CLFSeg: A Fuzzy-Logic based Solution for Boundary Clarity and Uncertainty Reduction in Medical Image Segmentation

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Introduction

- Growth of abnormal tissue in the colon are polyp that provide signs of **colorectal** cancer.
- Integrates **fuzzy logic** and various **convolution** modules in **a parallel** way to make the boundary **fuzzier** and for precise and efficient segmentation with **computational** efficiency.
- Tackle the **uncertainty**, **ambiguous** data, and **low-contrast** areas for robustness segmentation.

Discussion

- The proposed **CLFSeg** leverages a hybrid encoder-decoder structure enhanced with the **Fuzzy-Convolutional (FC)** module shown in Figure 1 and 2. The model captures both local and global features, reducing uncertainty and ambiguity in boundary regions.
- CLFSeg outperforms existing models in segmentation **accuracy**, **robustness**, and **computational efficiency** across all datasets, as shown in the results Table 1 and 2.
- Analysis of boundary clarity on DuckNet [1] and CLFSeg are shown in Table 3.
- Figure 3 shows that CLFSeg focuses on relevant regions, outperforming DuckNet in **boundary clarity** on the CVC-ColonDB dataset.
- The fuzzy logic integrated with convolutions allows CLFSeg to manage **uncertain** and **low-contrast** areas effectively, as seen in the improved segmentation maps in Figure 4.

Results

Dataset	Methods	DSC ↑	IoU ↑	Precision ↑	Recall ↑
CVC-ColonDB	FuzzyNet (PVT) [2]	0.8110	0.7280	-	-
	InCoLoTransNet [4]	0.9309	0.9013	0.9177	0.9156
	ASRDNet [5]	0.9337	0.8756	0.9327	0.9347
	DUCKNet (17 filter) [1]	0.9353	0.8785	0.9300	0.9392
	DUCKNet (34 filter) [1]	0.9230	0.8570	0.9100	0.9351
	DUCKNet (24 filter, re-train) [1]	0.9389	0.8848	0.9300	0.9413
	CLFSeg (17 filters, OURS)	0.9460	0.8970	0.9580	0.9342
	CLFSeg (24 filters, OURS)	0.9503	0.9053	0.9583	**0.9430**
	CLFSeg (34 filters, OURS)	**0.9593**	**0.9218**	**0.9634**	0.9401
CVC-ClinicDB	FuzzyNet (PVT) [2]	0.9370	0.8890	-	-
	CTHP [48]	0.9471	0.9021	0.9524	0.9444
	DUCKNet (17 filter) [1]	0.9450	0.8952	0.9488	0.9406
	DUCKNet (34 filter) [1]	0.9478	0.9009	0.9468	**0.9489**
	DUCKNet (24 filter, re-train) [1]	0.9430	0.8922	0.9539	0.9324
	CLFSeg (17 filters, OURS)	**0.9533**	**0.9108**	**0.9636**	0.9432
	CLFSeg (24 filters, OURS)	0.9530	0.9103	0.9594	0.9467
	CLFSeg (34 filters, OURS)	0.9500	0.9048	0.9568	0.9433
ETIS-LaribPolyp	FuzzyNet (PVT) [2]	0.7910	0.7020	-	-
	ASRDNet [5]	0.9313	0.8714	0.9055	0.9586
	InCoLoTransNet [4]	0.9316	0.9225	0.9283	0.9392
	DUCKNet (17 filter) [1]	0.9324	0.8734	0.9539	0.9118
	DUCKNet (34 filter) [1]	0.9354	0.8788	0.9309	0.9400
	DUCKNet (24 filter, re-train) [1]	0.9396	0.8861	0.9372	0.8861
	CLFSeg (17 filters, OURS)	0.9292	0.8678	0.9189	0.9396
	CLFSeg (24 filters, OURS)	0.9140	0.8416	0.8826	**0.9476**
	CLFSeg (34 filters, OURS)	**0.9487**	**0.9024**	**0.9596**	0.9380

Table 1. Comparing the performance of **CLFSeg** with SOTA methods.

Methods	DSC ↑	IoU ↑	# FLOPs (M) ↓	#Params (M) ↓
LHU-Net [6]	0.9266	-	-	-
Adaptive t-vMF [3]	0.9368	-	-	-
DUCKNet (17 filter, re-train) [1]	0.9380	0.8868	38	38
DUCKNet (24 filter, re-train) [1]	0.9373	0.8848	77	77
DUCKNet (34 filter, re-train) [1]	0.9388	0.8875	155	155
CLFSeg (17 filters, OURS)	0.9372	0.8848	**26**	**38**
CLFSeg (24 filters, OURS)	**0.9445**	**0.8975**	**54**	**71**
CLFSeg (34 filters, OURS)	0.9380	0.8833	**106**	**132**

Table 2. Comparing performance with SOTA methods on the **ACDC** dataset.

Dataset	CVC-ColonDB		CVC-ClinicDB		ACDC	
Filters	17	34	17	34	17	34
DuckNet [1]	1.97	2.00	4.44	6.39	0.90	1.36
CLFSeg	**1.43**	**1.50**	**3.54**	**5.97**	**0.58**	**0.81**

Table 3. Analysis of boundary clarity on **DuckNet** [1] and proposed **CLFSeg**.

Proposed CLFSeg Model

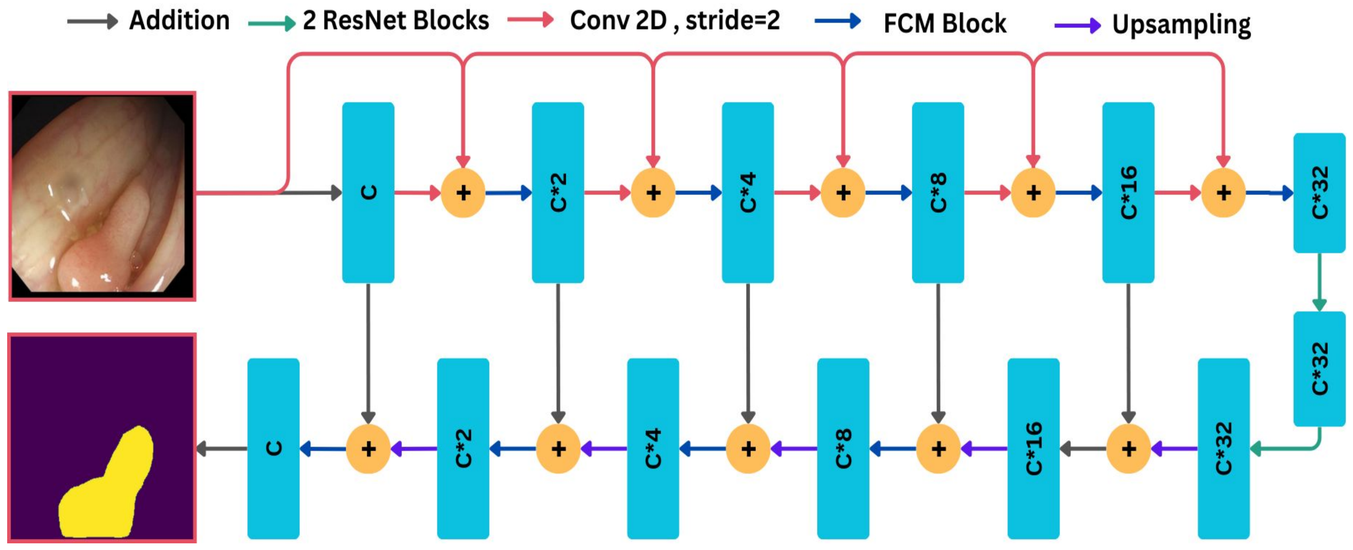

Figure 1. Overview of the proposed **CLFSeg** model.

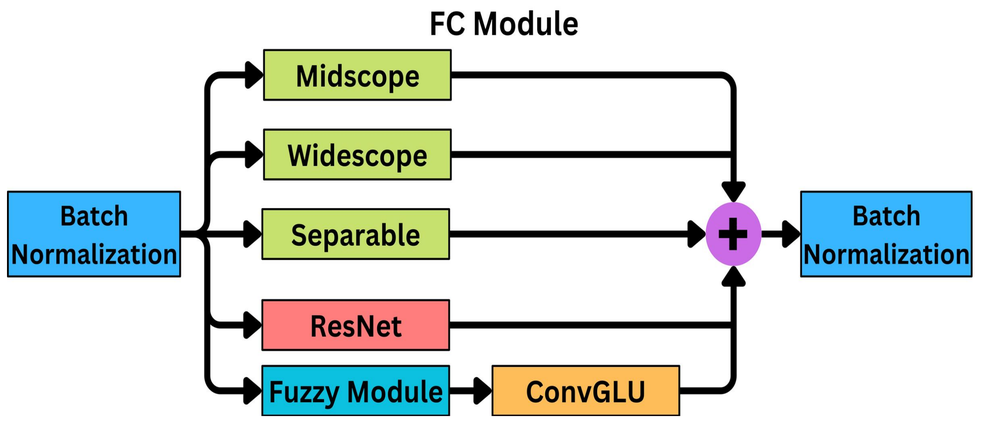

Figure 2. Overview of the **FC module**.

Visualization

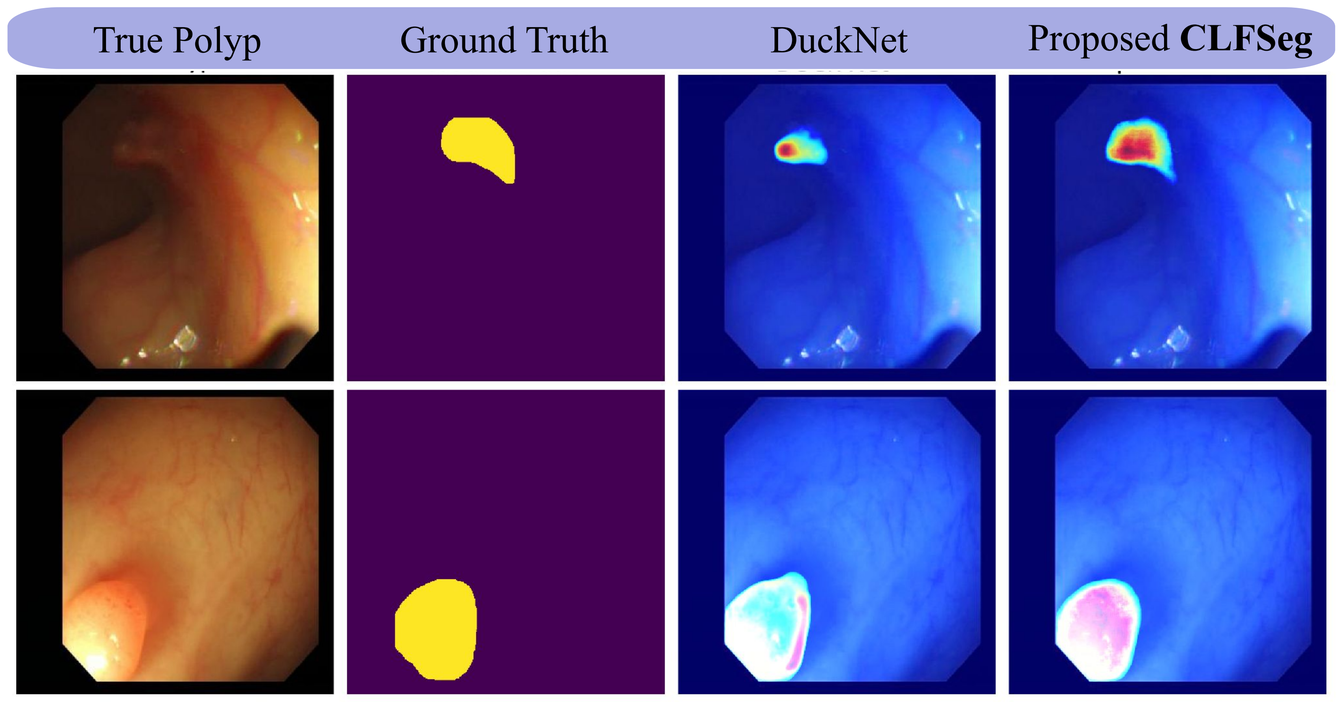

Figure 3. Comparison of GradCam++ Visualization between DuckNet [1] and CLFSeg for CVC-ColonDB.

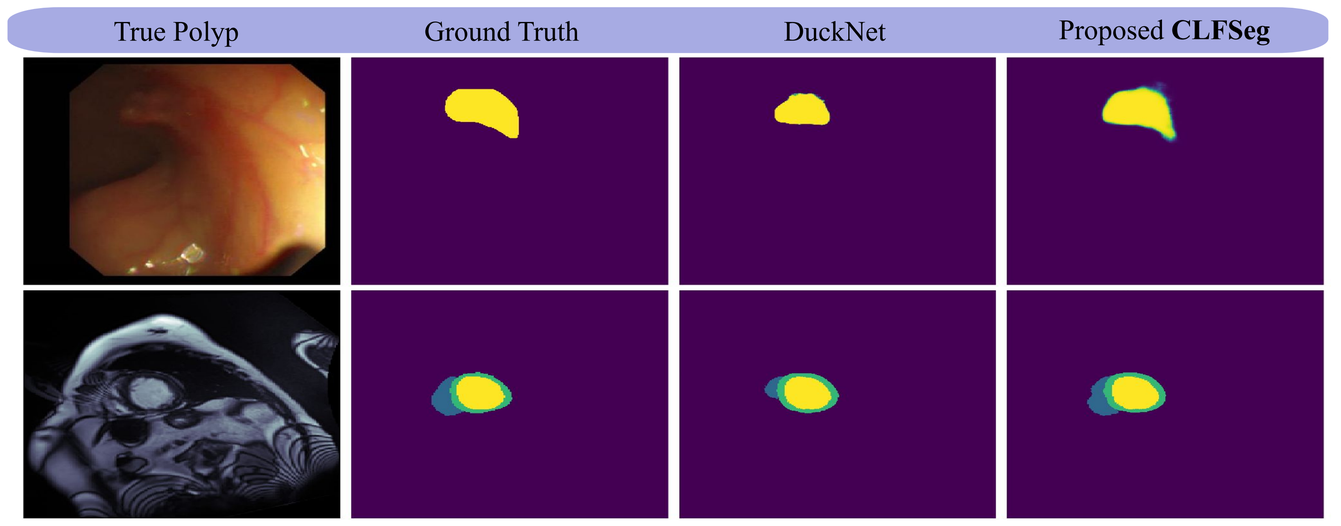

Figure 4. Comparison of Segmentation Map for CVC-ColonDB, and ACDC dataset.

Conclusion

- The proposed framework enhances automated medical segmentation in a **fast** and **efficient** way.
- Enhancing boundary precision and handling uncertainty, with strong potential for real-world clinical applications
- The model can be extended to other medical imaging tasks like **Organ-at-Risk (OAR)** and **tumor** segmentation, and further **privacy-focused** approaches will be explored to enhance clinical applicability.

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