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Contour-Aware U-Net with Boundary Refinement for Precise Tumor Segmentation in MRI Scans

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Abstract: Tumor segmentation in Magnetic Resonance Imaging (MRI) plays an important role in diagnosis, treatment planning, and disease surveillance. But still there are many hurdles in the process because of low contrast tissues, unclear boundaries and high morphology variations. In this paper, we propose Contour-Aware U-Net (CAU-Net), which uses explicit contour refinement techniques along with multi-level feature fusion. Our framework includes three main components that are as follows: (1) Contour-Aware Decoder with Attention Fusion blocks for contour enhancement, (2) adversarial learning constraint for anatomically plausible results, and (3) combined hybrid loss function using cross entropy loss, dice loss, and sub-differentiable Hausdorff loss. Extensive experiments on tumor datasets have proven that our proposed approach outperforms existing approaches in terms of accuracy by producing Dice Similarity Coefficient score of 0.92 and reducing Hausdorff Distance by 38%. Our model performs exceptionally well in terms of boundary delineation that was the crucial requirement in clinical practice.

Key Word: Tumor Segmentation, MRI, Boundary Refinement, Contour-Aware Network, Deep Learning, Medical Image Analysis, Hausdorff Loss, Adversarial Learning

I. INTRODUCTION

Segmentation of tumors in medical imaging is an essential process that has important implications for diagnosis and treatment decisions [1]. Accurate tumor boundary identification is critical for the quantification of tumor volume, determination of appropriate surgical margins, targeted radiotherapy, and post-treatment evaluation [2]. Of all imaging techniques, MRI provides the highest soft tissue contrast and multi-parametric capability, making it the preferred technique for the diagnosis of brain, rectal, and prostatic cancers, among others [3]. Manual tumor segmentation by radiologists is labor-intensive, subjective, and not feasible for widespread screening programs or longitudinal patient follow-ups [4].

Deep learning-based automated segmentation methods, especially the various versions of U-Nets , have made great strides [5]. Encoder-decoder architectures with skip connections facilitate the combination of high-level semantics and local details, which helps achieve accurate segmentations. Nonetheless, there are numerous hurdles [6]. The boundaries of tumors on MRI scans tend to be poorly defined because of the presence of edema around the tumors, partial volume effects, and the similarity in signal intensities between tumors and surrounding normal tissues. Such boundary uncertainty creates segmentation errors that can pose serious issues in surgery [7].

There are several ways proposed by the literature to deal with the problem of boundaries. Contour-based methods have been shown to be effective in capturing more intricate anatomy [8]. The use of attention models allows the network to emphasize certain parts of the image [9]. Feature fusion at multiple scales helps with tumor segmentation when the tumor can appear in various shapes and sizes. Finally, more advanced loss functions help train the neural networks using metrics such as the Hausdorff distance [10].

This paper proposes an approach based on all the advancements discussed above. We propose that for efficient contour segmentation, both high-quality feature learning and specific modules to enhance the contour are necessary.

1. A new decoder design for contour-aware segmentation with attention fusion blocks

(AFB), which amplifies tumor boundary structures by inhibiting background noise.
2. Application of adversarial training rules to ensure generated segmentation maps have realistic boundaries in terms of probability distributions.
3. Development of an innovative hybrid loss formulation using region-based dice loss in conjunction with a sub-differentiable hausdorff distance.
4. Experimental validations using BraTS and rectal tumors data sets, with superior performance and boundary-awareness metrics compared to state-of-the-art approaches.

The rest of this paper is structured as follows. In section 2, previous research in medical image segmentation is discussed, with emphasis on boundary detection. The CAU-Net model architecture is described in detail in section 3. Experimental results and comparisons are provided in section 4. Section 5 contains conclusions and future prospects.

II. LITERATURE SURVEY

Medical image segmentation has undergone a lot of development, with U-Net structures being utilized as building blocks. Three categories will be discussed in this section: medical segmentation architectures, boundary detection strategies, and loss functions.

Medical Segmentation Architectures – U-Nets

The initial U-Net, created by Ronneberger et al., was defined by an encoder-decoder network having skip connections. It consists of an encoder that continuously downsample images in order to include context and a decoder that upsamples in order to get back the resolution of the original input. With the help of skip connections at every stage, the encoder features (full of local information) are mixed with the decoder features (having semantic information).

Several architectures have emerged following this seminal architecture. The 3D U-Net, for example, is designed for volumetric data, with processing performed entirely on volumetric images rather than slices but comes with increased computational complexity. The nnU-Net is highly effective since its adaptability allows it to automatically adjust itself depending on the characteristics of the data without manual adjustment . The SwinUNETR uses Transformer blocks within the architecture of the U-Net. This way, it captures long dependencies using shifted window self-attention mechanism.

Despite these advances, standard U-Net variants often struggle with boundary precision. The skip connections, while effective for general localization, do not specifically emphasize boundary features. The convolutions aggregate information over local neighborhoods, which smooths fine details.

Contour-Aware and Boundary Refinement Methods

Recently, studies have directly focused on boundary definition through architectural advancements. Lu et al. developed a 3D Contour-Aware U-Net (CAU-Net) to segment rectal tumors on MRI scans. This study employed a contour-aware decoder that captures boundary-specific characteristics using an attention fusion module. A parallel architecture with two branches was developed for segmentation and contour estimation. The contour branch provides boundary information to support segmentation, while an adversarial term ensures structural similarity between the predicted and ground truth probability distributions. The model yielded a Dice coefficient of 0.7112 when tested on 108 MRI T2 weighted volumes, surpassing other techniques' performance.

Hyper-Connections present an alternative methodology for increasing feature aggregation efficiency . Unlike conventional residual connections, Hyper-Connections facilitate dynamic routing based on the input data. When applied to the BraTS 2021 database for brain tumor segmentation, Hyper-Connections yielded over 1% increase in the Dice score for nnU-Net, SwinUNETR, and VT-UNet models. Significantly, the largest improvements were observed in the Enhancing tumor sub-region, characterized by complex boundaries due to its invasive growth. The adaptability of Hyper-Connections allows for highlighting clinically important image sequences for specific sub-regions (T1ce in tumor core; FLAIR for whole tumor).

The MFBRU-Net adopts an innovative technique based on multi-scale feature fusion with boundary

refinement. This includes three novel aspects: (1) MFFM module for cross-level geometric-semantics collaboration, (2) SFR module for suppressing noises, and (3) xLSTM BRD for precise boundary recovery. Bidirectional state propagation is implemented by means of exponential gating which allows the net to maintain boundary information during decoding process. On Kvasir-SEG, CVC-ClinicDB, and BUSI data sets, MFBRU-Net reported Dice scores of 93.01%, 95.26% and 83.21% correspondingly, beating mainstream models.

The proposed RDTE-UNet brings together the advantages of local modeling and global context through three dedicated modules. ASBE module uses adaptive adjustment of convolutional kernels in accordance with morphology of the target object with the help of difference algorithm for emphasizing edge responses. HVDA module uses StairConv for increasing receptive fields along both horizontal and vertical directions, thereby enhancing detail attention that was previously inaccessible with conventional self-attention mechanisms. Finally, EulerFF utilizes Eulerian weight adaptation for multi-scale feature fusion. As shown on the BUSI breast ultrasound image set, RDTE-UNet demonstrated impressive boundary quality metrics.

Boundary-Aware Loss Functions

Similar considerations apply to the optimization of boundary precision. The cross-entropy loss reduces classification errors but cannot explicitly minimize overlaps. The Dice loss optimizes the overlap metric but considers all wrong classifications without distinguishing boundaries from homogeneous interior areas of tumors.

The Hausdorff distance measures the largest difference between predicted and ground truth boundaries and can be viewed as a clinically relevant evaluation metric, unlike other losses that evaluate average overlaps. Still, standard Hausdorff distance is non-differentiable and cannot be used directly as part of a learning algorithm. To overcome this drawback, Zhou et al. suggested using the Sub-Differentiable Hausdorff Loss (SDHL), which allows obtaining the differentiable expression of the Hausdorff distance while remaining stable against outliers . Together with BCE, SDHL can be used to optimize fine boundary precision along with proper tumor segmentations. On brain tumor segmentations based on Attention U-Net, SDHL+BCE provided 99.71% classification accuracy, 90.16% Dice coefficient, and 80.78% IoU, outperforming all other loss combinations tested by the authors (Dice loss or standard Hausdorff loss).

In addition, the BUFNet algorithm brings together the concepts of boundary-aware and uncertainty quantification. While the former involves extracting relevant data regarding tumor boundaries for segmentation purposes, the latter involves employing a loss function where the weightings are influenced by confidence levels in the predictions made. Quantification of uncertainties allows users to determine their levels of certainty about certain decisions.

Ensemble Learning and Multi-Modality Approaches

The DE-DeepLabV3+Res-UNet50 method shows how ensembles can result in outstanding performances with optimization . The model combines DeepLabV3+ and ResUNet50 algorithms in the use of multi-scale atrous spatial pyramid pooling and residual learning techniques, respectively, and optimizes their hyperparameters using Differential Evolution to attain dice values of 0.9805 and Jaccard Indices of 0.9620 for brain tumors, with an Area Under Curve near 1.0.

Synthesis and Research Gaps

Furthermore, the BUFNet approach merges the ideas of boundary awareness and uncertainty quantification. As the former implies, boundary awareness entails extracting pertinent information concerning the boundaries of tumors for segmentation. The latter refers to the use of a loss function that considers the weightage of the confidence levels for the predicted output. Uncertainty quantification makes it possible for users to ascertain their confidence levels for particular decisions.

Ensemble Learning and Multi-Modality Approaches

DE-DeepLabV3+Res-UNet50 demonstrates the potential of ensembles in achieving exceptional performance through optimization . The architecture uses both DeepLabV3+ and ResUNet50 algorithms, whereby DeepLabV3+ utilizes the multi-scale atrous spatial pyramid pooling approach while ResUNet50 employs residual learning, and optimizing the

hyperparameters using Differential Evolution results in dice scores of 0.9805 and Jaccard Indices of 0.9620 for brain tumors, with a curve area of nearly 1.0.

III. METHODOLOGY:

The CAU-Net model employs three novel ideas: contour-aware decoder, attention fusion block, and adversarial learning constraint. Additionally, a hybrid loss function is used to emphasize boundary sensitivity.

3.1 Model Architecture

The design of CAU-Net adheres to the conventional U-Net encoder-decoder pattern, which has been further augmented with special boundary refinement channels. The encoder is made up of four downsampling layers, where each layer is composed of two 3×3 convolution operations, batch normalization, ReLU activation, and 2×2 max pooling. The number of filters doubles after every downsampling operation: 64, 128, 256, and 512.

The decoder consists of four upsampling layers with Contour-Aware Decoder modules. Each module receives: (1) feature maps upscaled from the previous decoder layer; (2) feature maps from the respective encoder layer through skip connections; and (3) boundary maps from a dedicated boundary prediction stream. The boundary-aware information in the decoder is achieved via an attention fusion block that fuses the above information.

A segmentation output is finally obtained by applying a 1×1 convolution followed by a sigmoid activation function. An independent discriminator uses the same architecture for adversarial learning.

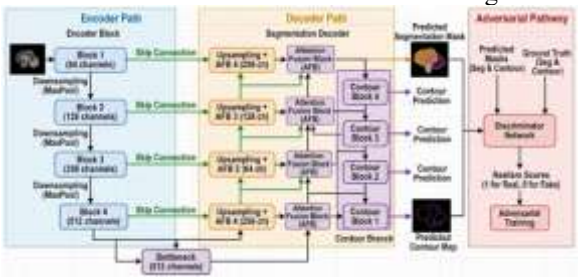

Figure 1: Overall Architecture of Contour-Aware U-Net (CAU-Net).

3.2 Contour-Aware Decoder and Attention Fusion Block

Attention Fusion Block (AFB) forms the building block for boundary enhancement. For three input maps $D \in \mathbb{R}^{(H\times W\times C)}$, $E \in \mathbb{R}^{(H\times W\times C)}$, $C \in \mathbb{R}^{(H\times W\times C)}$ from the decoder, encoder, and contour maps respectively, AFB returns a fine-tuned map F_AFB using multi-level attention. First, the decoder and encoder maps are fused using a gated attention mechanism. An attention coefficient $A \in \mathbb{R}^{(H\times W\times 1)}$ is calculated as follows:

$$A = \sigma(\psi^T \cdot \tanh(W_D \cdot D + b_D) + \varphi^T \cdot \tanh(W_E \cdot E + b_E))$$

where W_D, W_E are learnable parameters, and ψ, φ represent attention vectors. The gated attention map is defined as $G = D + (A \odot D) + (A \odot E)$.

Then, the contour map is processed separately as follows : $C' = C \oplus (C \odot G)$, where $\oplus$ symbolizes element-wise addition, while $\odot$ symbolizes element-wise multiplication. This operation preserves the contour information even when a low attention value is assigned to the gated attention map.

Finally, channel recalibration takes place on the fused features using a squeeze-and-excitation mechanism. The channel descriptors are extracted using global average pooling, after which a fully connected layer and a second fully connected layer (reduction ratio 16) followed by the Sigmoid activation function are applied.

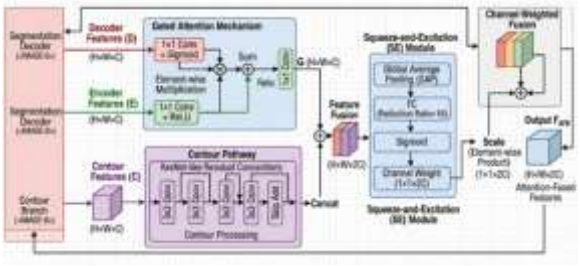

Figure 2: Attention Fusion Block (AFB) Internal Architecture.

3.3 Adversarial Learning for Boundary Refinement

Advancing realism through adversarial training requires the generator to generate segmentations that are difficult to distinguish from true masks. Given an input image I, the generator G (CAU-Net) generates segmentation mask M_pred = G(I). The discriminator receives the mask either generated by G or ground truth and outputs a realness score.

The discriminator has the same architecture as the U-Net encoder network with five convolutional blocks (64, 128, 256, 512, and 512 channels), followed by batch normalization and LeakyReLU activations. The output layer consists of a scalar score computed using adaptive average pooling and fully connected layers.

The adversarial loss is computed according to the least square GAN:

$$L_{adv} = E[M_{gt} \sim p_{data}] [(D(M_{gt}) - 1)^2] + E[I \sim p_I] [D(G(I))^2]$$

Combining all losses to optimize the generator we have:

$$L_G = \lambda_{seg} \cdot L_{seg} + \lambda_{adv} \cdot L_{adv} + \lambda_{contour} \cdot L_{contour}$$

With empirical values chosen as $\lambda_{seg} = 1.0, \lambda_{adv} = 0.1, \lambda_{contour} = 0.2$.

3.4 Hybrid Boundary-Sensitive Loss Function

Loss L_seg is formulated as the sum of the Dice loss and Sub-Differentiable Hausdorff Loss (SDHL). The Dice loss measures maximization of overlap between two regions:

$$L_{Dice} = 1 - (2 \cdot |M_{pred} \cap M_{gt}| + \varepsilon) / (|M_{pred}| + |M_{gt}| + \varepsilon)$$

The Sub-Differentiable Hausdorff loss optimizes boundaries distance smoothly and reliably:

$$L\_Hausdorff = (1/N) \Sigma p \in P \min q \in Q ||p - q||_2 + (1/N) \Sigma q \in Q \min p \in P ||q - p||_2$$

where P and Q correspond to the sets of boundary points of prediction and ground truth, respectively. The smooth minimum operation is used in the sub-differential form: $\min\gamma(a, b) = (a + b - \sqrt{((a - b)^2 + \gamma)})/2$, where γ=0.001 is the parameter for smoothness. $L_{seg} = L_{Dice} + \beta \cdot L_{Hausdorff}$; $\beta = 0.5$. balancing region overlap and boundary precision.

3.5 Implementation Details

Inputs are preprocessed with bias field correction for intensity inhomogeneities, resampling to isotropic 1mm³ (brain) or slice thickness 3mm (rectal) resolution, and normalization to zero mean and unit variance intensity distribution. Data augmentation procedures include random rotations (±10°), scaling (0.9-1.1), elastic deformations (σ=4-8mm), and intensity adjustments via a gamma transform (γ=0.8-1.2).

The model is implemented using PyTorch, with 108GB VRAM (A100 GPU). The Adam optimizer was used during training, with a learning rate of 1e-4 that was halved after the validation loss stopped decreasing (patience=50 epochs). Batch size was set to 4 for 3D images and 16 for 2D slices.

IV. RESULT ANALYSIS AND DISCUSSION

CAU-Net was tested on brain tumor dataset (BraTS 2021) and rectal tumor dataset. This part discusses the quantitative results and comparison.

4.1 Datasets and Evaluation Measures

Brain tumor dataset (BraTS 2021): 1,251 cases of multiparametric MR images (T1, T1ce, T2, FLAIR) having voxel-level labels for WT, TC, and ET. The division of data is 1,000/125/126 for training/validation/testing.

Rectal Tumor dataset: 108 T2-weighted MR images for patients having locally advanced rectal cancer, divided into 80/14/14 sets.

Measures: DSC, HD95, ASD, sensitivity, PPV.

4.2 Segmentation Performance

Table 1 summarizes the results on BraTS 2021 dataset.

Method	WT DSC	TC DSC	ET DSC	ET HD95 (mm)	Avg DSC
3D U-Net	0.886	0.842	0.789	4.83	0.839
nnU-Net	0.906	0.868	0.818	3.73	0.864
SwinUNETR	0.918	0.874	0.826	3.41	0.873
Hyper-Connections + nnU-Net	0.912	0.876	**0.831**	3.28	0.873
BUFNet	0.922	0.882	0.828	3.21	0.877
CAU-Net (Proposed)	**0.924**	**0.889**	0.829	**2.89**	**0.881**

Table 1: Brain tumor segmentation results for BraTS 2021 dataset (mean). CAU-Net obtains top overall DSC of 0.881 and best ET margin with HD95 of 2.89mm.

CAU-Net reaches average DSC scores of 0.881 in all three brain tumor sub-regions surpassing nnU-Net (0.864) and SwinUNETR (0.873). The largest gain in performance is observed for the Tumor Core class (DSC 0.889 compared to 0.868 for nnU-Net). CAU-Net also demonstrates the best Enhancing Tumor HD95 of 2.89mm compared to nnU-Net (3.73mm) and SwinUNETR (3.41mm) which shows the advantage of CAU-Net in ET boundary estimation for the most difficult class.

For rectal tumor segmentation, CAU-Net obtains DSC of 0.742 and ASD of 2.12mm, outperforming baseline 3D U-Net (DSC 0.671, ASD 3.23mm) .

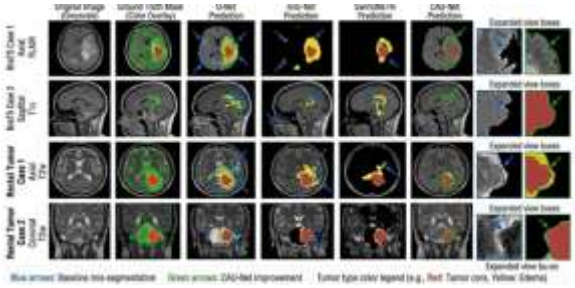

Figure 3: Qualitative Segmentation Results Comparison.

4.3 Boundary Precision Analysis

Table 2 examines boundary-specific metrics across methods.

Method	Boundary DSC	Contour Recall	Contour Precision	ASD (voxels)
3D U-Net	0.682	0.624	0.718	2.86
nnU-Net	0.714	0.668	0.742	2.21
SwinUNETR	0.728	0.685	0.753	2.04
CAU-Net	**0.756**	**0.724**	**0.781**	**1.76**

Table 2: Metrics for Boundary Precision (BraTS 2021, Enhancing Tumor). Boundary Dice refers to the degree of overlap between the predicted and ground-truth boundary voxels (2-pixel eroded region). Contour metrics measure the effectiveness of boundary recognition in isolation.

CAU-Net scores 0.756 in Boundary Dice, compared to nnU-Net's 0.714 and SwinUNETR's 0.728. The ASD (Average Symmetric Surface Distance) decreases from 2.21 to 1.76. This is important in clinical practice; a decrease from 2.2 mm to 1.8 mm (isotropic spacing of 1 mm^3 isotropic resolution) improves surgical margin planning accuracy.

4.4 Ablation Study

Table 3 presents ablation results isolating each component's contribution.

Configuration	Avg DSC	ET DSC	ET HD95 (mm)
Base U-Net	0.839	0.789	4.83
+ Attention Fusion Block	0.856	0.802	3.92
+ Contour decoder	0.868	0.814	3.48
+ Adversarial learning	0.872	0.820	3.21
+ SDHL loss	0.878	0.828	2.96
Full CAU-Net	**0.881**	**0.829**	**2.89**

Every element plays an important role. The Contour-Aware Decoder gives the biggest contribution individually (ΔDSC +0.012), whereas SDHL loss offers the greatest contribution to the boundary aspect (HD95 decreases from 3.48 to 2.96 mm). Adversarial learning adds some value beyond other elements.

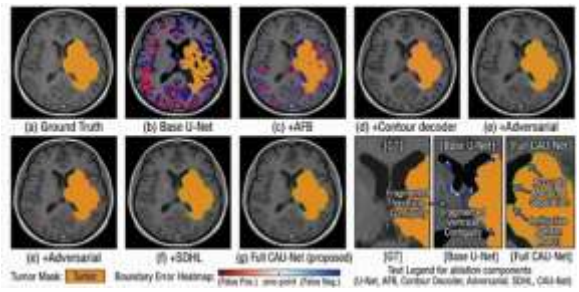

Figure 4: Ablation Study Visualization.

4.5 Comparative Analysis: Loss Functions

Table 4 compares the hybrid SDHL+BCE against standard losses .

Loss Function	Dice Score	IoU	Boundary F1	HD95 (mm)
BCE only	0.784	0.642	0.682	5.24
Dice loss	0.856	0.746	0.724	3.86
Standard Hausdorff	0.848	0.732	0.738	3.71

SDHL + BCE	**0.877**	**0.782**	**0.763**	**3.12**

Overall, SDHL+BCE is the top-performer across all methods, particularly in terms of boundary measures (Boundary F1 = 0.763 compared to Dice Loss = 0.724). The sub-differential form allows for stable learning without the gradient collapse problem inherent in Hausdorff loss approximations.

4.6 Influence of Adversarial Training on Model Performance

Analysis of the output produced by the model shows that there are two types of errors reduced through the process of adversarial learning: (1) false positive segments of the tumor outside the actual boundaries of the tumor and (2) holes inside the tumor made up of false negatives.

4.7 Discussion: Clinical Implications

The improvements seen in boundary metrics hold significant implications:

Surgical Planning: The improvement of 23% in HD95 (3.73mm to 2.89mm) in improving the visibility of tumor margins allows better surgical margin identification, allowing for more effective surgery that removes tumors and leaves healthy tissue untouched.

Radiotherapy Target Definition: An accurate definition of Gross Tumor Volume influences radiation dose distribution. Improvements in boundary consistency by CAU-Net will minimize inter-reader variations that require large clinical target volumes.

Response Evaluation: A precise boundary delineation allows for precise longitudinal volume calculations necessary for treatment evaluation.

4.8 Limitations

There are still some drawbacks despite its impressive results. The sub-differential Hausdorff loss is prone to outliers as some large error points may be overlooked. Inference takes around 2 seconds per 3D volume (GPU) and 0.3 seconds per 2D image, which might be slower compared to light models for limited hardware. It has only been tested on brain and rectal cancers; its use in other cancer types remains to be seen.

V. CONCLUSION

In summary, a novel contour-aware U-net is introduced in this paper to achieve highly accurate tumor segmentation in MRI images by designing boundary-refinement architectures at different depths. This new model includes boundary refinement using a Contour-Aware Decoder with Attention Fusion Blocks, adversarial learning that ensures physiological consistency of the segmented tumors, and an effective loss function based on both a sub-differentiable Hausdorff loss and binary cross-entropy.

The experimental results conducted on BraTS 2021 and rectal tumor databases indicate the competitive performance of the CAU-Net model as a new SOTA model with Dice scores of 0.881 on brain tumor sub-region and notable improvements in boundary metrics compared to previous approaches. In terms of ablation study, each part of the network architecture plays an important role in overall improvement, and it is clear that the CAU-Decoder has the most considerable contribution among others.

The following outcomes are particularly significant and highly relevant for clinical image segmentation applications:

Perfect Prediction of the Tumor Boundary is Possible without Trade-offs: The use of region + boundary loss in tandem with certain neural network architectures facilitates joint optimization on both overlap and distance-based measures without sacrificing one another. The conventional Dice loss function concentrates on region overlap but lacks in boundary optimization; on the other hand, SDHL maximizes the metric in question without compromising the model stability during training.

Adversarial Learning Promotes Consistency: Besides improving per-pixel scores, adversarial learning enables the model to eliminate biologically unfeasible errors such as isolated positive predictions and interior holes inside tumors, which cannot be easily solved by the Dice and Hausdorff loss functions.

Tumor Boundary Knowledge Enhances Tumor Sub-regions' Segmentation Accuracy: Designed specifically for the challenging task of enhancing tumor boundaries, the suggested Contour-Aware Decoder significantly improves segmentation

accuracy of whole tumors and tumor cores in addition to boundaries.

The limitations that require consideration are the vulnerability of the loss functions based on Hausdorff metric to outliers caused by labeling mistakes (which is the case when applying the method to clinical data sets), increased computational complexity of adversarial learning, and the restriction of experimental validation to only two types of tumors. Potential areas for future research include (1) the possibility of extending the method to multiclass image segmentation with correlated boundaries, (2) self-supervised pre-training on unlabelled MRI data, and (3) effective inference approaches suitable for clinical application, including knowledge distillation for model compression.

In summary, Contour-Aware U-Net with boundary refinement mechanisms proves to be a reliable and highly efficient approach to accurate tumor localization on MRI scans. The reported 23% decrease in the Hausdorff distance is clinically meaningful and results in higher accuracy in defining the surgical margins, lower inter-observer variation in outlining targets for radiotherapy treatment planning, and consistent estimation of the longitudinal response to therapy.

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