Multi-category Graph Reasoning for Multi-modal Brain Tumor Segmentation

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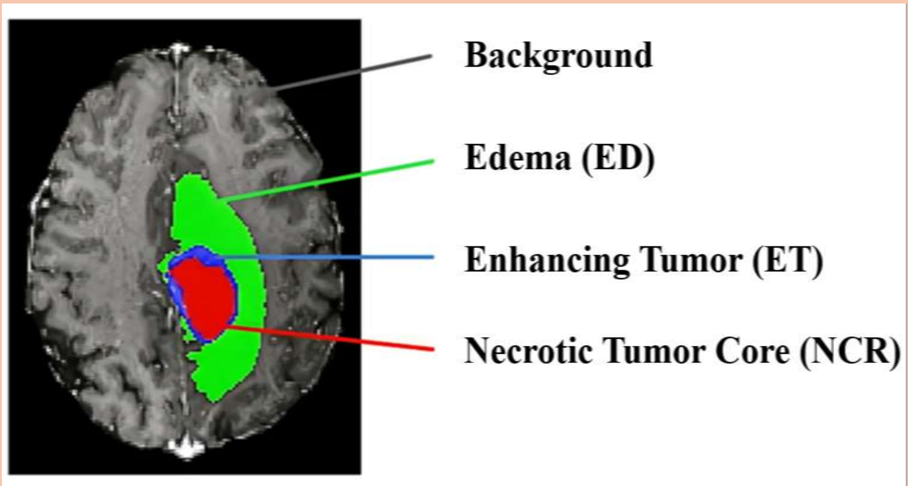
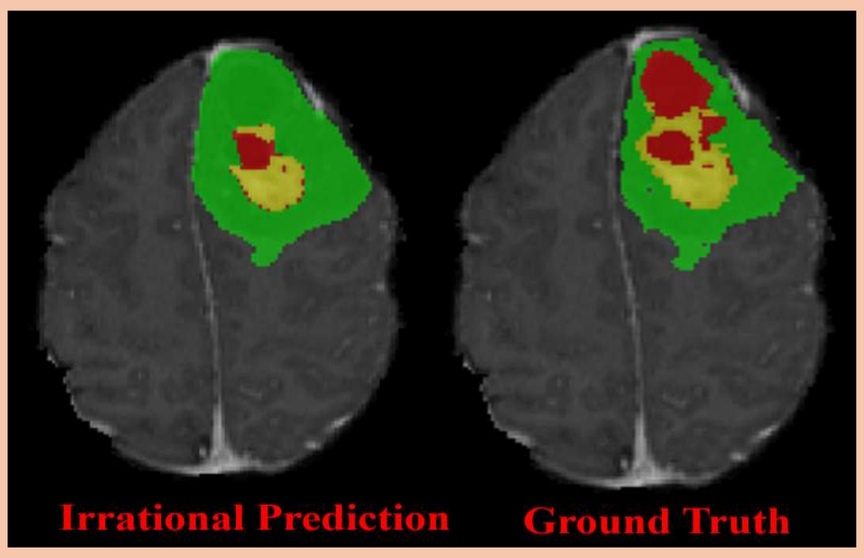
Background & Motivation

Four categories of sub-regions in brain tumor images: Background, Enhancing Tumor (ET), Edema (ED), and the Necrotic Tumor Core (NCR).



Limitations of exisiting studies

- ignore the **relationship between multiple categories** in brain tumor segmentation, leading to **irrational tumor area distribution** in the predictive results.



Inspiration: **Contours** are strongly structurally correlated with multi-category subregions:

- Provide **precise localization** and differentiation between multi-category subregions:
  I. Enhance the clarity of contours .
  II. Make the **boundary information** of multiple category areas more accurate.

Our idea:

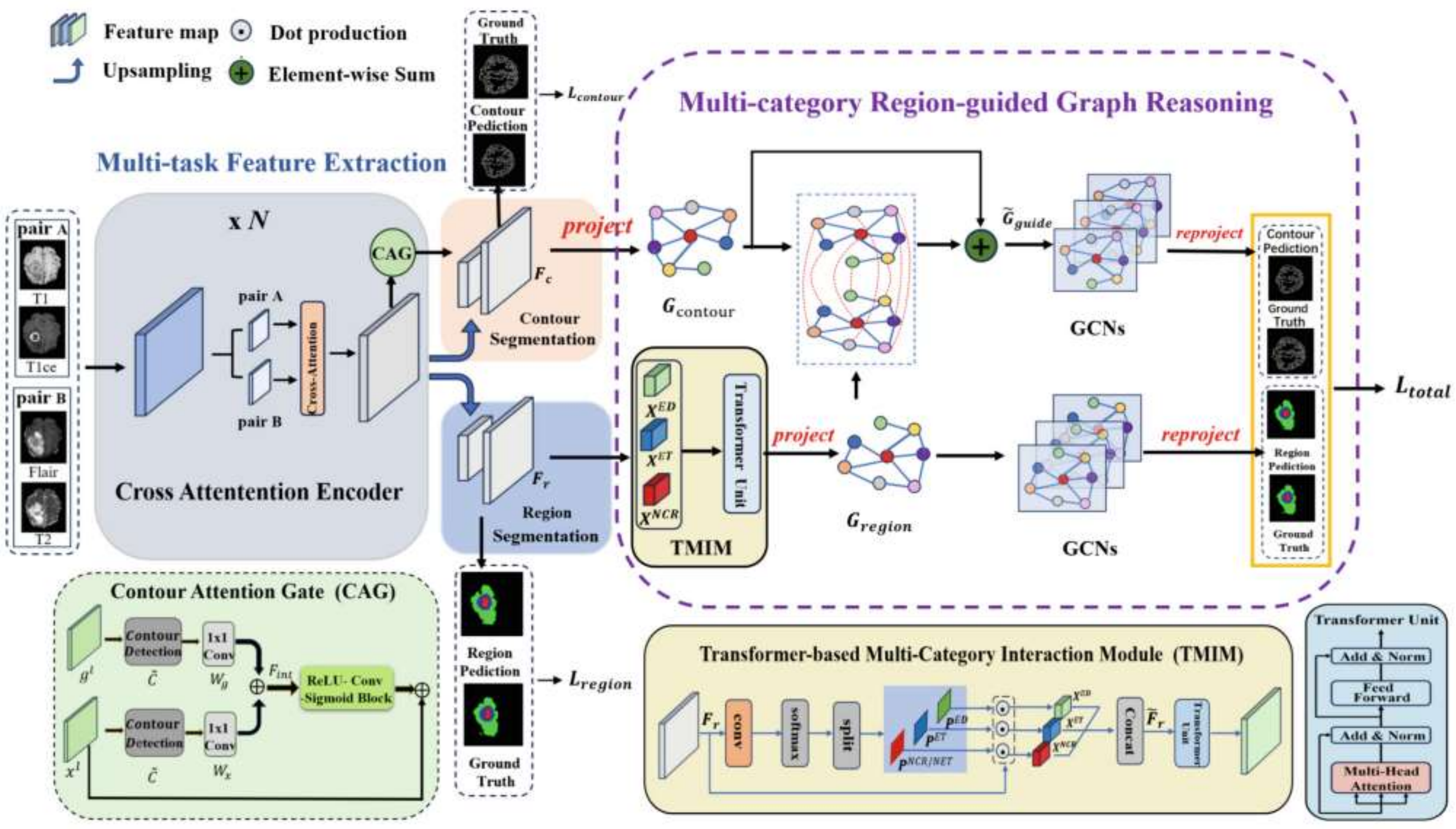
Integrating multi-category and contour information

- ✓ assist the localization of tumor regions
- ✓ alleviate the problem of edge blurring

Contribution

- Propose a Multi-category Region-guided Graph Reasoning Network that leverages multi-modal and multi-category information in brain tumor images and introduces contour information to assist segmentation.
- Develop a Transformer-based Multi-Category Interaction Module (TMIM) to capture the multi-category feature relationships among brain tumor subregions of NCT, ET, and ED.

Method



- **Multi-task Feature Extraction**: **1) The Multi-task Feature Extraction Network :** Effectively integrate information from multi-modal medical images and reduces the computational cost. **2) CAG:** Enhance the utilization of contour information ---- effective in reducing boundary errors and providing complementary information for subregion localization.

- **Multi-category Region-guided Graph Reasoning:** **1) Region-guided Reasoning:** Capture semantic relationships between regions and contours ---- facilitate the identification of tumor locations and guiding contour learning. **2) TMIM:** Identify and locate brain tumor subregions, addressing the challenge of contour overlap.

Results

Table1. Result Comparison on BraTS2019

Model	$Dice(\%)\uparrow$				$HD95(mm)\downarrow$			
	ET	TC	WT	Ave	ET	TC	WT	Ave
TransBTS	80.86	81.19	89.35	83.80	5.642	6.048	4.332	5.460
Nestedformer	82.11	86.42	**91.18**	86.57	5.534	5.906	5.317	5.585
SF-Net	80.08	82.33	88.61	83.67	4.787	7.440	7.288	6.505
ACM-Net	80.63	87.15	88.08	85.28	4.564	7.774	3.862	5.400
Eoformer	82.94	86.83	90.39	86.72	**4.053**	**5.843**	5.822	**5.239**
Ours	**83.23**	**89.10**	90.44	**87.59**	5.110	7.523	**3.775**	5.469

Table2. Result Comparison on BraTS2020

Model	$Dice(\%)\uparrow$				$HD95(mm)\downarrow$			
	ET	TC	WT	Ave	ET	TC	WT	Ave
TransBTS	80.89	83.25	90.10	84.08	5.873	6.875	4.876	5.824
Nestedformer	82.85	86.48	**91.20**	86.84	5.721	6.115	4.598	5.528
SF-Net	81.10	83.84	89.01	84.65	**4.305**	7.661	7.720	6.562
ACM-Net	82.42	87.75	90.08	86.75	4.492	7.624	3.956	5.375
Eoformer	83.54	87.12	90.87	87.17	5.911	**6.041**	3.852	**5.268**
Ours	**84.38**	**89.21**	90.77	**88.12**	5.413	7.759	**3.844**	5.672

Table3. Ablation Study

Model	$Dice(\%)$			
	ET	TC	WT	Ave
(1) Unet	79.10	81.00	87.93	82.67
(2) Unet+CAG	80.73	83.23	89.62	84.52
(3) Unet+GCN	80.93	85.09	88.12	84.71
(4) Unet+CAG+GCN	81.69	88.12	90.11	86.64
Proposed	**83.23**	**89.10**	**90.44**	**87.59**

Visual Results on BraTS2019