# The Centerline-Cross Entropy Loss for Vessel-Like Structure Segmentation: Better Topology Consistency Without Sacrificing Accuracy

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The **centerline-Cross Entropy (clCE) loss** combines:

- The **topological consistency** of the **clDice** [1]
- The **robustness** of the **Cross Entropy**

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**https://github.com/cesaracebes/centerline_CE**

Our method provides a **topology-preserving** solution **without sacrificing segmentation performance**.

## clCE Loss Formulation:

$$\text{CE-}\mathcal{T}_{\text{prec}}(\mathbf{T},\widehat{\mathbf{P}}) = -\frac{1}{\|\mathbf{S_T}\|_1}\sum_{i\,|\,\mathbf{x}_i\in\mathbf{S_T}}\mathbf{T}_i\log(\widehat{\mathbf{P}}_i).$$

$$\text{CE-}\mathcal{T}_{\text{recall}}(\mathbf{T},\widehat{\mathbf{P}}) = -\frac{\sum_{i\,|\,\mathbf{x}_i\in\mathbf{S}_{\widehat{\mathbf{P}}}}(\mathbf{T}_i\log(\widehat{\mathbf{P}}_i)+(1-\mathbf{T}_i)\log(1-\widehat{\mathbf{P}}_i))\cdot\widehat{\mathbf{P}}_i}{\sum_{i\,|\,\mathbf{x}_i\in\mathbf{S}_{\widehat{\mathbf{P}}}}\widehat{\mathbf{P}}_i}.$$

The **clCE** loss balances segmentation accuracy combining topological **precision** and **recall** components as follows:

$$\boxed{\mathcal{L}_{\text{clCE}}(\mathbf{T},\widehat{\mathbf{P}}) = \text{CE-}\mathcal{T}_{\text{prec}}(\mathbf{T},\widehat{\mathbf{P}})+\text{CE-}\mathcal{T}_{\text{recall}}(\mathbf{T},\widehat{\mathbf{P}}).}$$

T: target, $S_T$: skeleton of the target,
P: prediction, $S_P$: skeleton of the prediction.

## Experiments and Results:

For 2D retinal vessel segmentation: **small U-Net architecture** [2].
Datasets: HRF, DR-HAGIS, TREND, FIVES.

For 3D coronary artery segmentation: **nnU-Net framework** in full-resolution [3]. Dataset: ASOCA.

| Dataset | Baseline ($\mathcal{L}_{Dice}$) | | clDice ($\mathcal{L}_{Dice}$+0.5$\mathcal{L}_{clDice}$) | | Ours-clCE ($\mathcal{L}_{Dice}$+$\mathcal{L}_{clCE}$) | |
|---|---|---|---|---|---|---|
| | DSC | cl-DSC | DSC | cl-DSC | DSC | cl-DSC |
| **HRF** | 78.93 | 77.46 | 75.60 | **83.83** | **79.34** | **78.94** |
| **DR-HAGIS** | 69.22 | 68.73 | 66.62 | **74.20** | **70.65** | **70.06** |
| **TREND** | 63.92 | 65.32 | 61.04 | **71.35** | **64.54** | **67.04** |
| **ASOCA** | 84.59 | 84.81 | 83.42 | 84.76 | **84.80** | **84.95** |
| **FIVES-N** | 83.06 | 80.29 | 77.14 | **83.37** | **83.40** | **81.28** |
| **FIVES-A** | 83.81 | 79.50 | 80.80 | **84.48** | **84.10** | **80.64** |
| **FIVES-G** | 71.75 | 66.88 | 66.03 | 67.81 | **71.83** | **67.91** |
| **FIVES-D** | 78.62 | 73.35 | 74.59 | **79.03** | **79.04** | **74.65** |

Table 1. Quantitative results for segmentation accuracy (DSC) and for topological consistency (cl-DSC) using different loss functions over multiple open-source datasets. **Bold**: improves the baseline performance.

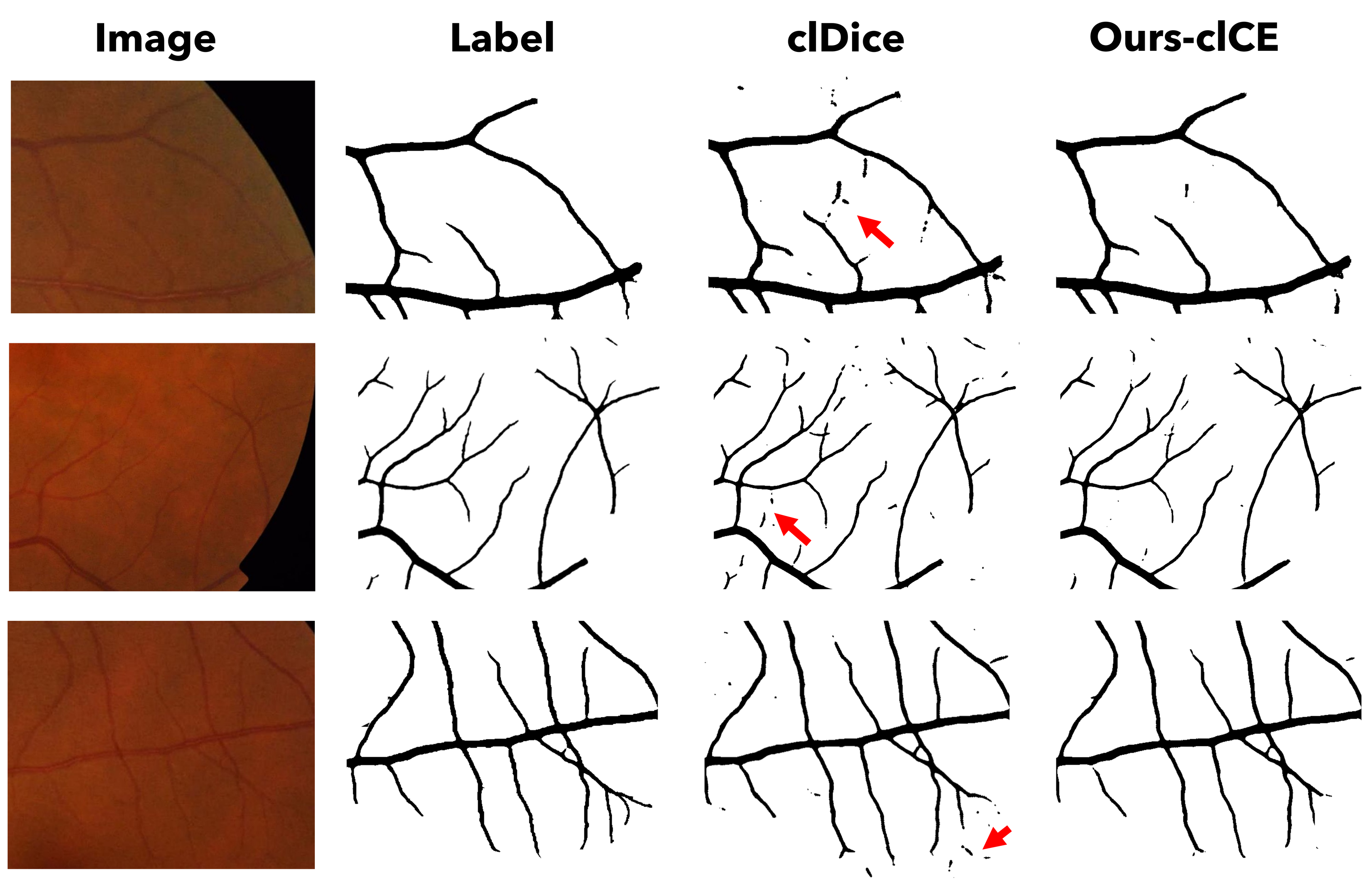


Fig 1. Qualitative results for the FIVES dataset using our proposed clCE loss function versus the clDice loss. Red arrows: areas with false positives not present in the predictions using the clCE.

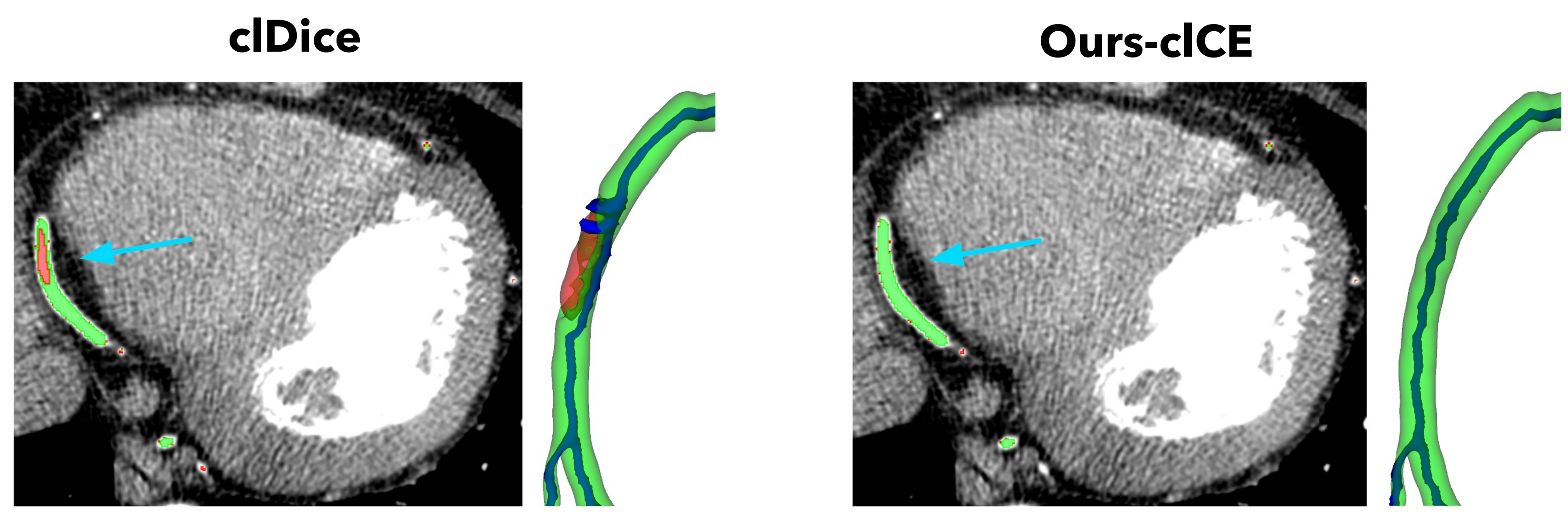


Fig 2. Qualitative results for the ASOCA dataset using our proposed clCE loss function versus the clDice loss. Green: TPs. Red: FPs and FNs.

[1] **Shit, S., et al.: clDice - a Novel Topology-Preserving Loss Function for Tubular Structure Segmentation** In: Computer Vision and Pattern Recognition (Jun 2021). https://doi.org/10.1109/CVPR46437.2021.01629
[2] **Galdran, A., et al.: State-of-the-art retinal vessel segmentation with minimalistic models** Scientific Reports 12(1) (Apr 2022). https://doi.org/10.1038/s41598-022-09675-y
[3] **Isensee, F., et al.: nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation** Nature Methods 18(2), 203–211 (Feb 2021). https://doi.org/10.1038/s41592-020-01008-z

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