SAM-KG: Knowledge Graph-Enhanced Tumor Segmentation with Zero-Shot Foundation Models

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Introduction

Accurate tumor segmentation in medical imaging is challenging due to anatomical variability, tumor heterogeneity, and data scarcity. While deep learning models like UNet, Swin-UNETR, and D-LKA Net achieve strong results, they require extensive labeled data and struggle with generalization. Zero-shot models like SAM and MedSAM offer promising alternatives but lack volumetric consistency and structured spatial reasoning. We propose SAM-KG, a knowledge graph-enhanced segmentation framework that integrates multi-modal feature extraction, uncertainty-guided refinement, and anatomical relationship modeling to improve segmentation accuracy and interpretability. Evaluated on the Liver Tumor Segmentation (LiTS) and Medical Segmentation Decathlon (MSD) Pancreas datasets, SAM-KG surpasses state-of-the-art models, achieving superior boundary delineation and volumetric consistency, advancing AI-driven medical image analysis.

Significance of Research & Objectives

Accurate tumor segmentation in abdominal CT scans is challenging due to **low contrast**, **irregular tumor boundaries**, and **anatomical complexity**. Our framework, **SAM-KG**, addresses these challenges by combining **zero-shot segmentation** using the Segment Anything Model (SAM) with **spatial knowledge graphs** for enhanced accuracy and interpretability.
By modeling tumor-organ relationships—including coverage, proximity, and resectability—SAM-KG supports informed clinical decision-making and enables scalable, explainable, and generalizable medical image analysis across diverse datasets.

Methodology

We propose a spatially-aware framework for abdominal organ and tumor segmentation using the Segmentation Anything Model (SAM), optimized for medical imaging. The pipeline includes six core stages:

- **SAM-Based Segmentation**
  We use SAM to segment organs and tumors, optimized with medical image-specific prompting.
- **Point-Based Refinement with DBSCAN**
  DBSCAN clusters high-density tumor regions to improve segmentation accuracy and reduce false positives.

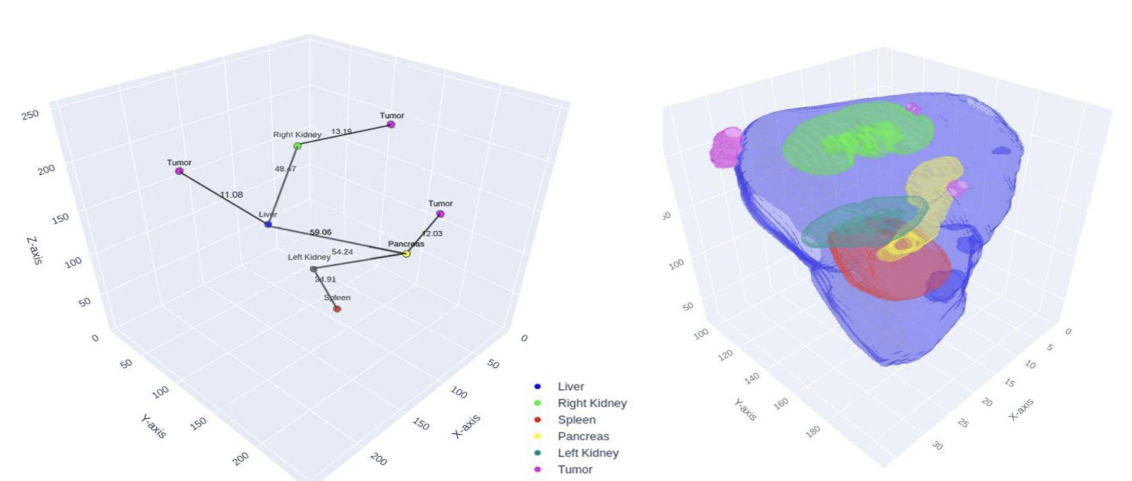


Figure 1. Graph-based representation of organ-tumor spatial relationships. Each node represents an organ or tumor centroid, while edges encode adjacency and volumetric interactions.

- **3D Centroid Representation**
  From 2D slices, we calculate 3D centroids to model spatial organ-tumor relationships.
- **Feature Extraction**
  We compute key features such as organ and tumor volume, centroid distance, and tumor coverage (% of organ occupied).
- **Graph-Based Explainability**
  A spatial graph encodes organ-tumor relationships, enabling visual interpretability and interaction modeling.
- **3D Reconstruction**
  We stack refined 2D masks into a 3D model and apply Delaunay triangulation for a smooth, volumetric representation.

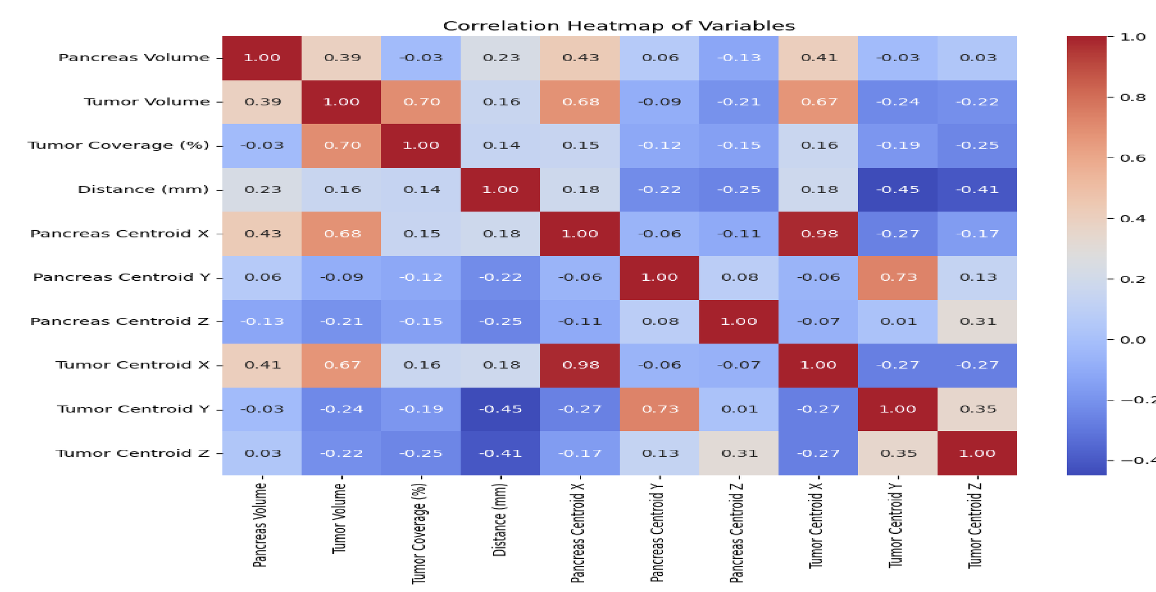


Figure 2. Correlation heatmap showing spatial and volumetric relationships in pancreatic tumor segmentation, highlighting dependencies between tumor size, organ volume, and centroids.

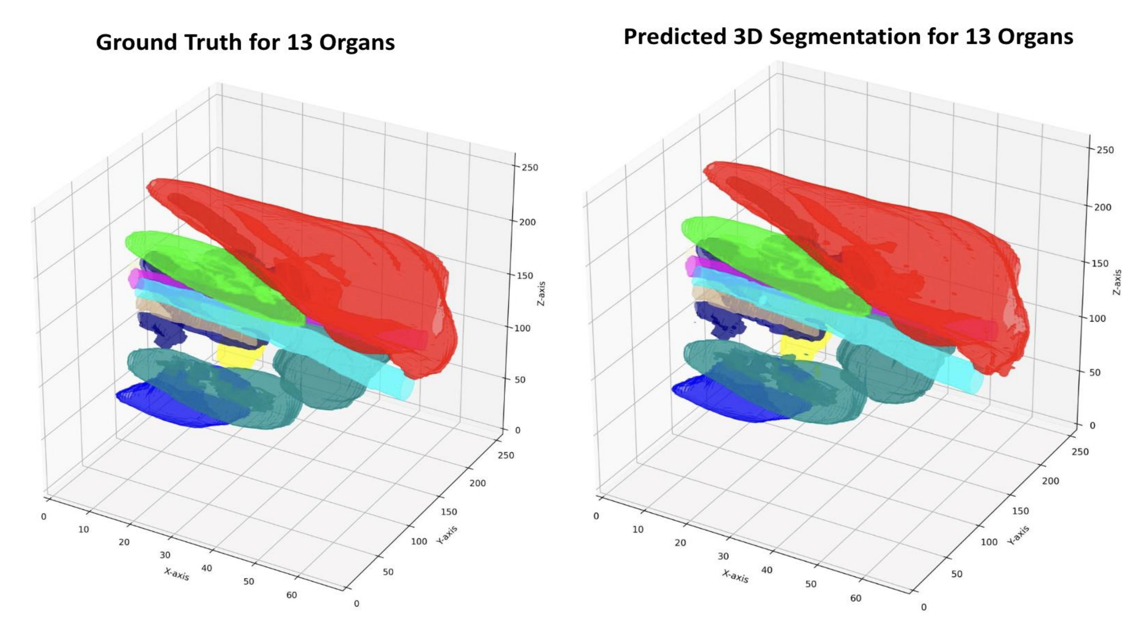


Figure 3. 3D reconstruction of SAM-based segmentation for 13 abdominal organs (FLARE 2022), comparing ground truth with predicted segmentation for volumetric accuracy.

Figure 4 provides a comprehensive overview of the SAM-KG framework, illustrating the integration of segmentation, knowledge graph construction, and spatial analysis. The structured pipeline incorporates adaptive prompting, dynamic segmentation refinement, and topological encoding to enhance medical image segmentation. The framework follows a multi-step approach. SAM-based segmentation results are first refined, stored in a model bank, and later used to build spatial graphs that improve medical decision-making..

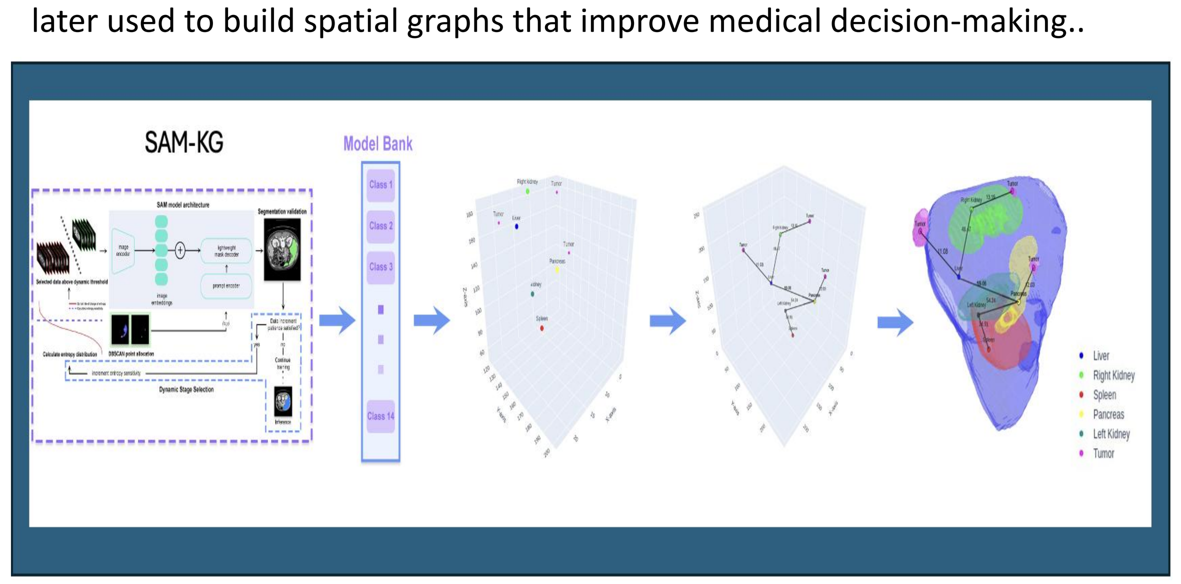


Figure 4. Overview of SAM-KG: From SAM-based segmentation with DBSCAN prompting to graph-based spatial modeling and 3D knowledge graph construction for clinical interpretation.

This framework bridges zero-shot segmentation with spatial reasoning, offering a robust and interpretable approach to tumor localization. To quantify spatial context, we compute tumor-organ adjacency as:

$$A = \frac{1}{d + \epsilon}$$

where d is the Euclidean distance between tumor and organ centroids, and ϵ\epsilonϵ ensures numerical stability.

Results & Analysis

We evaluated SAM-KG on three public datasets for abdominal organ and tumor segmentation:

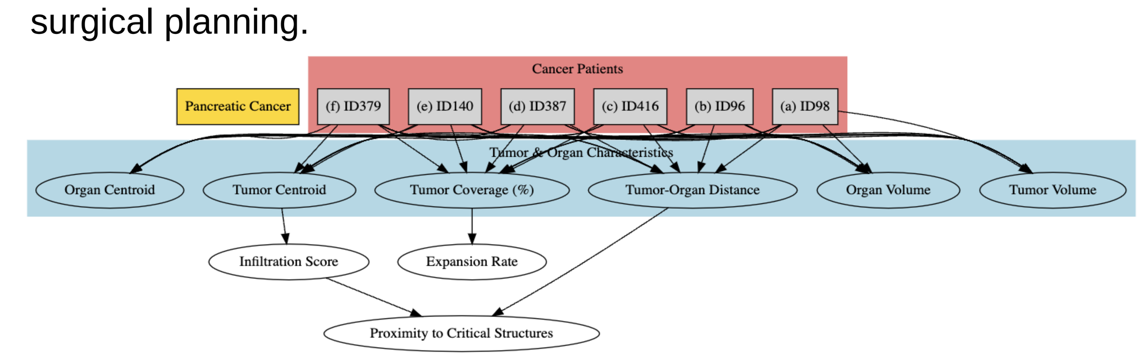
- **LiTS (Liver Tumors)**
  SAM-KG achieved the **highest DSC of 92.67%** and **IoU of 86.80%**, outperforming state-of-the-art models like D-LKA Net and PHNet.
- **MSD (Pancreas + Tumor)**
  SAM-KG reached **87.6% DSC** for pancreas and **62.13% DSC** for tumors, closely matching the best tumor segmentation score (SAM-Med3D: 65.89%).
- **FLARE 2022 (Zero-Shot Evaluation)**
  Demonstrated SAM's potential in segmenting liver and pancreas without task-specific training, reinforcing its generalization ability.

Model	DSC (%)	IoU (%)
SwinUNETR [28]	91.72	85.10
D-LKA Net [4]	92.05	85.54
CTO-Net [19]	91.50	84.59
MA-SAM [6]	90.25	—
MedSAM-U [35]	90.85	—
3DSAM-adapter [11]	89.71	—
PHNet [20]	92.17	85.68
MSML-AttUNet [14]	87.74	—
SAM-KG (Ours)	**92.67**	**86.80**

Table 1. Tumor segmentation results on LiTS using DSC and IoU. SAM-KG outperforms all baselines; best scores are bolded.

❑ **Spatial and Statistical Insights**
We analyzed tumor coverage, centroid distance, and boundary uncertainty to support clinical interpretability:

- **Liver Tumors**:
  High Dice scores overall, but boundary challenges and multi-focal tumors reduce consistency. Tumor-lobe proximity affects resectability.
- **Pancreatic Tumors**:
  Variability in tumor volume and centroid shifts near vessels complicate segmentation. Graph-based modeling improves localization and surgical planning.



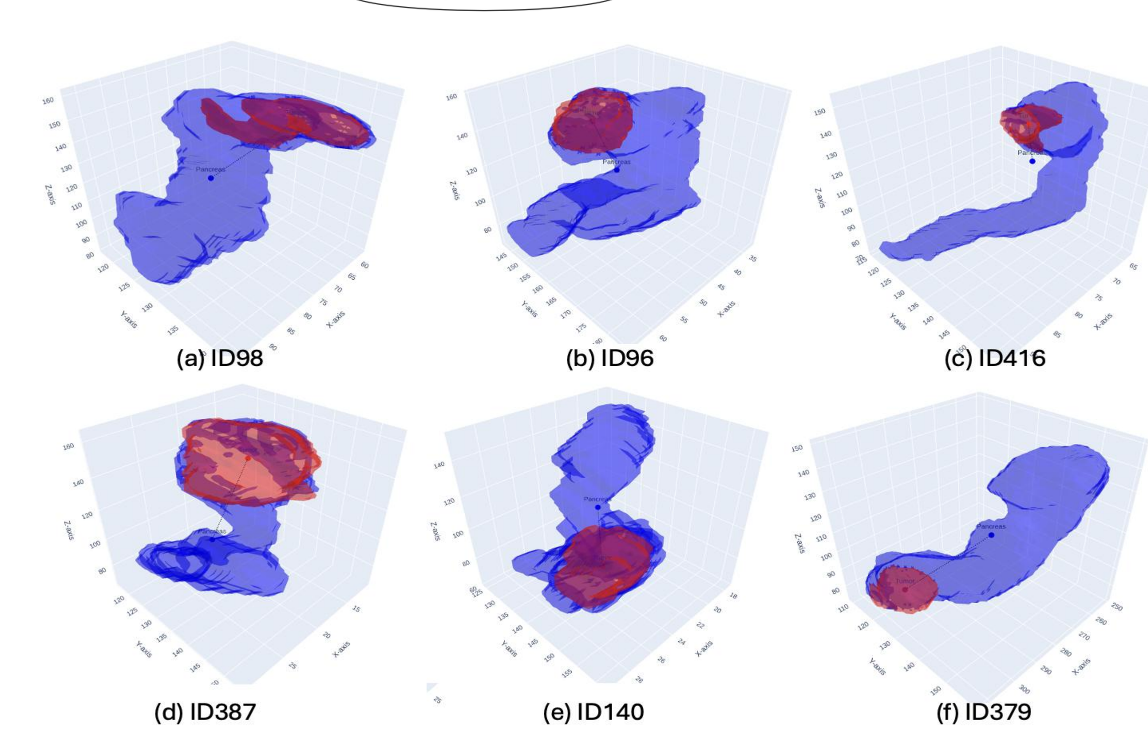


Figure 5. Graph-based spatial modeling of pancreatic tumors from the MSD dataset, highlighting tumor adjacency, centroid location, and 3D segmentation. Blue: pancreas, Red: tumors. Supports clinical tasks like localization and surgical planning.

❑ **Clinical Relevance**
Spatial graphs reveal tumor-organ proximity, aiding surgical planning and treatment decisions. Supports explainable AI for resectability and risk assessment.

Discussion

Our proposed **SAM-KG framework** demonstrates superior segmentation performance by integrating **zero-shot learning (SAM)** with **spatially-aware knowledge graphs**.

Key Findings:

- ➢ Outperforms CNN and transformer-based models on **liver and pancreas datasets** (LiTS, MSD).
- ➢ Effectively segments **small or low-contrast tumors** using DBSCAN-based prompting and **3D centroid modeling**.
- ➢ Graph-based spatial analysis enhances **tumor localization**, resectability estimation, and **clinical decision support**.

Clinical Impact:
SAM-KG's explainable outputs, such as tumor-organ distance and volumetric coverage, offer actionable insights for **surgical planning**, **treatment assessment**, and **risk evaluation**. This bridges the gap between AI performance and real-world medical applicability.

Limitations:

- ▪ Segmentation accuracy decreases in cases with **anatomical irregularities or multi-organ involvement**.
- ▪ Current evaluation is **CT-only**; future work includes extending to **MRI**, **PET**, and **multi-modal fusion**.
- ▪ Real-time **clinical deployment** and integration with **electronic health systems** remain key next steps.

Conclusion

We introduced **SAM-KG**, a novel framework integrating the Segment Anything Model with structured spatial reasoning:

- ❖ Achieved **state-of-the-art accuracy** on liver and pancreas segmentation (LiTS, MSD).
- ❖ Delivered **interpretable, spatially-aware insights** for surgical planning.
- ❖ Enabled **3D modeling** and explainable tumor localization.
- ❖ Demonstrated robustness in **low-contrast and multi-focal tumors** using adaptive prompting and spatial graphs.
- ❖ Supports future expansion to **multi-modal imaging** (e.g., MRI) and **real-time clinical deployment**.

By bridging **foundation models** with **clinical spatial knowledge**, SAM-KG offers a robust, explainable, and generalizable solution for medical image segmentation.
Future Work: We aim to extend SAM-KG across different imaging modalities (e.g., MRI, PET), integrate it into clinical workflows, and support longitudinal tumor tracking with language-guided interpretability.

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