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# EdgeFormer-Med: Boundary-Adaptive Transformer for Precise Segmentation of Small and Low-Contrast Anatomical Structures

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**ABSTRACT**
Accurate segmentation of brain tumors from magnetic resonance imaging (MRI) is an important task in computer-aided diagnosis, treatment planning, and disease monitoring. However, small tumor regions and irregular anatomical structures remain difficult to segment because of weak boundaries, low contrast, class imbalance, scale variation, and the loss of fine spatial information during feature extraction and downsampling. Existing medical image segmentation approaches have explored boundary-aware attention, multi-scale feature learning, Transformer-based global context modeling, and specialized loss functions, but these techniques often address individual aspects of the problem. This paper proposes EdgeFormer-Med, a boundary-adaptive Transformer framework designed for precise segmentation of small and low-contrast anatomical structures in brain MRI. The proposed framework combines multi-scale feature representation with Transformer-based contextual modeling and an edge-guided attention mechanism to preserve fine boundary information. A boundary-adaptive feature fusion stage is proposed to integrate edge, local, and global features, while a small-object-aware loss is designed to place greater optimization emphasis on difficult and small target regions. The framework is planned for evaluation using the BraTS Adult Glioma (BraTS-GLI) benchmark dataset and standard segmentation metrics such as Dice Similarity Coefficient, Intersection over Union, Precision, Recall, and HD95. As this work is presented as a research framework without completed experiments, no numerical performance results are claimed. The proposed methodology establishes a structured basis for future implementation, quantitative evaluation, and ablation analysis.

**KEYWORDS:** Brain Tumor Segmentation, Medical Image Segmentation, Edge-Guided Attention, Boundary-Aware Segmentation, Multi-Scale Transformer, Small-Object Segmentation, Low-Contrast Lesions, Small-Object-Aware Loss, BraTS-GLI.

## 1. INTRODUCTION

Medical image segmentation is the process of identifying and separating anatomical structures or pathological regions from medical images. In brain imaging, segmentation of tumor regions from MRI scans can support diagnosis, treatment planning, response assessment, and quantitative analysis. Deep learning has become an important approach for medical image segmentation because it can learn hierarchical representations directly from image data.

Convolutional Neural Network (CNN)-based encoder-decoder architectures have demonstrated strong performance by combining high-level semantic features with spatial information. However, repeated downsampling can reduce fine-grained information and make small structures difficult to recover during decoding. The problem becomes more severe when the target region has weak contrast against surrounding tissue or when the target occupies only a small portion of the image.

Recent studies have investigated edge-aware networks to preserve anatomical boundaries. DGAM-Net introduces edge-guided attention together with detail enhancement, while MEGANet uses an Edge-Guided Attention module and a Laplacian operator to emphasize weak boundaries. MEGANet-W further explores directional edge information using Haar wavelets. These studies demonstrate the importance of explicit boundary information for precise segmentation.

Transformer-based medical segmentation methods provide another direction by modeling long-range dependencies and contextual relationships. SSCFormer combines convolutional and Transformer components for intra-scale and inter-scale feature learning. Other multi-scale Transformer approaches similarly show that processing information at multiple spatial scales can improve representation of both local details and broader context.

Loss functions have also been investigated to improve segmentation of difficult regions. Attentive Depth-Mapped Dice Loss uses distance information to emphasize hard boundary regions, while Boundary-Sensitive Loss incorporates boundary and location constraints and increases attention to small objects. These works indicate that improving the optimization objective is important when small structures and weak boundaries are involved.

Although these research directions provide valuable solutions, a combined framework specifically designed to address small, low-contrast, and weak-boundary brain tumor regions remains a relevant research opportunity. Therefore, this work proposes EdgeFormer-Med, which integrates edge-guided attention, multi-scale Transformer representation, boundary-adaptive feature fusion, and small-object-aware optimization within a unified segmentation framework.

**1.1 Problem Statement**

Small anatomical structures and tumor regions are difficult to segment because of weak boundaries, class imbalance, low contrast, scale variation, and information loss during feature downsampling. Existing segmentation networks may prioritize large regions and produce inaccurate boundaries for small targets. Therefore, a boundary-adaptive segmentation framework is required to preserve fine spatial information and improve the detection and delineation of small and irregular anatomical structures in brain MRI.

**1.2 Research Objective**

- To develop a boundary-adaptive segmentation framework for small and low-contrast brain tumor regions.
- To incorporate edge-guided attention for preserving weak and irregular tumor boundaries.
- To use multi-scale Transformer representations for capturing local details and global contextual dependencies.
- To design a small-object-aware loss that provides greater optimization emphasis to small and difficult target regions.
- To establish an evaluation framework suitable for future implementation on the BraTS-GLI benchmark.

### 1.3 Proposed Innovation

- Edge-guided attention for explicit boundary representation.
- Multi-scale Transformer feature learning for local-global contextual modeling.
- Boundary-Adaptive Feature Fusion for dynamically integrating edge and semantic information.
- Small-object-aware loss for improving optimization of small and hard-to-segment regions.

## 2. LITERATURE REVIEW

Existing research relevant to EdgeFormer-Med can be grouped into boundary-aware segmentation, small-object segmentation, Transformer-based medical image segmentation, and specialized loss functions. The literature review used for this work contains ten relevant studies covering these directions.

### 2.1 Boundary-Aware Medical Image Segmentation

DGAM-Net focuses on detail enhancement and edge guidance for polyp segmentation. Its Edge-Guided Attention mechanism is designed to help the network focus on important regions and improve edge segmentation. MEGANet addresses weak polyp boundaries by combining an edge detection technique with attention, while MEGANet-W uses Haar wavelet edge maps and Wavelet Edge-Guided Attention to preserve directional high-frequency information. Boundary Aware Networks for Medical Image Segmentation similarly emphasize explicit anatomical boundary representation. These studies motivate the use of boundary information in EdgeFormer-Med.

### 2.2 Small-Object Medical Image Segmentation

CLD-Net specifically targets medical small-object segmentation and introduces Local Edge Feature Extraction and Local-Global Feature Fusion to preserve detailed information during upsampling. CaraNet focuses on small medical objects using context axial reverse attention and feature pyramid modules. DCSNet addresses sparse medical targets by using detection-guided cropping and multiscale feature aggregation. Spatial-Depth Coupled Attention for Small Target Segmentation in 3D Medical Images considers minute lesions, complex boundaries, multimodal variation, and uneven lesion scales. Together, these studies highlight the importance of preserving fine features and scale-aware representations.

### 2.3 Transformer-Based Medical Segmentation

SSCFormer revisits the ConvNet-Transformer hybrid design from scale-wise and spatial-channel-aware perspectives and demonstrates the value of intra-scale and inter-scale feature modeling. A multi-scale Vision Transformer approach combines Transformer processing with multi-scale representations to capture low-level and high-level semantic information. Multi-scale feature fusion with Transformer architectures further supports the use of global context together with spatially detailed representations. These studies provide the motivation for the multi-scale Transformer component of EdgeFormer-Med.

### 2.4 Boundary and Small-Object-Aware Loss Functions

Attentive Depth-Mapped Dice Loss addresses limitations of region-based Dice loss by incorporating distance maps derived from ground-truth masks to emphasize difficult boundary regions. Boundary-Sensitive Loss with Location Constraint focuses on hard-to-segment boundaries and small objects while reducing background interference. Surface Loss for medical image segmentation also emphasizes the importance of contour and surface information when foreground-background imbalance is severe. These studies motivate the inclusion of a dedicated small-object-aware optimization component in the proposed framework.

### 2.5 Literature Comparison

| Method / Study | Main Technique | Primary Focus | Relevance to EdgeFormer-Med |
|---|---|---|---|
| DGAM-Net (2025) | Mamba + detail enhancement + EGA | Detail and boundary preservation | Supports edge-guided attention |
| MEGANet (2024) | Multi-scale + EGA + Laplacian | Weak boundaries | Supports explicit edge modeling |
| MEGANet-W (2025) | Haar wavelet + W-EGA | Weak / low-contrast boundaries | Supports high-frequency boundary cues |
| SSCFormer (2024) | ConvNet + Transformer | Intra/inter-scale context | Supports multi-scale Transformer |
| MWPT + Dynamic Loss (2025) | Wavelet pooling Transformer + scale-aware loss | Small object representation | Supports scale-aware optimization |
| CLD-Net (2022) | Local edge features + local-global fusion | Medical small objects | Supports fine-detail preservation |
| CaraNet (2021) | Reverse attention + feature pyramid | Small medical objects | Supports small-object feature learning |
| DCSNet (2026) | Detection-guided cropping + MSFA | Sparse small targets | Supports background suppression and multiscale fusion |
| ADD Loss (2025) | Distance / signed-distance maps | Small lesions and boundaries | Supports boundary-aware loss |
| Boundary-Sensitive Loss (2023) | Boundary + location constraint | Hard regions and small objects | Supports small-object-aware optimization |

### 2.6 Research Gap

The reviewed studies demonstrate that edge guidance, multi-scale representation, Transformer-based context modeling, and specialized loss functions can each improve difficult segmentation cases. However, these directions are frequently investigated as separate components or within task-specific architectures. For small and low-contrast brain tumor regions, the combined challenge is to retain fine boundary information while simultaneously modeling multi-scale context and preventing small targets from being underweighted during optimization. EdgeFormer-Med addresses this gap by integrating these complementary mechanisms and adding a boundary-adaptive fusion stage that explicitly connects edge information with multi-scale semantic representations.

## 3. METHODOLOGY

The proposed EdgeFormer-Med framework is designed as a research model for precise segmentation of small and low-contrast anatomical structures in brain MRI. The methodology consists of dataset preparation, MRI preprocessing, multi-scale feature extraction, Transformer-based contextual modeling, edge-guided attention, boundary-adaptive feature fusion, decoder-based reconstruction, and small-object-aware optimization.

### 3.1 Dataset Selection: BraTS Adult Glioma (BraTS-GLI)

The BraTS Adult Glioma (BraTS-GLI) benchmark is selected as the primary dataset for the proposed research because it is designed for adult glioma MRI segmentation and provides multimodal MRI inputs together with segmentation annotations for training data. The dataset includes four commonly used MRI modalities: T1-weighted, contrast-enhanced T1-weighted (T1ce), T2-weighted, and FLAIR images. The availability of tumor segmentation masks makes the dataset suitable for supervised development and future quantitative evaluation of the proposed model.

For the final implementation, the exact dataset version, access conditions, preprocessing convention, and train/validation split will be recorded in the experimental version of this paper. This draft intentionally avoids claiming a fixed sample count or numerical split because no experiment has yet been performed.

### 3.2 MRI Data Preprocessing

- Verify the integrity of all multimodal MRI volumes and segmentation masks.
- Ensure consistent spatial alignment across modalities and labels.
- Normalize MRI intensity values to reduce variation between scans.
- Crop or retain the relevant brain region according to the selected implementation strategy.
- Resize or resample volumes only when required by the model configuration.
- Apply training-time augmentation such as spatial transformations and intensity variations where appropriate.
- Maintain identical transformations between image modalities and the corresponding segmentation masks.

### 3.3 Multi-Scale Feature Extraction

The encoder is designed to produce hierarchical representations at multiple spatial scales. Shallow layers preserve fine spatial information such as tumor edges and small structures, while deeper layers capture broader semantic context. Multi-scale representations are important because tumor regions can vary in size and shape, and a single receptive field may not adequately represent both small lesions and surrounding anatomical context.

### 3.4 Multi-Scale Transformer Encoder

The Transformer component is used to model long-range contextual relationships that may not be captured effectively by local convolution alone. Features from different scales are transformed into contextual representations and processed through attention-based interactions. The objective is to combine local detail with global information so that a small tumor region can be interpreted using both its immediate appearance and its surrounding anatomical context.

### 3.5 Edge-Guided Attention Module

The Edge-Guided Attention Module is designed to emphasize features around weak or ambiguous tumor boundaries. An edge representation can be obtained from feature maps using an edge extraction operation, followed by an attention mechanism that recalibrates semantic features. Instead of relying only on region-level similarity, the module encourages the network to preserve high-frequency information associated with anatomical boundaries.

### 3.6 Boundary-Adaptive Feature Fusion

Boundary-Adaptive Feature Fusion is proposed as the main integration stage of EdgeFormer-Med. The module receives multi-scale Transformer features and edge-guided features and learns to combine them according to the spatial characteristics of the target region. Regions with strong semantic evidence can retain contextual features, whereas uncertain or boundary-dominated regions can receive stronger edgerelated information. This adaptive interaction is intended to reduce boundary blurring and improve the delineation of small irregular structures.

### 3.7 Decoder and Boundary Refinement

The decoder progressively reconstructs the spatial resolution of the segmentation representation. Skip connections transfer useful fine-grained information from earlier encoder stages to the decoder. The final refinement stage combines reconstructed semantic information with boundary-aware features to generate the segmentation mask.

### 3.8 Small-Object-Aware Loss

Small tumor regions may contribute fewer pixels than large regions, which can cause a standard region-based loss to underemphasize them. The proposed loss therefore includes a component that increases the optimization contribution of small and difficult target regions. A conceptual formulation is given below:

$$L\_total = \lambda_1 L\_Dice + \lambda_2 L\_Boundary + \lambda_3 L\_Small$$

where L_Dice measures region overlap, L_Boundary emphasizes boundary agreement, L_Small increases the contribution of small target regions, and $\lambda_1$, $\lambda_2$, and $\lambda_3$ are weighting coefficients to be determined during future experimentation.

### 3.9 Proposed Algorithm – Conceptual Steps

- Input the aligned multimodal brain MRI volumes.
- Apply normalization and selected preprocessing operations.
- Extract hierarchical features at multiple spatial scales.
- Generate contextual representations using the Transformer encoder.
- Extract boundary-related features and apply edge-guided attention.
- Adaptively fuse edge and multi-scale semantic features.
- Decode the fused representation to reconstruct the segmentation map.
- Apply boundary refinement to improve tumor delineation.
- Compute the combined small-object-aware loss.
- Optimize the network parameters during future model training.

## 4. MAIN RESULT FRAMEWORK

The overall workflow of EdgeFormer-Med follows the same research-framework style as the reference papers, while the content and proposed components are specific to brain tumor segmentation.

| |
|---|
| **BraTS Adult Glioma (BraTS-GLI) Dataset** |
| ↓ |
| **Multimodal MRI Preprocessing** |
| ↓ |
| **Multi-Scale Feature Extraction** |
| ↓ |
| **Multi-Scale Transformer Encoder** |
| ↓ |
| **Edge Feature Extraction** |
| ↓ |
| **Edge-Guided Attention** |
| ↓ |
| **Boundary-Adaptive Feature Fusion** |

| ↓ |
|---|
| **Decoder + Boundary Refinement** |
| ↓ |
| **Brain Tumor Segmentation Mask** |
| ↓ |
| **Small-Object-Aware Loss** |

**Figure 1. Proposed EdgeFormer-Med workflow (editable text-based framework).**

### 4.1 Workflow Description

The workflow begins with the BraTS-GLI multimodal MRI dataset. The input volumes are preprocessed to ensure spatial consistency and suitable intensity representation. The encoder extracts features at multiple scales, after which the Transformer component models contextual relationships. An edge-guided attention module highlights boundary-related information, and the Boundary-Adaptive Feature Fusion stage combines edge and semantic representations. The decoder reconstructs the segmentation map and applies boundary refinement. During future training, the combined loss function provides supervision for region overlap, boundary accuracy, and small-object emphasis.

### 4.2 Dataset Description

| **Attribute** | **Proposed Research Setting** |
|---|---|
| Dataset | BraTS Adult Glioma (BraTS-GLI) |
| Application | Adult brain tumor / glioma segmentation |
| Input | Multimodal MRI volumes |
| Modalities | T1, T1ce, T2, FLAIR |
| Ground Truth | Tumor segmentation masks in training data |
| Learning Type | Supervised medical image segmentation |
| Current Status | Selected for future implementation; no experiment completed |

### 4.3 Data Preprocessing Steps

| **Step** | **Purpose** |
|---|---|
| Data Integrity Check | Verify MRI volumes and corresponding masks |
| Spatial Alignment | Maintain correspondence between modalities and labels |
| Intensity Normalization | Reduce intensity variation |
| Brain/ROI Preparation | Focus computation on relevant anatomical region |
| Resampling / Resizing | Create model-compatible spatial representation when required |
| Data Augmentation | Improve robustness and reduce overfitting during future training |

### 4.4 Multi-Scale Transformer Module

The Multi-Scale Transformer Module receives hierarchical encoder features and models contextual relationships across spatial scales. The design is motivated by prior work showing that intra-scale and inter-scale interactions can improve medical image segmentation. In EdgeFormer-Med, the Transformer is not used as a standalone component; it is coupled with boundary-aware feature processing so that contextual reasoning does not remove fine spatial details.

### 4.5 Edge-Guided Attention Module

The Edge-Guided Attention Module produces an attention representation from boundary-related feature cues and uses it to recalibrate the corresponding semantic feature maps. The objective is to make the network more sensitive to weak and irregular tumor boundaries, particularly in regions where tumor and healthy tissue have similar intensity characteristics.

### 4.6 Boundary-Adaptive Feature Fusion

The Boundary-Adaptive Feature Fusion stage combines multi-scale Transformer features with edge-guided features. The fusion is intended to be adaptive rather than a simple concatenation so that the contribution of boundary information can vary across the image. This stage forms the central architectural link between the proposed boundary-aware and Transformer-based components.

### 4.7 Small-Object-Aware Optimization

The optimization stage combines region-level overlap supervision with boundary and small-object emphasis. The exact weighting strategy and hyperparameters will be selected only after implementation and validation. This prevents unsupported numerical claims while preserving the intended research contribution.

### 4.8 Performance Evaluation Metrics

| Metric | Purpose |
|---|---|
| Dice Similarity Coefficient (DSC) | Measures overlap between predicted and ground-truth segmentation |
| Intersection over Union (IoU) | Measures region intersection relative to union |
| Precision | Measures the proportion of predicted target pixels that are correct |
| Recall | Measures the proportion of ground-truth target pixels detected |
| HD95 | Measures boundary-distance error using the 95th percentile Hausdorff distance |
| Boundary F1 / Boundary metric | Evaluates quality of predicted anatomical boundaries |

## 5. EXPERIMENTAL EVALUATION

This paper is a proposed research framework and has not yet been experimentally implemented. Therefore, this section defines the planned evaluation protocol rather than reporting fabricated numerical results. Once the model is implemented, the same structure can be retained and populated with measured values.

### 5.1 Planned Baseline Comparison

| Model | Role in Future Evaluation | Dice | IoU | Precision | Recall | HD95 |
|---|---|---|---|---|---|---|
| U-Net | CNN encoder-decoder baseline | — | — | — | — | — |
| Attention U-Net | Attention-based baseline | — | — | — | — | — |
| Transformer Baseline | Transformer segmentation baseline | — | — | — | — | — |

| | | | | | | |
|---|---|---|---|---|---|---|
| Existing Boundary-Aware Method | Boundary-focused comparison | — | — | — | — | — |
| EdgeFormer-Med | Proposed framework | — | — | — | — | — |

### 5.2 Planned Ablation Study

| Variant | Edge Attention | Multi-Scale Transformer | Small-Object Loss | Purpose |
|---|---|---|---|---|
| Baseline | No | No | No | Reference performance |
| A | Yes | No | No | Measure boundary module contribution |
| B | No | Yes | No | Measure Transformer contribution |
| C | No | No | Yes | Measure loss contribution |
| D | Yes | Yes | No | Measure combined architecture |
| EdgeFormer-Med | Yes | Yes | Yes | Full proposed framework |

### 5.3 Expected Research Analysis

The future experimental analysis will investigate whether the proposed architecture improves segmentation of small and low-contrast tumor regions without sacrificing overall segmentation quality. Particular attention will be given to Dice and IoU for region overlap, HD95 and boundary-based measures for contour accuracy, and ablation experiments for determining the contribution of each proposed component.

### 5.4 Advantages of the Proposed Framework

- Explicit attention to weak and irregular tumor boundaries.
- Multi-scale contextual representation for tumors with different sizes.
- Combination of local detail and global semantic information.
- Dedicated optimization emphasis for small target regions.
- A unified architecture linking edge guidance, Transformer modeling, and small-object-aware optimization.
- Suitable foundation for future 2D or 3D medical image segmentation experiments.

### 5.5 Limitations

- The proposed framework has not yet been experimentally validated.
- Transformer-based processing may require substantial computational and memory resources.
- Multimodal 3D MRI processing can increase implementation complexity.
- The final performance may depend on dataset quality, preprocessing choices, and training configuration.
- The exact loss weights and architectural hyperparameters require future empirical optimization.

### 5.6 Future Work

- Implement and train EdgeFormer-Med using the selected BraTS-GLI dataset.
- Perform quantitative comparison against established segmentation baselines.

- Conduct ablation studies for edge attention, Transformer features, adaptive fusion, and small-object-aware loss.
- Investigate 3D volumetric implementation and memory-efficient Transformer designs.
- Evaluate generalization on additional brain tumor or multimodal medical datasets.
- Explore explainable visualization of boundary attention and Transformer feature responses.
- Investigate lightweight variants for faster inference and possible clinical-support applications.

## 6. CONCLUSION

This research proposes EdgeFormer-Med, a boundary-adaptive Transformer framework for precise segmentation of small and low-contrast anatomical structures in brain MRI. The proposed research is motivated by the difficulty of segmenting small tumor regions affected by weak boundaries, low contrast, class imbalance, scale variation, and information loss during feature downsampling. The framework combines multi-scale Transformer representation, edge-guided attention, Boundary-Adaptive Feature Fusion, and small-object-aware optimization to address these challenges in a unified manner.

The BraTS Adult Glioma (BraTS-GLI) benchmark is selected as the planned dataset because it provides multimodal MRI data and segmentation annotations appropriate for supervised brain tumor segmentation research. Since the current work has not yet been experimentally implemented, no numerical performance claims are made. Future implementation will evaluate the proposed model using Dice, IoU, Precision, Recall, HD95, and boundary-aware metrics, together with baseline comparison and ablation studies.

The main research contribution is the integration of complementary boundary, multi-scale contextual, and small-object-aware mechanisms within the proposed EdgeFormer-Med framework. The model is intended to provide a structured research direction for improving the delineation of small, irregular, and low-contrast brain tumor regions and can be extended in future work toward volumetric and clinically oriented segmentation studies.

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