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# ARTIFICIAL INTELLIGENCE FOR MRI-BASED RECTAL TUMOR SEGMENTATION AND PROGNOSTICATION


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Scan for Details

## BACKGROUND

Accurate segmentation of rectal cancer is essential for preoperative staging, treatment planning, and response assessment.

- In pelvic MRI, rectal tumor ROIs often have small size relative to large background areas.
- Ambiguous boundaries between tumor and normal rectal wall lead to high False Negative (FN) rates and unstable model convergence.
- Standard U-Net models struggle with class imbalance and label noise in MRI datasets.

## OBJECTIVE

To establish a robust U-Net-based rectal tumor segmentation model for pelvic MRI and analyze instability factors.

- Analyze training instability caused by **data noise/imbalance** and loss function combinations in MRI segmentation tasks.
- Develop a stabilization strategy to improve tumor boundary detection performance.

## DATA & EVALUATION

**Dataset:** Pelvic MRI scans for Rectal Cancer (T2-weighted images)

**Split:** Patient-level split (Train / Validation / Test)

**Metrics:** Intersection over Union (IoU), Dice Coefficient

**Architecture:** Standard 2D U-Net (Encoder-Decoder with skip connections)

## METHODS: TRAINING STRATEGY

**Observation:** Performance spikes observed in late training stages (overfitting signs with high train-val gap).

**Hypothesis:**

- Label noise (missing masks/ambiguous boundaries in MRI) confuses model.
- Gradient conflict between Dice (global overlap) and Focal (hard pixel) losses.

**Solution: Curated Learning Strategy**

Prioritize cases with verified MRI masks for stable initial learning, then expand distribution via transfer learning.

## LEARNING ANALYSIS

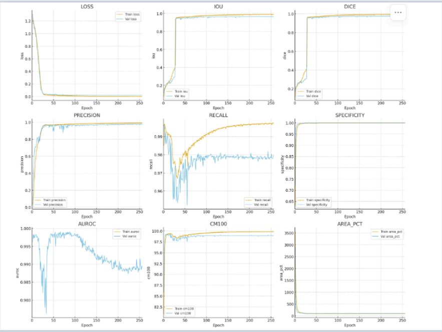

*Figure 2. Learning curves showing training vs validation gaps. Note the initial instability and eventual convergence.*

Learning curves indicate that standard training suffers from fluctuations. By curating MRI data quality, we achieved smoother convergence.

## QUANTITATIVE RESULTS

**Benchmarking (Internal Validation on Pelvic MRI):**

| Model Setting | Avg IoU | Avg Dice |
|---|---|---|
| Baseline (Internal Val) | 0.514 | 0.639 |
| **Sensitivity Improved** | **0.574** | **0.712** |

**Augmentation Effect:** Horizontal flip augmentation yielded best results (IoU 0.582 / Dice 0.718).

## QUALITATIVE RESULTS

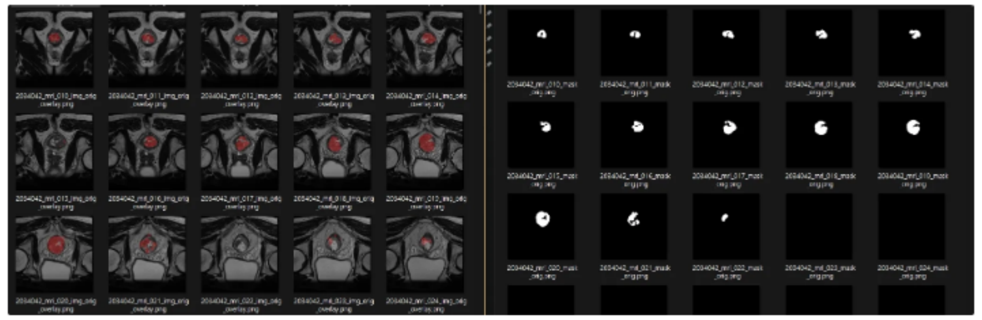

*Figure 1. Pelvic MRI slices (left) and corresponding segmentation masks (right). The improved model successfully delineates rectal tumor boundaries.*

## DISCUSSION

- **Context Size:** Excessively large context in small rectal tumor ROI tasks can degrade performance by including irrelevant background noise.
- **Label Quality:** Systematic label noise (missing annotations in MRI) is a primary driver of training instability.
- **Loss Function:** Balancing Dice and Cross-Entropy/Focal loss is crucial for stable gradients.

## CONCLUSION

1. **Data Curation** based on MRI mask reliability is more effective than simple data augmentation for stabilization.
2. The proposed **Sensitivity Improved Model** significantly outperformed baseline (Dice 0.639 → 0.712) in rectal cancer segmentation.

## LIMITATIONS & FUTURE WORK

Need to establish a quantitative QA pipeline for Ground Truth quality. Future work will include multi-center external validation on diverse MRI datasets.


**References:** [1] Ronneberger et al., U-Net: Convolutional Networks for Biomedical Image Segmentation (arXiv:1505.04597). [2] Internal Benchmarking Report 2025.



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