

DEFINING TOPOLOGICAL PRIORS TO CONSTRAIN LEARNING-BASED IMAGE SEGMENTATION

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PLAN

1. Introduction and motivation
2. Context
 - a. Topology : persistent homology
 - b. Diffusion models
3. The ControlNet and TopoDiffNet pipeline
4. Results
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INTRODUCTION & MOTIVATION

WHY DO WE NEED TOPOLOGY IN MEDICAL IMAGE SEGMENTATION ?

- Traditional loss functions (e.g., Dice, Cross-Entropy) operate at the pixel/voxel level
- These losses ignore global structure: connectivity, holes, loops, etc.
- In medical imaging, topology can carry clinical meaning (e.g., a tumor should be a single connected region, a vessel can't be cut in two, a cell wall can't be broken, etc.)
- Without topological constraints, models can:
 - Produce disconnected lesions
 - Miss thin bridges or small holes
- Goal: Use topological priors to guide the model toward anatomically plausible segmentations

WHY DO WE NEED SYNTHETIC DATA FOR MEDICAL IMAGE SEGMENTATION ?

- **Limited data:** Real medical data is scarce due to privacy and cost.
- **Expensive annotation:** Segmenting MRIs needs expert time.
- **Class imbalance:** Some diseases or structures are rare.

CONTEXT

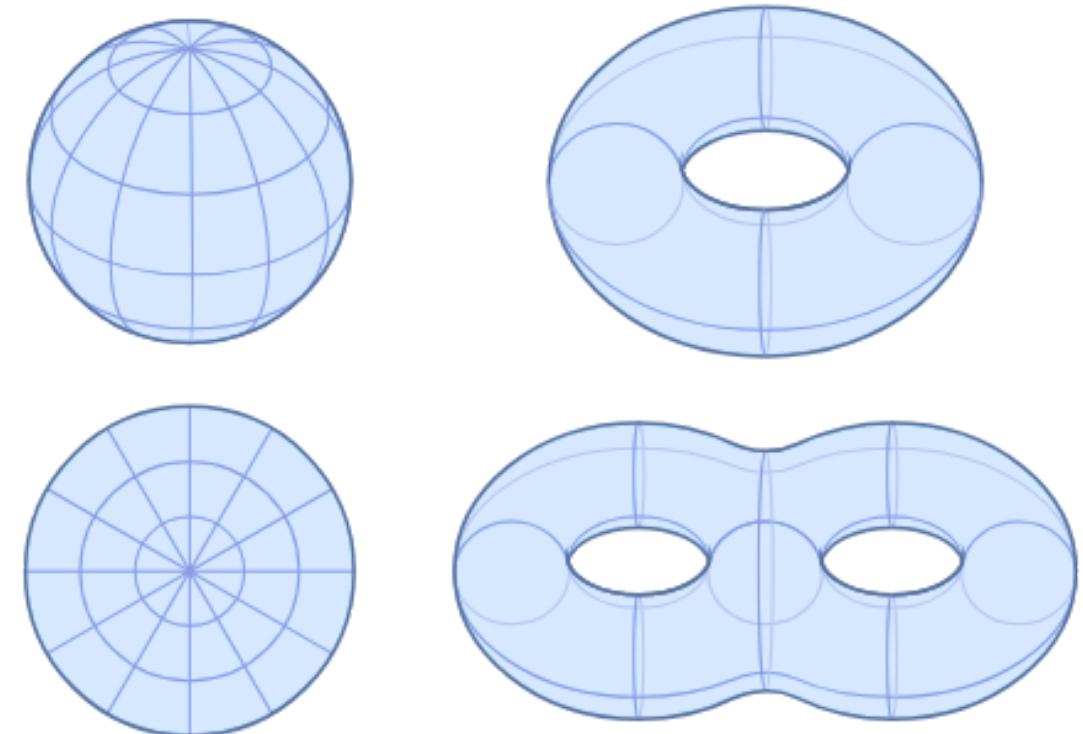
TOPOLOGY

TOPOLOGY

“

Topology is the branch of mathematics concerned with the properties of a geometric object that are preserved under continuous deformations, such as stretching, twisting, crumpling, and bending; that is, without closing holes, opening holes, tearing, gluing, or passing through itself.

”



TOPOLOGICAL DATA ANALYSIS

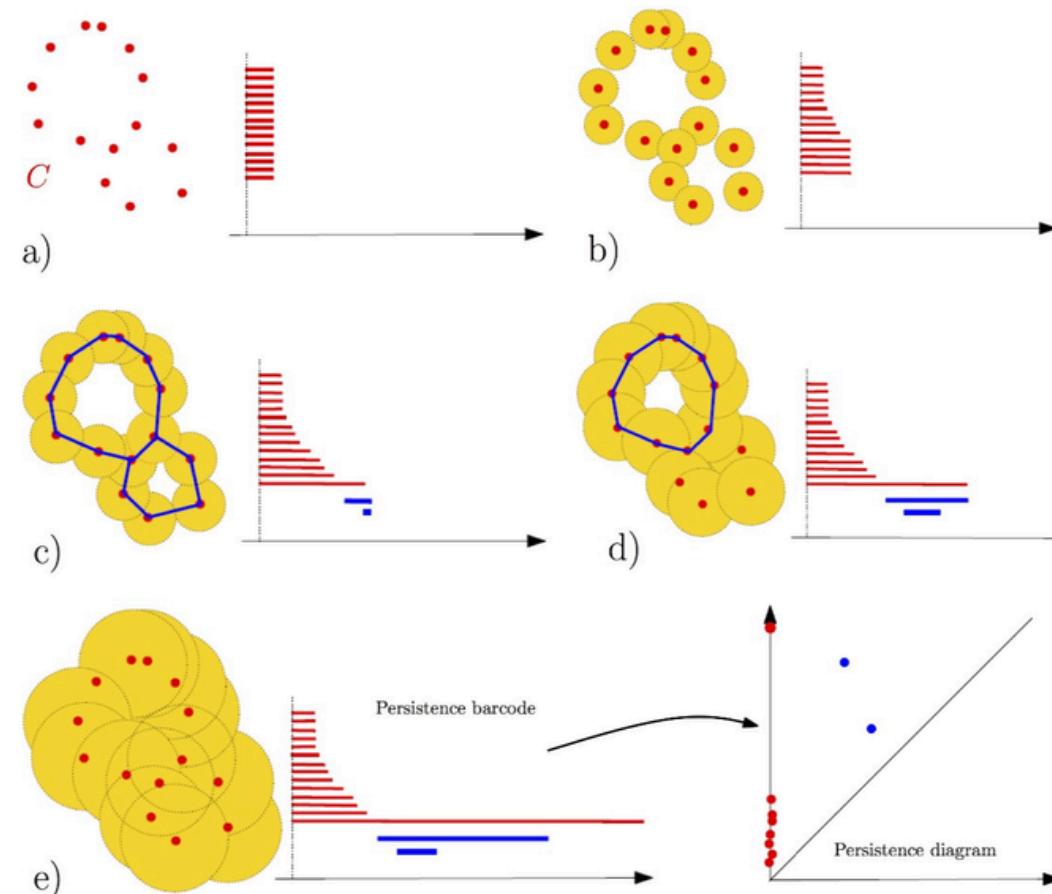
TDA applies ideas from topology to study the shape of data

- Goal: capture global structure beyond local or pixel-wise patterns
- Works on:
 - Functions (e.g., segmentation outputs)
 - Point clouds
 - Images
- Extracts features like:
 - Connected components
 - Holes / loops
 - Enclosures / voids
- Outputs robust features that are invariant to small deformations
- Core tool: persistent homology

PERSISTENT HOMOLOGY

Captures how topological features (components, holes, voids) appear and disappear across scales, which helps quantify how strong or relevant a topological feature is

- Build a filtration: threshold the function at different values
- Tracks when features appear (birth) and disappear (death)
- Result: a persistence barcode or diagram

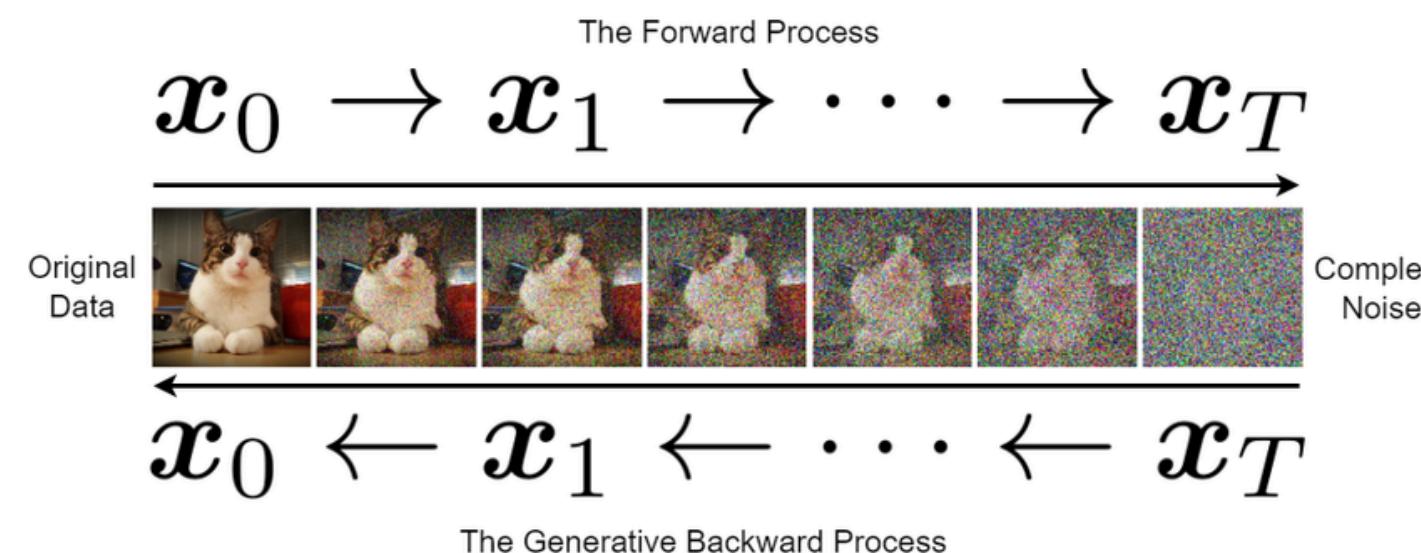


DIFFUSION MODELS

DIFFUSION MODELS

They are generative models that learn to generate data by reversing a noising process

- Two key steps:
 - a. Forward process: gradually adds Gaussian noise to data
 - b. Reverse process: learns to denoise step-by-step and recover the original data
- Recently used in:
 - Image generation (e.g., DALL·E, Stable Diffusion)
 - Medical imaging synthesis and segmentation (e.g. MedSegDiff (Luo et al., 2023))



PIPELINE

PURPOSE

This pipeline generates topologically accurate (i.e. anatomically plausible) MRI images of brains with gliomas (brain tumors).

The goal is to verify the importance of :

- **topological constraints in segmentation in general**
- **enforcing rules on class interactions**
- **cf. TopoDiffNet paper : generating multiple instances from the same mask**

LIBRARIES USED

- PyTorch
- MONAI

DATA

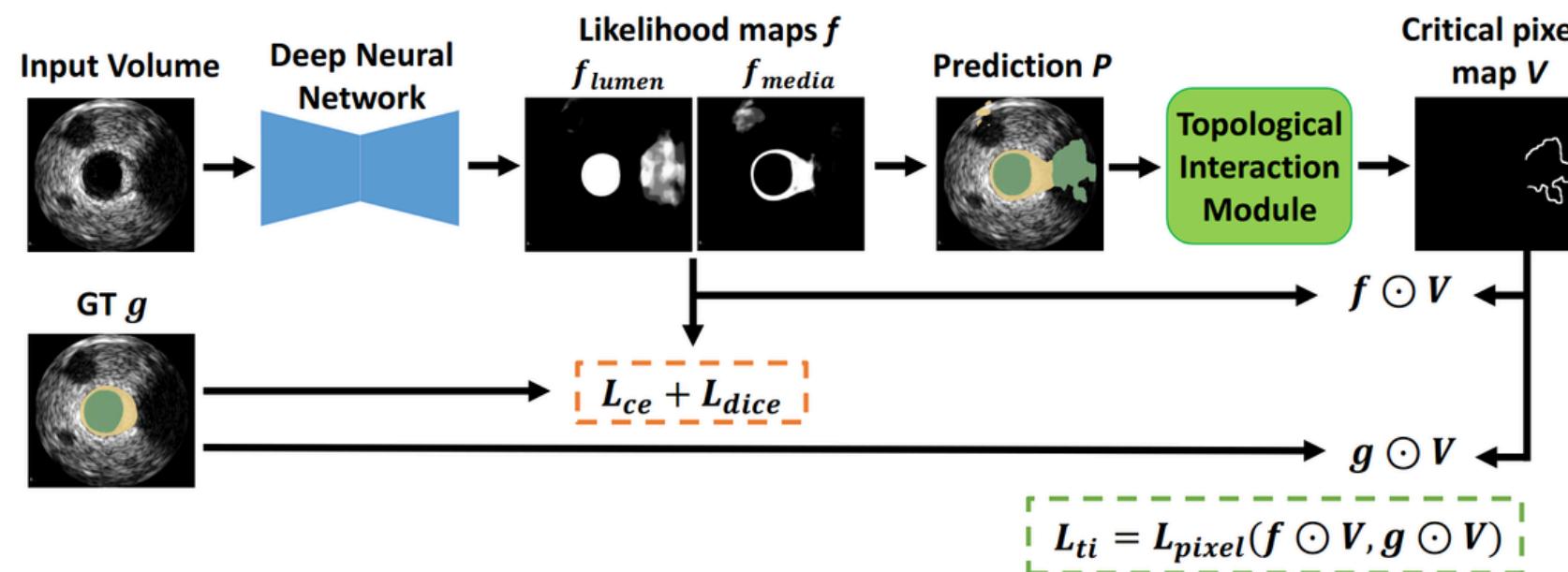
- **BraTS 2019** : The Brain Tumor Segmentation Challenge (BraTS) is an international competition focused on automating segmentation of brain tumors from multi-modal MRI scans.
- 4 modalities : FLAIR, T1, T1Gd, T2
- Each patient (data sample) has an associated segmentation mask that identifies the main tumor subregions. These masks are 3D volumes where each voxel is labeled : 1 for the necrotic and non-enhancing core (NCR/NET), 2 for the edema (ED), and 4 for the enhancing tumor (ET). Areas without tumor are labeled as 0.
- (extracted from MONAI)

MODELS

- **ControlNet**
 - Original paper : “Adding Conditional Control to Text-to-Image Diffusion Models” by Lvmin Zhang et al., 2023
 - Goal : Introduces a framework to guide diffusion models with external conditions (e.g., canny edges, segmentation maps), enabling precise control over the generation process without sacrificing image quality.
- **TopoDiffusionNet**
 - Original paper : “TopoDiffusionNet: Topology-Aware Segmentation Using Diffusion Models” by Saumya Gupta et al., 2024
 - Goal : Proposes the use of diffusion models for segmentation while enforcing topological priors through a topological interaction (TI) loss encouraging outputs that respect medically relevant structures.

LOSS FUNCTION

- Topological Interactions loss
 - Original paper : “Learning Topological Interactions for Multi-Class Medical Image Segmentation” by Saumya Gupta et al., 2022



$$L_{total} = L_{ce} + \lambda_{dice} L_{dice} + \lambda_{ti} L_{ti}$$

adding this loss (weighted) to a simple loss (MSE in this case)

$$\mathcal{L}_{\text{simple}} + \lambda \mathcal{L}_{\text{top}}$$

THE PIPELINE

1. Train a **ControlNet** to generate MRI images based on segmentation masks (using the BraTS ground truth data)
2. Train a **Diffusion Model** with the TI loss to generate topologically accurate segmentation masks from noise (using the BraTS ground truth data)
3. Infer on the **Diffusion Model** to generate synthetic segmentation masks
4. Infer on the **ControlNet** to generate MRI images based on the segmentation masks generated in step 3

DATA SPLITTING

- Same training set for :
 - the base diffusion model for ControlNet
 - the ControlNet itself
 - the diffusion model with TI loss
- Same validation set for :
 - the base diffusion model for ControlNet
 - the ControlNet itself
- Separate validation set for the diffusion model with TI loss

THE PIPELINE (AGAIN, NOW THAT WE KNOW THE SPLITS)

- **ControlNet : training**
 - **Base diffusion model**
 - **Input : (MRI, label)**
 - **ControlNet**
 - **Input : (MRI, label)**
 - **Constrain : label**
- **Diffusion model with TI loss : training**
 - **Input : (MRI, label)**
- **Diffusion model with TI loss : inference**
 - **Output : generated label**
- **ControlNet : inference**
 - **Input : generated label**
 - **Output : generated MRI**

RESULTS

CONTROLNET

Conditioning label



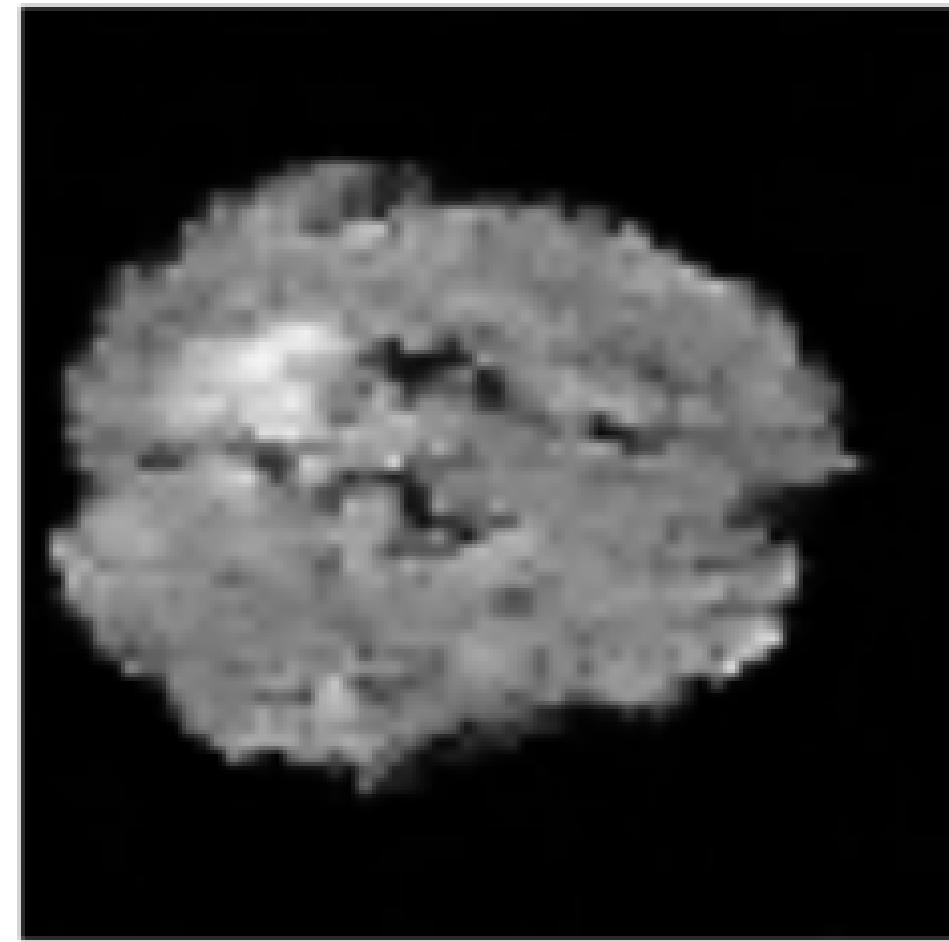
Sample image



Conditioning label



Sample image

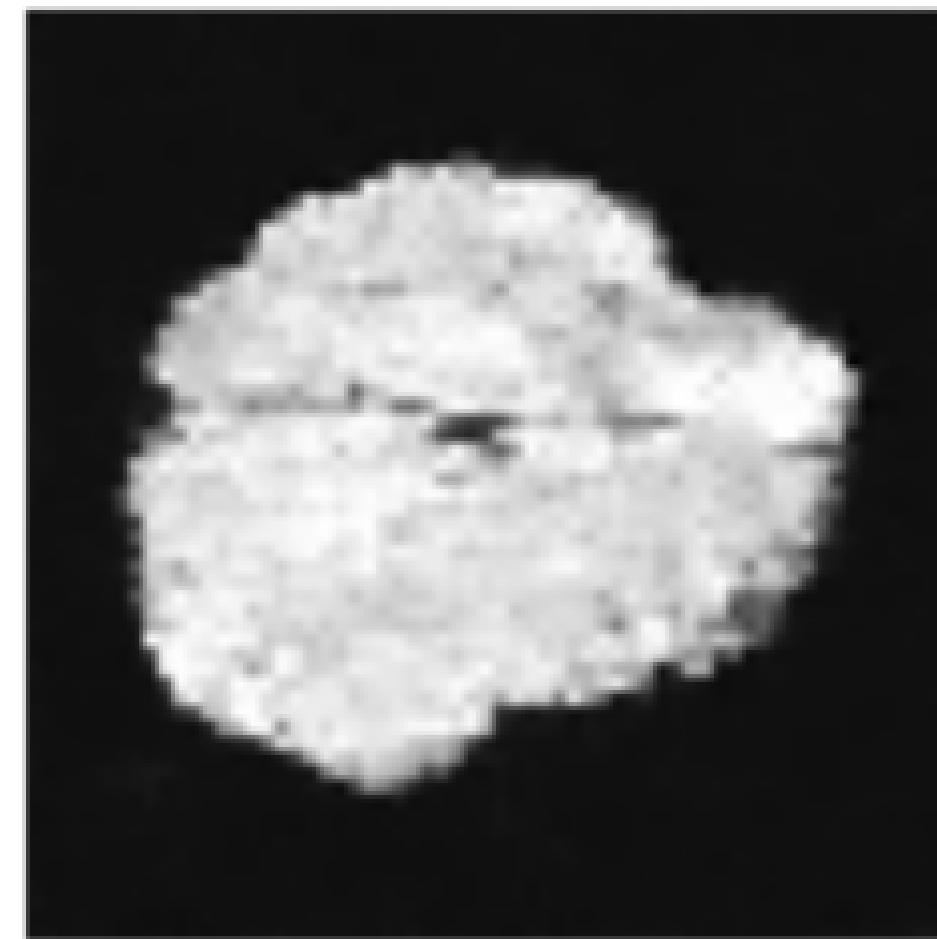


FULL PIPELINE

Generated label



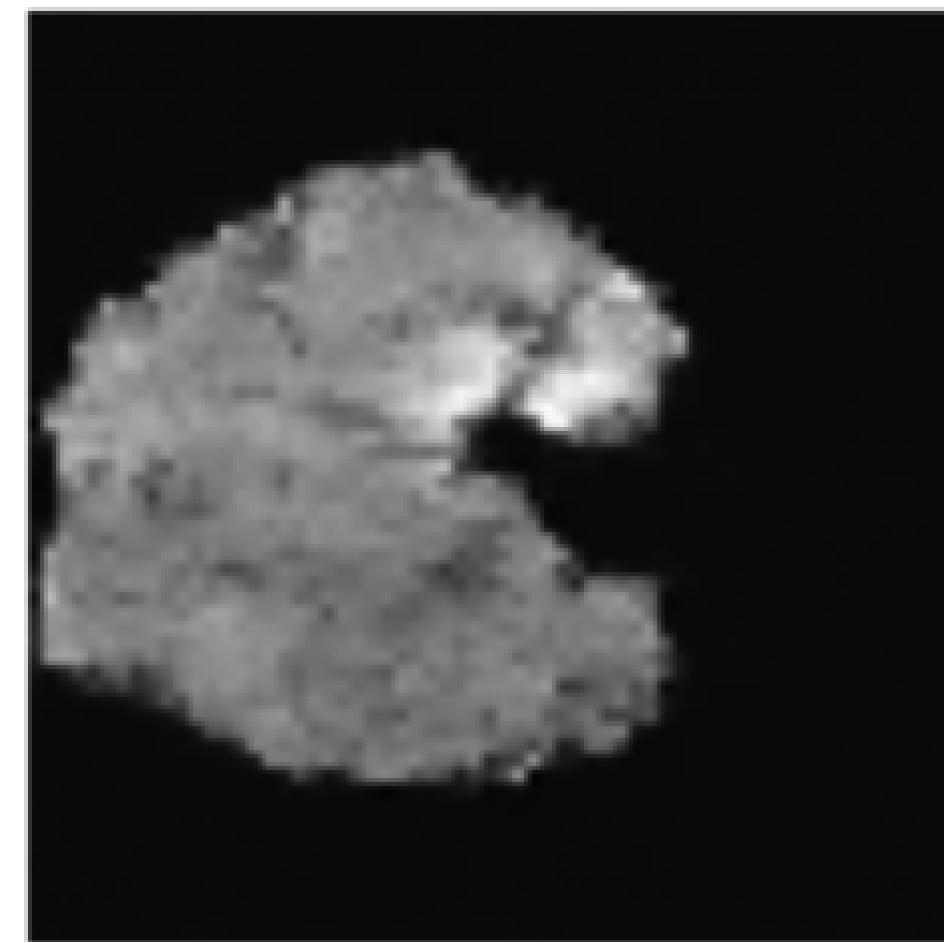
Generated MRI



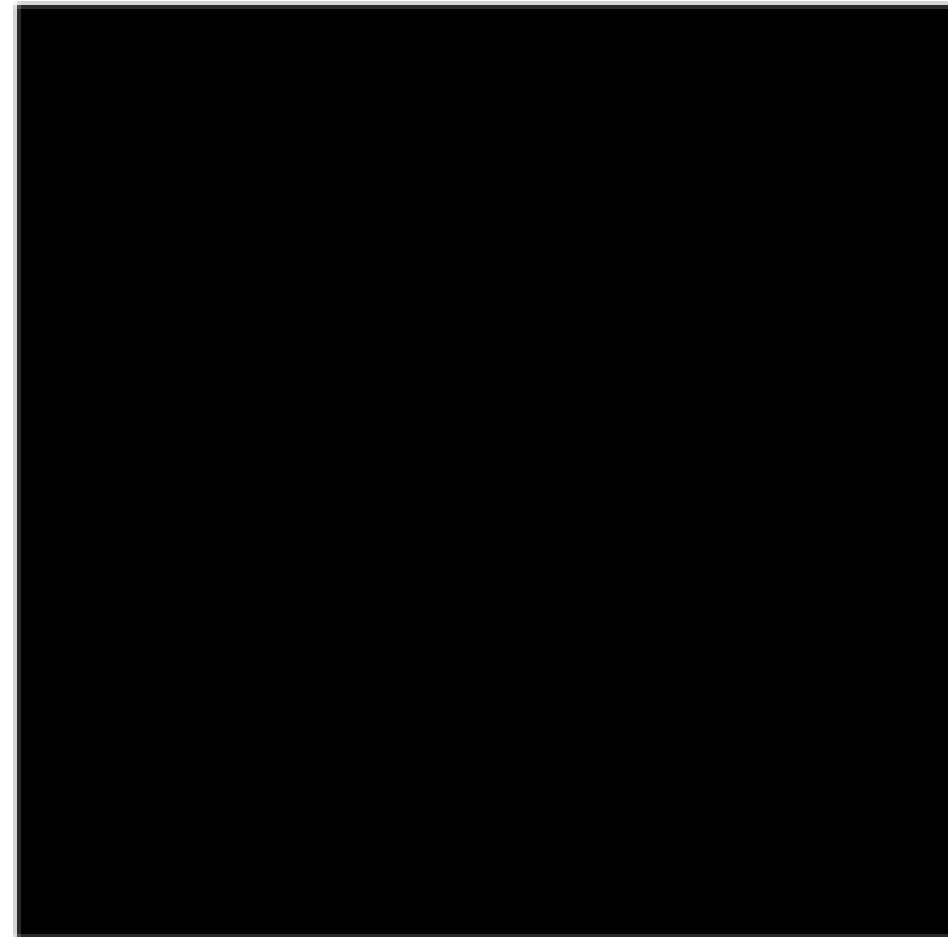
Generated label



Generated MRI



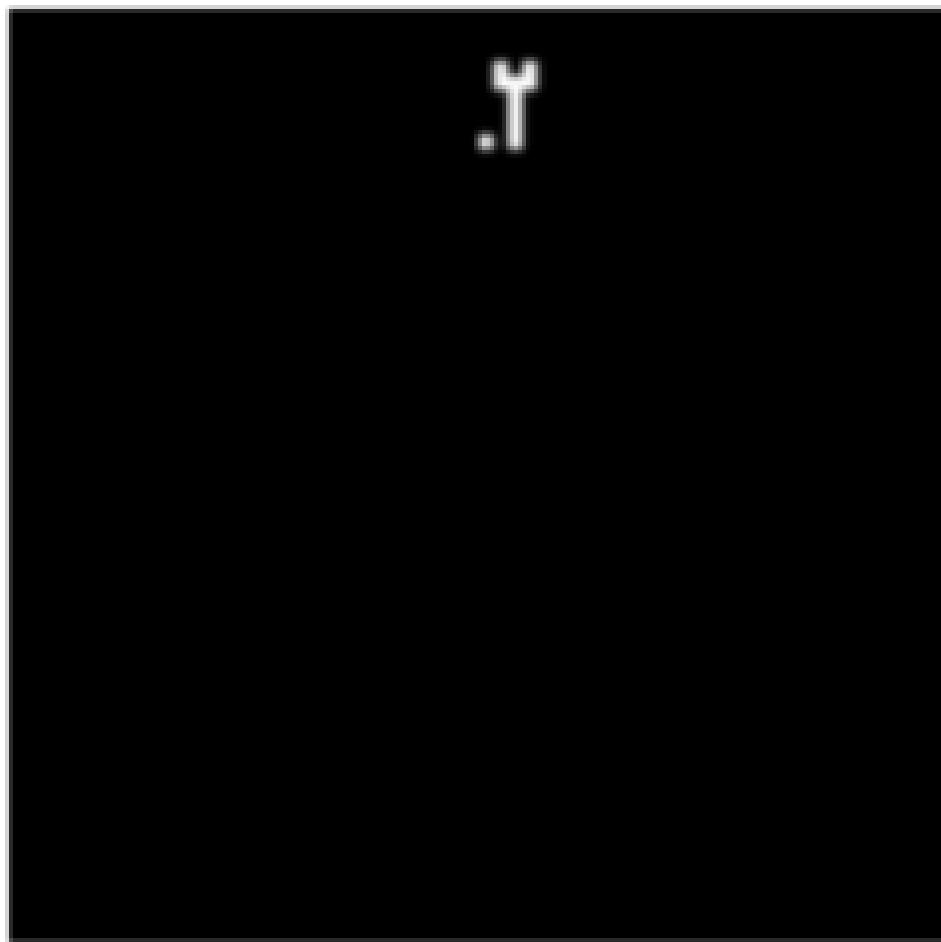
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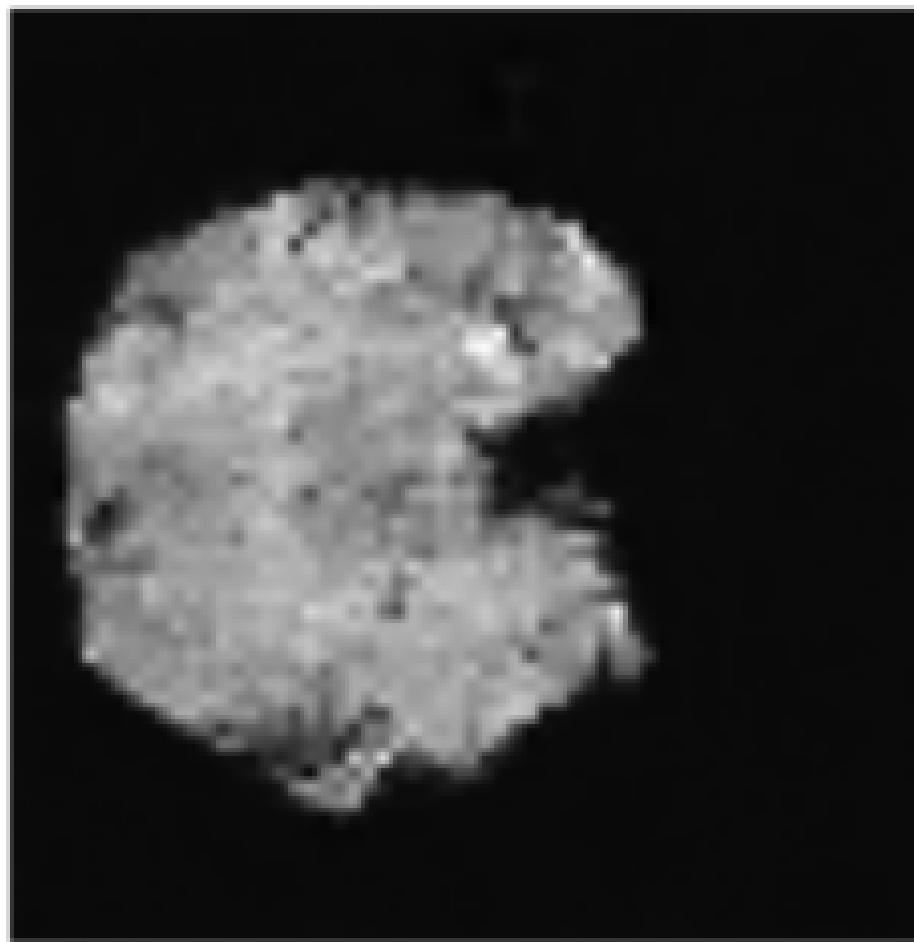
Generated MRI

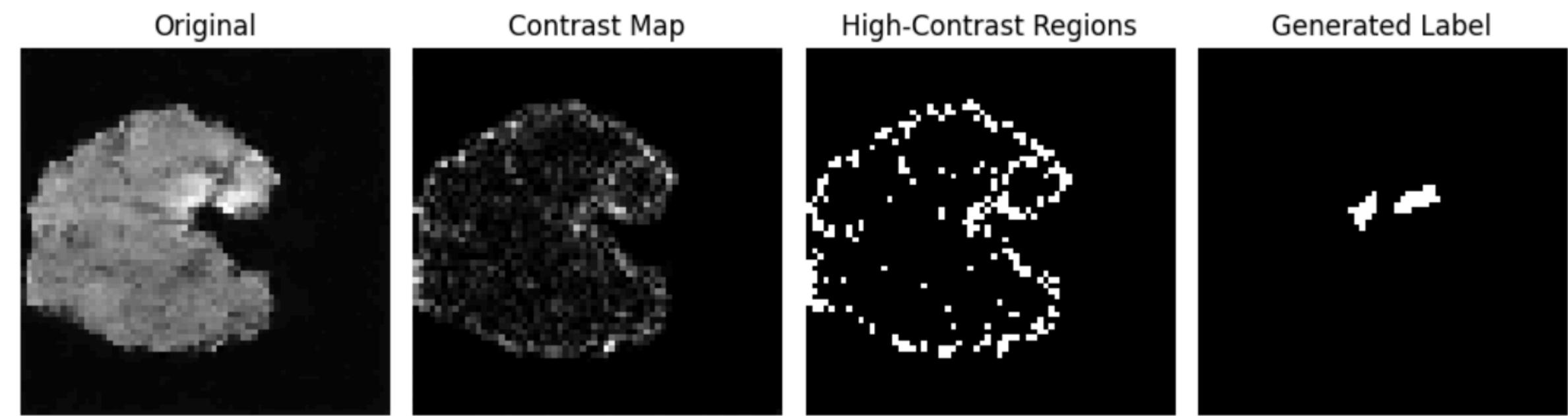


Generated label



Generated MRI





LIMITATIONS & FUTURE WORK

LIMITATIONS OF MY WORK

- In a real scenario, computationally intensive training due to diffusion models and topological losses (used only 100, 150 or 200 epochs)
- Sensitivity to hyperparameters such as TI loss weight (used only 1e-5 cf. TopoDiffNet paper, no fine-tuning or model selection)
- Limited scalability to 3D or higher resolution images (used only 64x64)

FUTURE WORK

- Add position-based constraints in order to generate mostly where the tumor is
- Generalize to 3D
- Metrics to test the MRIs : SSIM and PSNR
- Metrics to test the mask : Dice loss, 95th percentile Hausdorff distance (HD95)
- Train a segmentation model using this generated data

THANK YOU