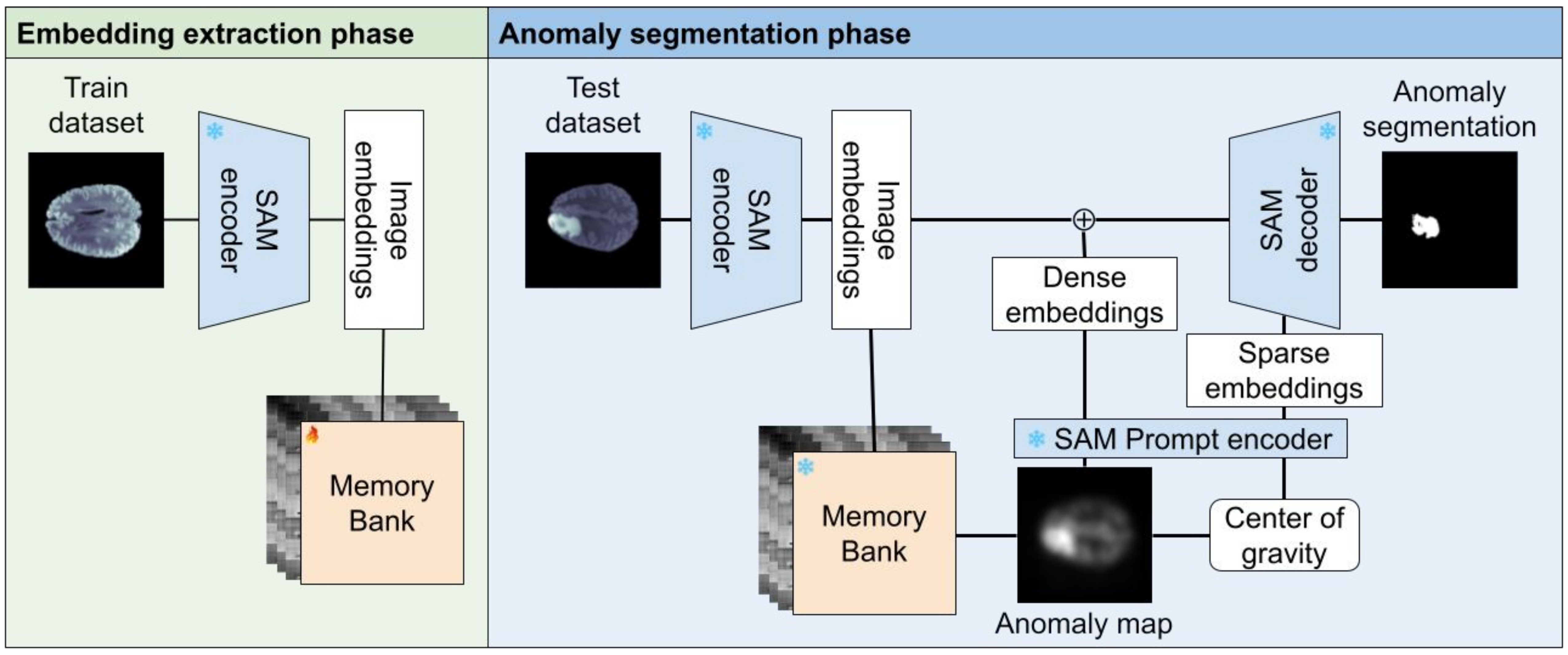
Introduction

- **Context**: Pixel-level expert annotations are costly, slow, and impractical at scale. Unsupervised anomaly detection eliminate the need for labeled anomalies.
- **State of the art: Unsupervised anomaly segmentation** addresses this problem by learning normal anatomy and detecting deviations as potential pathologies. SOTA approaches typically follow a two-step pipeline:
  - Generate a feature- or reconstruction-based **anomaly map**.
  - Apply a **threshold** to derive the segmentation mask.
- **Problems:**
  - Defining the threshold requires a validation set. Since it is unavailable, existing solutions rely on an arbitrary value or a biased value computed on the test-set.
  - Anomaly maps are inherently **coarse** and fail to generate precise lesion boundaries in clinical scenarios.
- **Solution**: MIAS-SAM adopts feature anomaly segmentation using SAM's zero-shot capabilities. This removes the need of a threshold selection for the anomaly segmentation maps and generates precise segmentations also along the boundaries.

Framework



Method

Embedding Extraction Phase (training):

- Encode normal training images using **SAM ViT-B encoder**
- Extract 5×5 patch embeddings
- Populate a **memory bank** indexing normal features

Anomaly Segmentation Phase (Inference):

- Extract embeddings from a test image and compare patches to the memory bank
- Generate an **anomaly map** via patch distance scoring
- Compute **center of gravity** of the anomaly map → used as a **point-prompt** to SAM
- SAM decoder returns 3 hierarchical masks → **the fine-grained mask is the final segmentation**

Experimental Results

Method	Brain MRI		Liver CT		Retina OCT	
	P-AUROC	DICE	P-AUROC	DICE	P-AUROC	DICE
RD4AD (CVPR22)	96.45	28.28	96.01	10.72	96.18	33.51
PatchCore (CVPR22)	**96.97**	32.82	96.43	10.49	96.48	**57.04**
CFA (Access22)	96.33	30.22	97.24	14.93	91.10	36.57
CFlow-AD (WACV22)	93.76	19.50	92.41	7.58	93.78	44.83
SimpleNet (CVPR23)	94.76	28.96	97.51	12.26	77.14	30.28
ReContrast (NiPS23)	95.64	12.57	**98.02**	15.03	97.96	25.02
MIAS-SAM (Ours)	96.35	**37.04** ▲ ~ 13%	97.56	**42.85** ▲ ~ 185%	**99.76**	51.21 ▼ ~ 11%

Table: Anomaly segmentation performance compared to baselines.

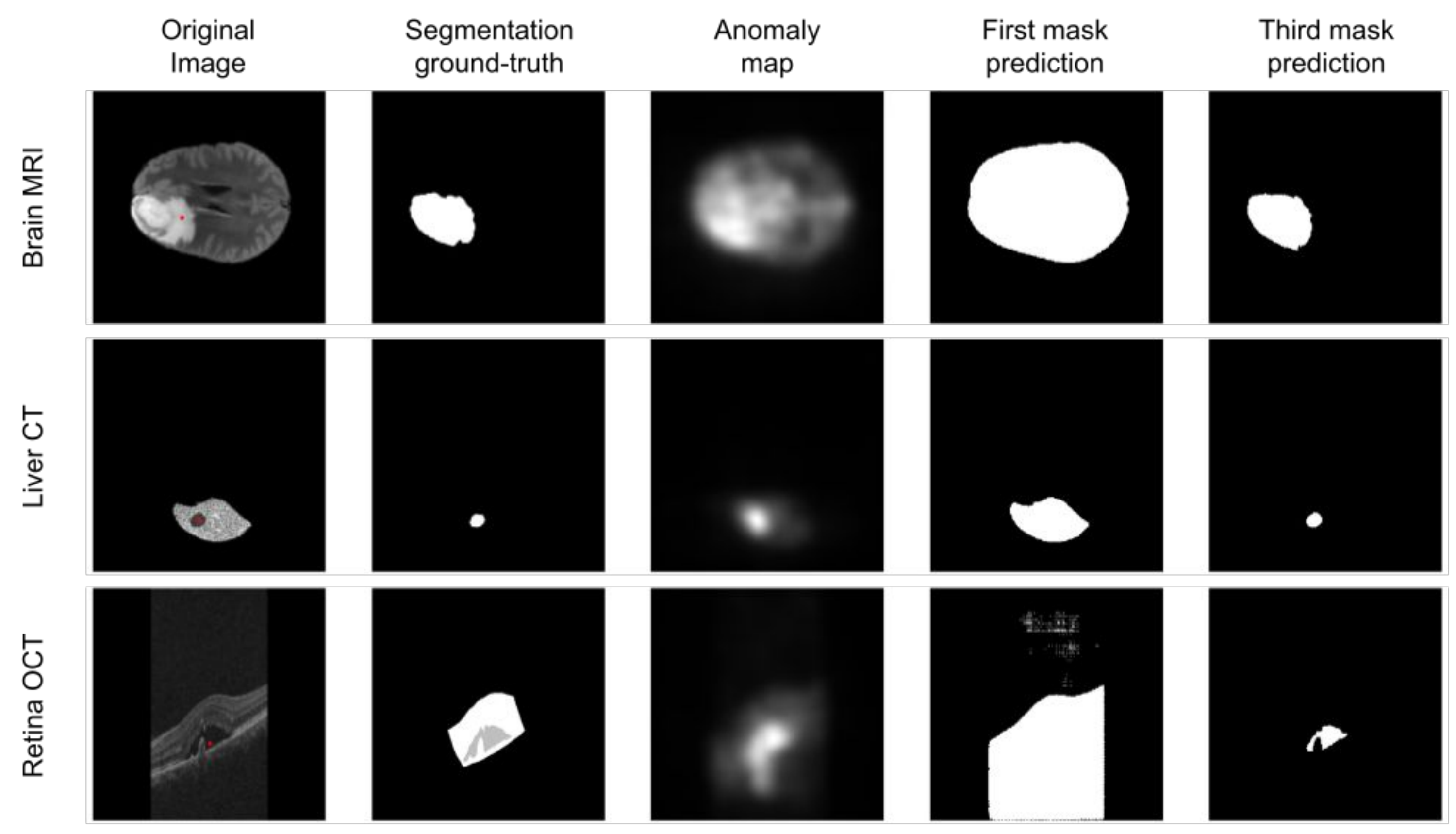


Figure: Anomaly maps and segmentation examples (center of gravity in red).

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