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Enhancing Polyp Segmentation Using Attention U-Net with CLAHE

Ramdaniah Ramdaniah [1,a,*]; Bayu Adrian Ashad [2,b]
[1] *Department of Informatics Engineering, Universitas Muslim Indonesia, Urip Sumoharjo Street Km. 05, Makassar 90231, Indonesia*
[2] *Department of Electrical Engineering, Universitas Muslim Indonesia, Urip Sumoharjo Street Km. 05, Makassar 90231, Indonesia*
[a] ramdaniah@umi.ac.id; [b] bayuadrianashad@umi.ac.id
* *Corresponding author*

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Abstract

Colorectal cancer remains one of the leading causes of death worldwide, where early detection of polyps through colonoscopy plays a vital role in prevention. This study investigates the effect of integrating Contrast Limited Adaptive Histogram Equalization (CLAHE) into an Attention U-Net architecture for polyp segmentation. An ablation study was conducted by comparing Attention U-Net without CLAHE and Attention U-Net with CLAHE. Experiments were performed using CVC-ClinicDB as the primary dataset and Kvasir-SEG for cross-domain evaluation. The models were trained using a combination of Binary Cross-Entropy and Dice losses. Performance was evaluated using Dice coefficient and Intersection over Union (IoU). Results show that on CVC-ClinicDB, Attention U-Net achieved a Dice score of 0.287 and IoU of 0.193, outperforming the CLAHE-enhanced model (Dice 0.256, IoU 0.166). Conversely, on Kvasir-SEG, Attention U-Net + CLAHE achieved better performance with Dice 0.372 and IoU 0.235, compared to the baseline model (Dice 0.350, IoU 0.220). Statistical analysis using the Wilcoxon signed-rank test indicates that the improvement on Kvasir-SEG is statistically significant ($p < 0.05$), while no significant difference is observed on CVC-ClinicDB ($p > 0.05$). These findings demonstrate that CLAHE improves generalization under challenging illumination conditions but is not always beneficial for datasets with stable visual characteristics.

Keywords*—Attention U-Net, CLAHE, Colorectal Cancer, Deep Learning, Polyp Segmentation*

1. Introduction

Colorectal cancer remains one of the leading causes of cancer-related mortality worldwide, ranking third after lung and liver cancers (WHO, 2024). Early detection of colorectal polyps through colonoscopy plays a crucial role in preventing cancer progression, as most malignant tumors originate from benign polyps that remain undetected in their initial stages (Nie et al., 2024). However, manual polyp identification during colonoscopy still depends heavily on the clinician's expertise and visual conditions, which may be affected by uneven illumination, camera motion, and large morphological variability of the polyps (Wang et al., 2025). These factors often lead to missed or inaccurate segmentation, particularly in low-contrast regions or under complex mucosal textures.

Recent advances in deep learning have significantly improved the accuracy of automated detection and segmentation of colorectal polyps. Convolutional neural networks (CNNs) have become the backbone of modern computer-aided diagnosis (CAD) systems, showing superior pixel-level accuracy compared to traditional feature-based approaches (Zhou et al., 2023; Santone et al., 2025). Among them, the U-Net architecture has been widely adopted because of its ability to preserve spatial detail through skip connections between the encoder and decoder layers. Nevertheless, recent studies have shown that standard U-Net architectures still struggle to focus on small or low-contrast targets within complex backgrounds (Huynh et al., 2024).

To address these limitations, the Attention U-Net model introduces attention gates that allow the network to selectively emphasize relevant regions while suppressing irrelevant background noise (Huynh et al., 2024; Jiang et al., 2023). This attention mechanism effectively enhances boundary localization and accelerates convergence during training, especially for small organ segmentation tasks (Fan et al., 2023). Despite these improvements, the overall performance of such models remains sensitive to lighting inconsistencies and poor image contrast commonly found in endoscopic imaging (Kim et al., 2023).

To overcome these limitations, Contrast Limited Adaptive Histogram Equalization (CLAHE) has been increasingly utilized as a preprocessing technique for medical and endoscopic images. CLAHE enhances local contrast while minimizing noise amplification, making fine structural details more distinguishable (Li et al., 2023; Tang et al., 2024). Recent studies have demonstrated that integrating CLAHE in preprocessing pipelines can strengthen polyp boundary visibility, balance uneven illumination, and improve segmentation accuracy in CNN-based models (He et al., 2025; Zhou et al., 2023).

This study proposes an end-to-end pipeline combining Attention U-Net with CLAHE to improve segmentation robustness under varying illumination and contrast conditions in colonoscopy images. The model was evaluated on two widely used benchmark datasets, CVC-ClinicDB and Kvasir-SEG, which differ in illumination distribution and polyp morphology (Wang et al., 2025; Nie et al., 2024). Performance evaluation employed standard metrics, including Dice Coefficient, Intersection over Union (IoU), Precision, Recall, and spatial accuracy measures such as Hausdorff Distance (HD95) and Average Symmetric Surface Distance (ASSD) to ensure a comprehensive assessment (Ma et al., 2024).

The findings of this study indicate that the effectiveness of CLAHE is dataset-dependent. While contrast enhancement does not improve performance on datasets with relatively stable illumination such as CVC-ClinicDB, it provides statistically significant gains on the more challenging Kvasir-SEG dataset. This observation highlights the importance of evaluating preprocessing techniques under cross-domain conditions rather than assuming universal performance improvement.

This study differs from previous works by providing a systematic ablation analysis of CLAHE within an attention-gated architecture and evaluating its cross-domain robustness. Instead of assuming universal improvement, this work demonstrates that the effectiveness of CLAHE depends strongly on dataset characteristics, particularly illumination variability.

2. Method

2.1 Dataset

This study employed two widely used colonoscopy polyp segmentation datasets, namely CVC-ClinicDB and Kvasir-SEG, both of which provide RGB colonoscopy images paired with binary ground-truth masks. These datasets are commonly utilized as benchmarking resources for evaluating deep learning-based segmentation models due to their high-quality annotations and diverse visual characteristics.

CVC-ClinicDB contains 612 images with a resolution of 384×288 pixels, each annotated by expert gastroenterologists to precisely delineate polyp boundaries (Bernal et al., 2015). The dataset was divided into training, validation, and testing sets with a ratio of 70:15:15. The splitting process was performed at the image level due to the unavailability of patient-wise metadata. Therefore, patient-independent splitting could not be guaranteed, which is acknowledged as a limitation of this study, as images from the same patient might appear across different subsets.

Due to the absence of patient-wise metadata in CVC-ClinicDB, patient-independent splitting could not be guaranteed. This may introduce potential data leakage, which is acknowledged as a limitation of this study.

In contrast, Kvasir-SEG, developed as part of the broader Kvasir dataset collection, offers more diverse illumination conditions, mucosal textures, and polyp geometries. This dataset was introduced by Pogorelov et al. (2017) as a multi-class endoscopic image resource for gastrointestinal disease detection. In this study, Kvasir-SEG was used exclusively for external testing to evaluate the cross-domain generalization capability of the proposed models and was not involved in the training process.

2.2 Preprocessing and Data Augmentation

Prior to model training, two preprocessing strategies were applied to enable ablation analysis: (1) baseline preprocessing without CLAHE and (2) CLAHE-based preprocessing. For the proposed model, CLAHE was applied independently to each RGB channel to enhance local contrast and mitigate illumination inconsistencies commonly found in colonoscopy imaging. This process improves the visibility of mucosal textures and subtle polyp boundaries that are often difficult to detect under low-contrast conditions.

Following preprocessing, data augmentation techniques were applied, including random rotations (±15°), horizontal and vertical flipping, brightness scaling, and Gaussian noise injection. All images were resized to 320×320 pixels and normalized using z-score normalization. The overall preprocessing pipeline utilized in this study is depicted in Figure 1, illustrating the sequential operations applied before feeding data into the model.

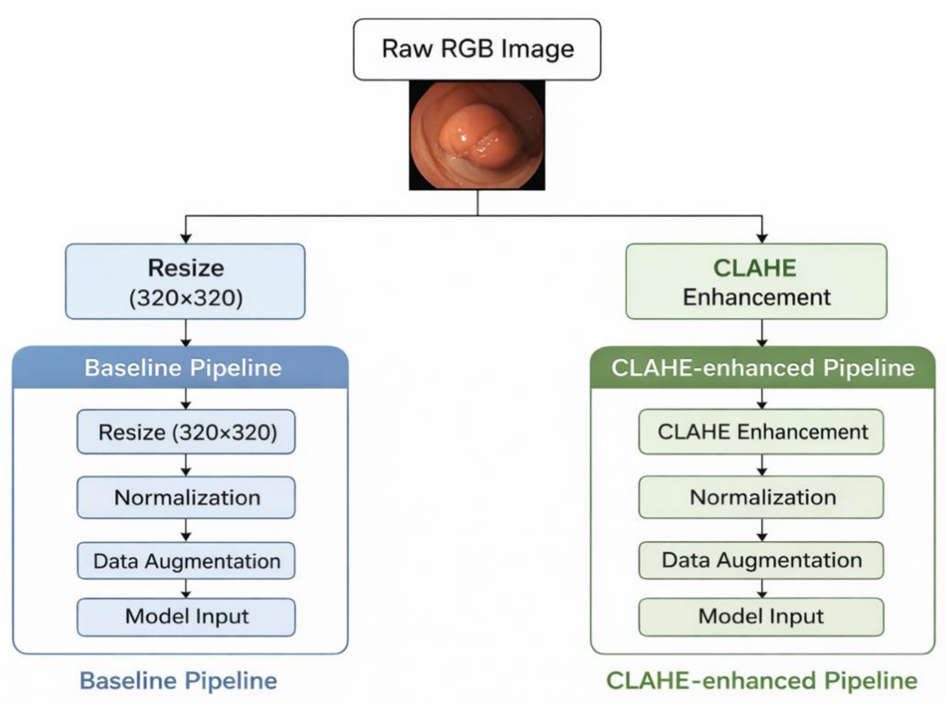

Figure 1. Preprocessing Workflow for Baseline and CLAHE-Enhanced Models

2.3 Proposed Architecture

The segmentation model employed in this study is based on the Attention U-Net architecture, an enhanced version of the classical U-Net that integrates attention gates into the skip connections (Oktay et al., 2018; Jiang et al., 2023). These attention gates suppress irrelevant background features while selectively emphasizing salient regions, allowing the network to focus more precisely on polyp areas that may appear small, low-contrast, or partially occluded.

The network follows an encoder–decoder structure consisting of five hierarchical stages with convolutional blocks containing 32, 64, 128, 256, and 512 filters, respectively. Downsampling is performed using max-pooling layers, while upsampling is implemented using transposed convolutions. Skip connections bridge corresponding encoder and decoder layers to preserve spatial information. The attention modules refine the propagated features by dynamically weighting informative regions before fusion.

A schematic representation of the Attention U-Net used in this study is presented in Figure 2, highlighting the encoder–decoder pathway and the attention gate mechanisms integrated into the model.

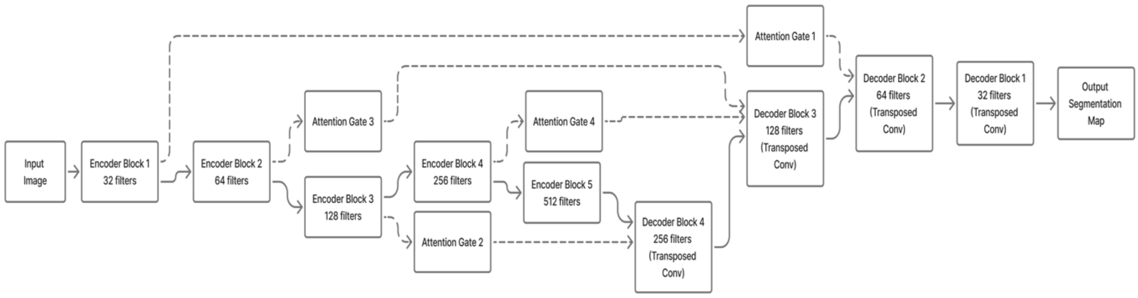

Figure 2. Architecture of the Attention U-Net

2.4 Loss Function and Optimization

To balance pixel-level accuracy and region overlap, the training objective combines Binary Cross-Entropy (BCE) and Dice Loss (Milletari et al., 2016; Ma et al., 2024). The composite loss function is formulated as:

$$L = 0.5\,.\,L_{BCE} + 0.5\,.\,L_{Dice} \tag{1}$$

where:
L_{BCE}: Binary Cross-Entropy Loss
L_{Dice}: Dice loss
L: Total composite loss used for model optimization
The coefficients 0.5 ensure an equal contribution from both loss components

Model optimization was performed using the AdamW optimizer with a learning rate of 3×10^{-4}, weight decay of 1×10^{-5} and early stopping after six epochs without validation improvement (Loshchilov & Hutter, 2019).

2.5 Experimental Setup

All experiments were implemented using the PyTorch deep learning framework and executed on an NVIDIA Tesla T4 GPU in the Google Colab environment. The models were trained for 20 epochs, which was empirically selected to balance learning convergence and computational efficiency. Preliminary experiments showed that performance improvements saturated after 20 epochs, while longer training introduced overfitting tendencies. Due to GPU memory limitations, a batch size of 8 was utilized to ensure stable optimization.

The dataset was split into training, validation, and testing subsets using a 70:15:15 ratio. The validation set was used for hyperparameter monitoring and early stopping, while the test set was used exclusively for final evaluation. In order to ensure reproducibility, all random operations including weight initialization, data shuffling, and data augmentation were controlled using a fixed random seed (seed = 42). The models were optimized using AdamW optimizer. Early stopping was applied if validation loss did not improve for six consecutive epochs. No hyperparameter tuning was performed; instead, parameters were selected based on commonly adopted values in related segmentation studies.

2.6 Evaluation Metrics

Model performance was quantitatively evaluated using two standard segmentation metrics, namely the Dice Coefficient and Intersection over Union (IoU), which are widely adopted in medical image segmentation studies (Taha & Hanbury, 2015; Ma et al., 2024).

The Dice coefficient, which measures the degree of overlap between the predicted mask and the ground-truth annotation, is defined as:

$$Dice = \frac{2TP}{2TP+FP+FN} \quad (2)$$

The Intersection over Union (IoU), also known as the Jaccard Index, quantifies the ratio between the intersection and union of the predicted segmentation and the ground truth (Taha & Hanbury, 2015):

$$IoU = \frac{TP}{TP+FP+FN} \quad (3)$$

where:
TP (True Positive): polyp pixels correctly classified
FP (False Positive): background pixels incorrectly classified as polyp
FN (False Negative): polyp pixels incorrectly classified as background

Both metrics provide complementary perspectives on segmentation quality. Dice emphasizes region overlap, while IoU penalizes over-segmentation and under-segmentation more strictly. These measures are considered reliable indicators for evaluating segmentation performance in medical imaging applications (Ma et al., 2024).

Collectively, these metrics provide a reliable assessment of segmentation performance by measuring the spatial overlap between the predicted masks and the ground-truth annotations. Dice coefficient evaluates the degree of region agreement, while IoU offers a stricter measure by penalizing both over-segmentation and under-segmentation. These metrics are widely adopted in medical image segmentation and are suitable for evaluating model performance in this study.

2.7 Statistical Analysis

Statistical analysis was conducted to evaluate whether there was a significant difference in segmentation performance between the baseline Attention U-Net and the CLAHE-enhanced model. The Wilcoxon signed-rank test was employed, as it is a non-parametric test suitable for comparing paired samples without assuming normal distribution.

This test was applied to the Dice coefficient values obtained from both models for each test image. A significance level of $\alpha = 0.05$ was used. A p-value lower than 0.05 indicates a statistically significant difference between the two methods.

3. Results And Discussion

The experimental results evaluate the effectiveness of the proposed CLAHE-enhanced Attention U-Net through an ablation study by comparing it with the baseline Attention U-Net. Quantitative results on both datasets are summarized in Table 1, which reports Dice coefficient and Intersection over Union (IoU) scores.

Table 1. Quantitative Comparison Between Baseline and CLAHE-enhanced Models

Dataset	Model	Dice	IoU
CVC-ClinicDB	Attention U-Net	**0.287**	**0.193**
CVC-ClinicDB	Attention U-Net + CLAHE	0.256	0.166
Kvasir-SEG	Attention U-Net	0.350	0.220
Kvasir-SEG	Attention U-Net + CLAHE	**0.372**	**0.235**

Table 1 shows that on CVC-ClinicDB, the baseline Attention U-Net outperforms the CLAHE-enhanced model, achieving a Dice score of 0.287 and IoU of 0.193, compared to 0.256 and 0.166, respectively. This indicates that CLAHE does not provide performance improvement on datasets with relatively stable illumination and consistent visual characteristics. In fact, contrast enhancement may slightly distort texture information, leading to marginal performance degradation.

Conversely, on the Kvasir-SEG dataset, the Attention U-Net + CLAHE model demonstrates superior performance, achieving a Dice score of 0.372 and IoU of 0.235, compared to the baseline model (Dice 0.350, IoU 0.220). This improvement suggests that CLAHE enhances model generalization under challenging illumination conditions commonly present in Kvasir-SEG, such as uneven lighting, specular reflections, and low-contrast regions. To statistically validate these findings, a Wilcoxon signed-rank test was conducted between the baseline and CLAHE-enhanced models. The test shows a statistically significant improvement on Kvasir-SEG ($p < 0.05$), indicating that CLAHE contributes meaningfully to performance enhancement under cross-domain conditions. However, no statistically significant difference was observed on CVC-ClinicDB ($p > 0.05$), confirming that CLAHE does not consistently improve segmentation when image quality is already stable.

To further analyze model behavior, qualitative segmentation results are presented in Figure 3 and Figure 4. Each figure displays the original input image, ground truth mask, predicted segmentation, and overlay visualization.

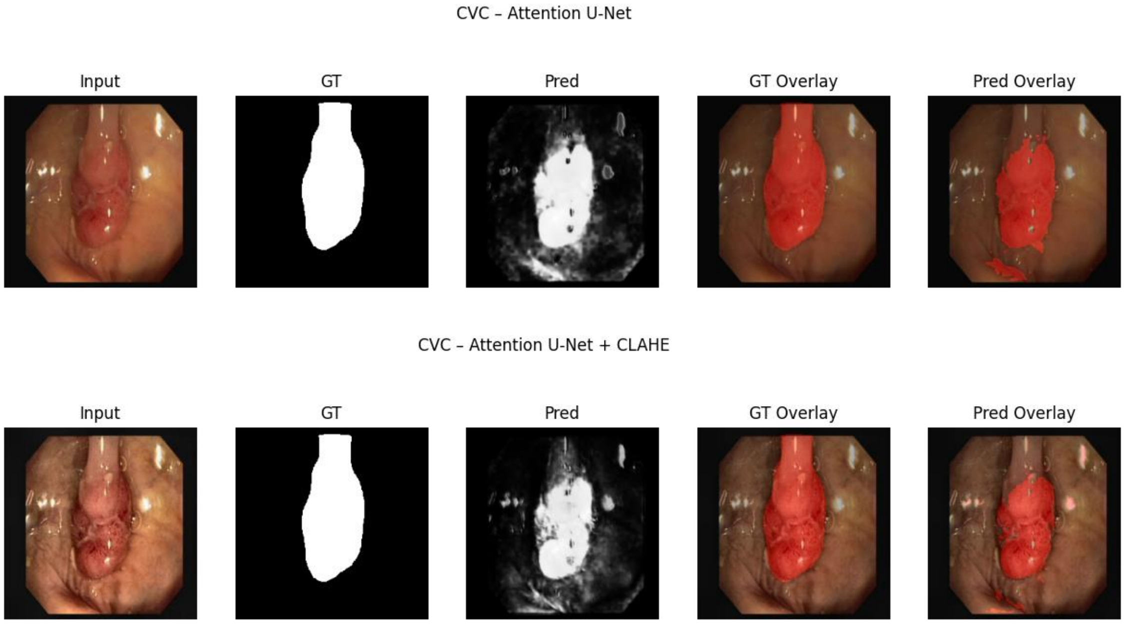

Figure 3. Qualitative Segmentation Results on CVC-ClinicDB Dataset

Figure 3 illustrates representative results on the CVC-ClinicDB dataset. Both models successfully segment polyp regions with clear boundaries. The baseline Attention U-Net produces predictions that closely match the ground truth, particularly in cases where polyps exhibit well-defined edges and uniform illumination. In contrast, the CLAHE-enhanced model occasionally introduces minor false positives around textured mucosal regions, which explains the slight performance degradation observed quantitatively.

Figure 4 presents segmentation results on the Kvasir-SEG dataset. The baseline model tends to under-segment polyps in low-contrast regions and in areas affected by uneven illumination. The CLAHE-enhanced model shows improved boundary delineation and clearer separation between poly and background tissues. This visual improvement aligns with the quantitative gains reported in Table 1, confirming the effectiveness of CLAHE under challenging imaging conditions.

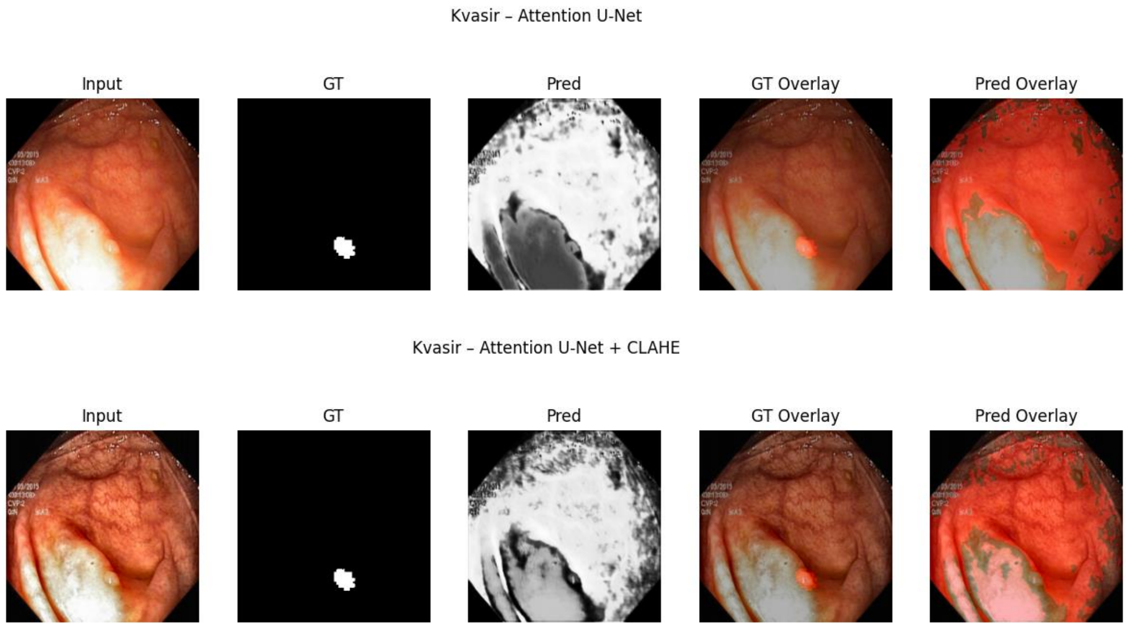

Figure 4. Qualitative Segmentation Results on Kvasir-SEG Dataset.

Overall, the qualitative analysis supports the quantitative findings and demonstrates that CLAHE is beneficial for datasets characterized by heterogeneous illumination, such as Kvasir-SEG. However, for datasets with relatively stable visual characteristics like CVC-ClinicDB, CLAHE may introduce unnecessary contrast amplification the does not translate into segmentation performance improvement.

4. Conclusions

This study investigated the impact of Contrast Limited Adaptive Histogram Equalization (CLAHE) on the performance of Attention U-Net for colorectal polyp segmentation through a systematic ablation study. Experiments were conducted using CVC-ClinicDB as the primary dataset and Kvasir-SEG for cross-domain evaluation.

The results demonstrate that the effectiveness of CLAHE is highly dataset-dependent. On CVC-ClinicDB, which exhibits relatively stable illumination and consistent visual characteristics, the baseline Attention U-Net outperformed the CLAHE-enhanced model, indicating that contrast enhancement is not always beneficial when image quality is already sufficient. In contrast, on the more challenging Kvasir-SEG dataset, which contains significant illumination variability and complex mucosal textures, the Attention U-Net with CLAHE achieved superior segmentation performance. Statistical analysis using the Wilcoxon signed-rank test confirmed that the performance improvement on Kvasir-SEG is statistically significant ($p < 0.05$), while no significant difference was observed on CVC-ClinicDB ($p > 0.05$).

These findings highlight that CLAHE can effectively improve model generalization under adverse imaging conditions, particularly in cross-domain scenarios. From a clinical perspective, this improvement may help reduce missed polyp detection in low-visibility colonoscopy cases, thereby supporting more reliable computer-aided diagnosis systems.

In conclusion, this study provides empirical evidence that contrast enhancement should be applied selectively rather than universally in deep learning-based medical image segmentation. Future work will focus on integrating domain adaptation strategies, transformer-based architectures, and temporal information from colonoscopy videos to further improve robustness and clinical applicability.

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