NEURAL INFORMATION PROCESSING SYSTEMS

北京大學 PEKING UNIVERSITY

医准智能 MEDICAL AI

GraphMorph: Tubular Structure Extraction by Morphing Predicted Graphs

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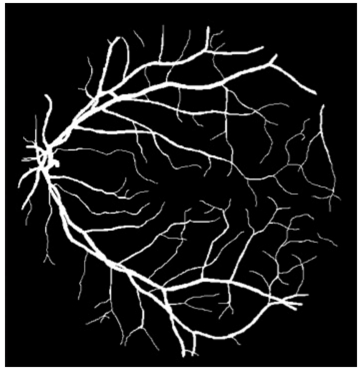
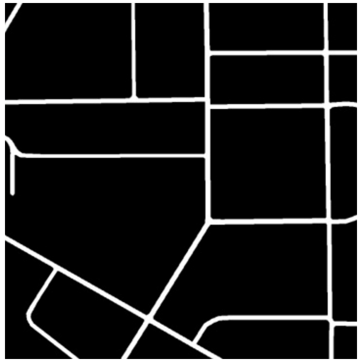
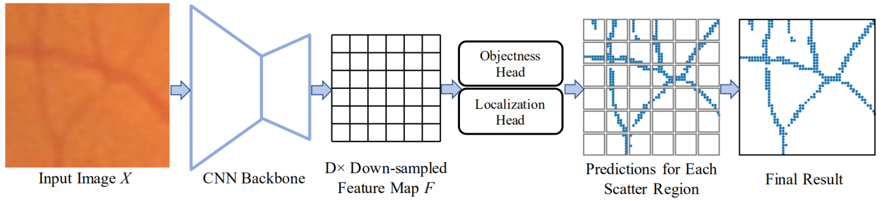
Tubular Structure Extraction

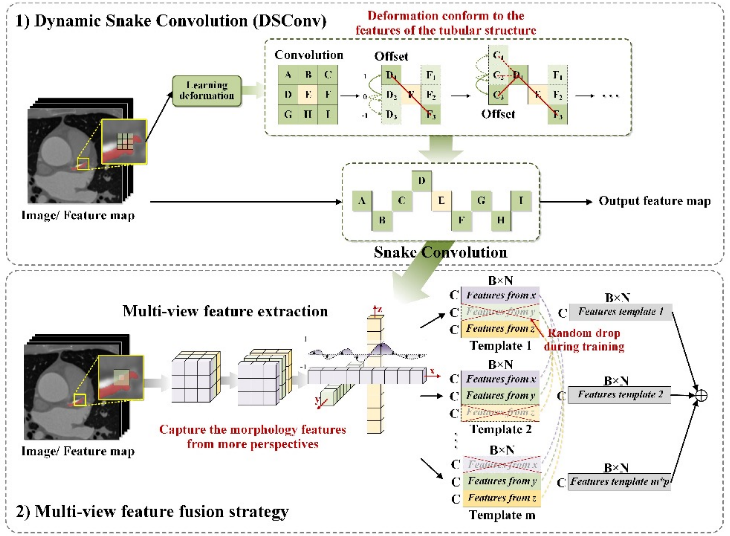





PointScatter

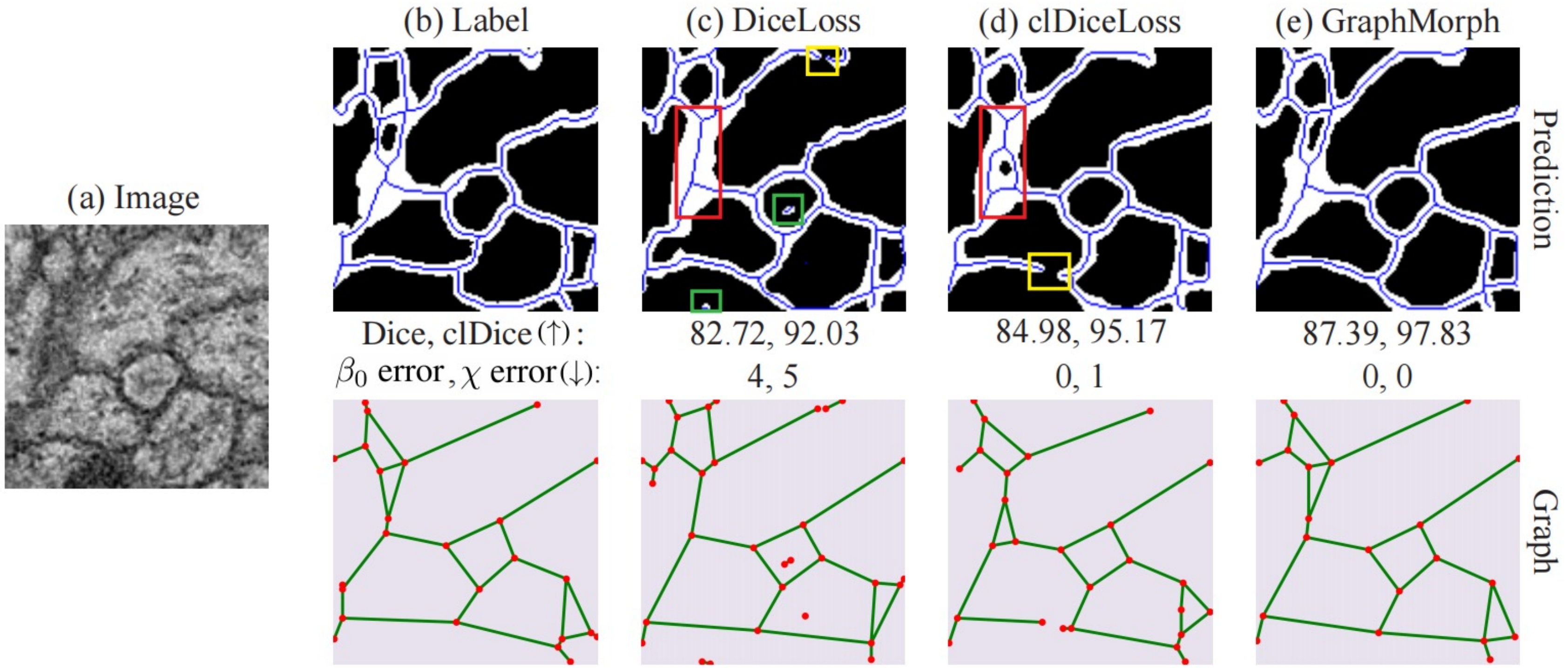


DSCNet

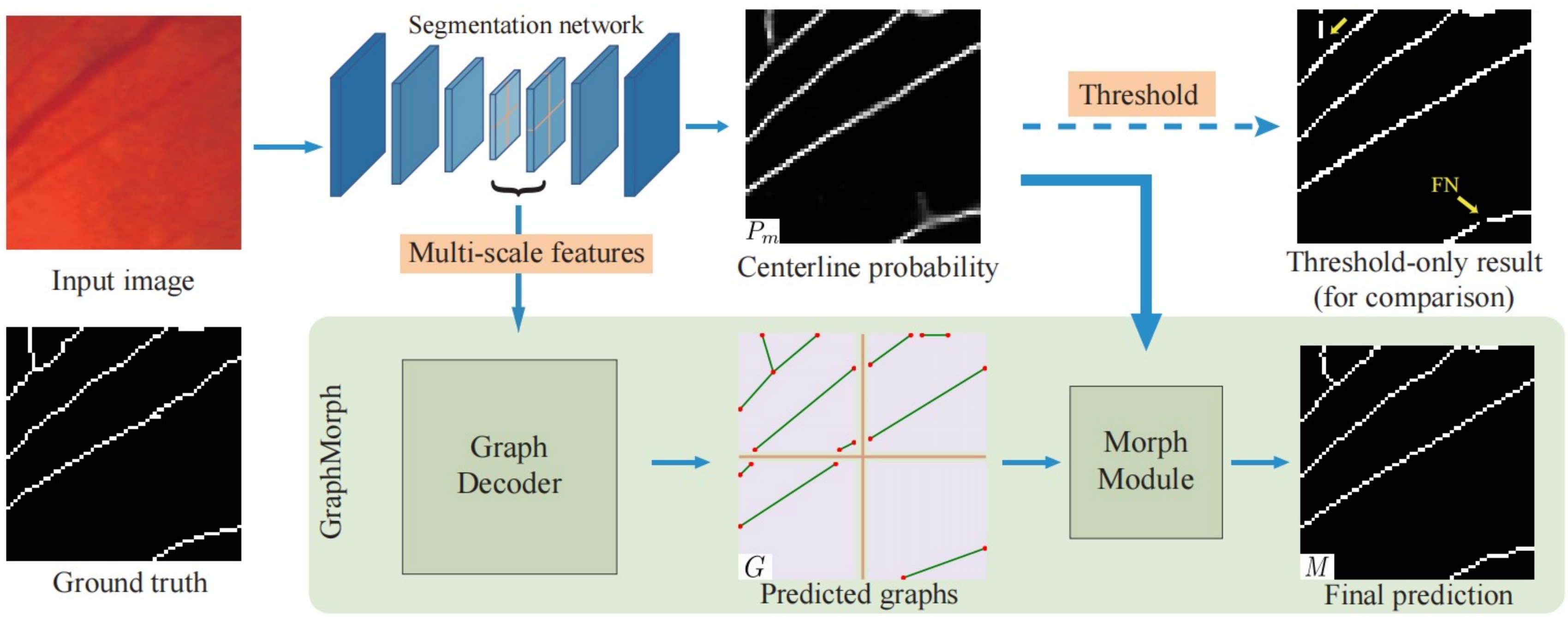


Motivation & Introdution

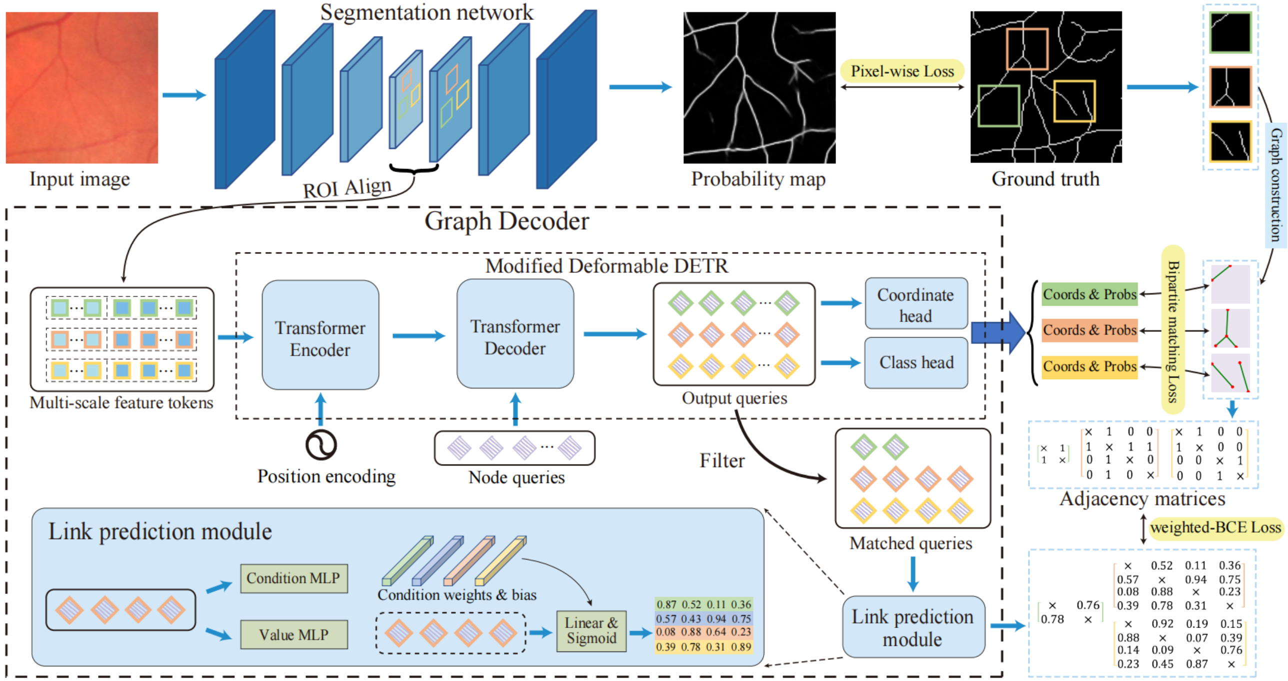
***Branch-level features** are more essential for accurately capturing the nuances of tubular structures!*



Overview of GraphMorph



Graph Decoder



Loss functions

$$\mathcal{L}_{\text{Hungarian}}(y,\hat{y}) = \sum_{r=1}^{R}\sum_{i=1}^{K}\left[\lambda_{\text{class}}\cdot\mathcal{L}_{\text{focal}}(\hat{s}^{r}_{\hat{\sigma}(i)}, c^{r}_{i}) + \lambda_{\text{coord}}\cdot\mathbb{1}_{\{c^{r}_{i}\neq\varnothing\}}\mathcal{L}_{\text{coord}}\left(\hat{v}^{r}_{\hat{\sigma}(i)}, v^{r}_{i}\right)\right]$$

$$\mathcal{L}_{\text{Adjacency}}(y,\hat{y}) = \sum_{r=1}^{R}\{\frac{0.5}{N_{\text{pos}}}\sum_{i\neq j}^{P_r}\sum_{j=1}^{P_r}(A^{r}_{ij}\log\widetilde{A}^{r}_{ij}) + \frac{0.5}{N_{\text{neg}}}\sum_{i\neq j}^{P_r}\sum_{j=1}^{P_r}[(1-A^{r}_{ij})\log(1-\widetilde{A}^{r}_{ij})]\}$$

Morph Module

Algorithm 1 Morph Module

Input: Node set V, Edge set E, Probability map P_m
Output: Centerline mask M

```
Initialize M as a zero matrix with the same size as P_m
Initialize C_m where C_m[i][j] = 1 − P_m[i][j] for each element
for all edges (u, v) in E do
    path ← SkeletonDijkstra(u, v, C_m, p_thresh)
    for all points p in path do
        Set M[p.x][p.y] = 1
    end for
end for
return M
```

Algorithm 2 SkeletonDijkstra Algorithm

Input: Start point s, End point e, Cost map C, Path threshold p_{thresh}
Output: Minimum cost path from s to e under threshold p_{thresh}

```
Initialize priority queue Q with (0, [s])
Initialize visited set Vis
while not Q empty do
    (cost, path) ← Q.pop()
    curr ← last element of path
    Add curr to Vis
    if curr = e then
        avg ← cost/ length(path)
        if avg > p_thresh then
            return ∅
        end if
        return path
    end if
    for each n in neighbors of curr do
        if n in Vis then
            continue
        end if
        neis_in_path ← count of n's neighbors in path
        if neis_in_path ≤ 1 then
            path ← path concatenated with [n]
            cost ← cost + C[n.x][n.y]
            Q.push((cost, path))
        end if
    end for
end while
```

Evaluation

Datasets

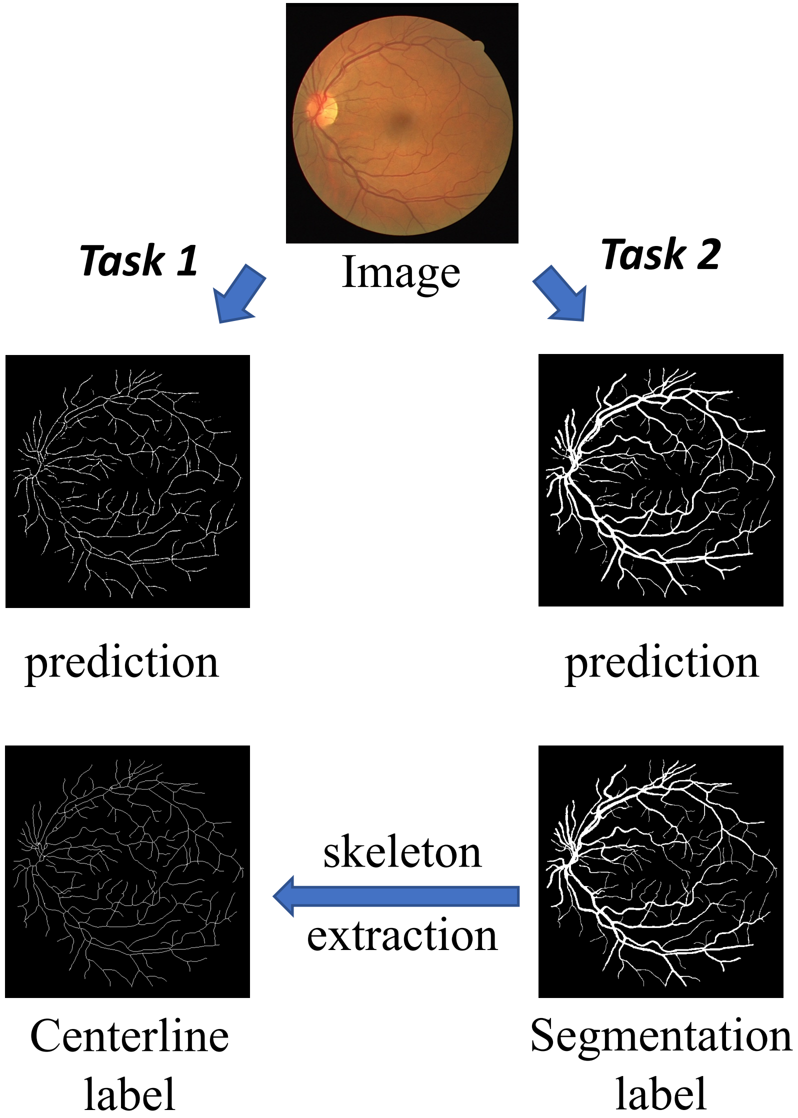
- Medical datasets: ***DRIVE, STARE and ISBI12***
- Satellite dataset: ***Massachusetts Roads***

Tasks

- ***Centerline extraction (Task 1)***
- ***Tubular structure segmentation (Task 2)***

Metrics

- ***Volumetric metrics:*** Dice, Accuracy, AUC, clDice, etc.
- ***Topology-based metrics:*** β_{0error}, β_{1error}, χ_{error}



Experimental Results

Centerline extraction

- *__Graph Decoder__ during training enables the network to learn branch-level features, leading to enhanced performance in both volumetric and topological metrics.*
- *The combined use of __Graph Decoder__ and __Morph Module__ showcases the ability to preserve the crucial topological characteristics.*

Table 1: Centerline extraction performance on four public datasets based on UNet.

Dataset	Method	Volumetric metrics (↑)			Topological metrics (↓)		
		Dice	AUC	ACC	β_0 error	β_1 error	χ error
DRIVE	softDice [26]	0.7353 ± 0.0127	0.9333 ± 0.0089	0.9768 ± 0.0013	2.169 ± 0.112	1.590 ± 0.107	2.537 ± 0.139
	PointScatter [40]	0.7381 ± 0.0133	0.9401 ± 0.0078	0.9775 ± 0.0013	3.259 ± 0.153	2.080 ± 0.120	3.500 ± 0.176
	softDice [26] + Graph Decoder	**0.7506 ± 0.0127**	**0.9481 ± 0.0082**	**0.9783 ± 0.0012**	1.552 ± 0.094	1.382 ± 0.106	1.899 ± 0.125
	softDice [26] + Graph Decoder + Morph Module	0.7496 ± 0.0118	/	0.9776 ± 0.0012	**0.555 ± 0.038**	**1.074 ± 0.073**	**0.893 ± 0.061**
ISBI12	softDice [26]	0.6428 ± 0.0104	0.8937 ± 0.0063	0.9737 ± 0.0013	4.045 ± 0.191	2.696 ± 0.112	4.294 ± 0.205
	Pointscatter [40]	0.6546 ± 0.0089	0.9104 ± 0.0057	**0.9747 ± 0.0013**	6.398 ± 0.277	3.156 ± 0.124	6.548 ± 0.290
	softDice [26] + Graph Decoder	0.6486 ± 0.0095	**0.9240 ± 0.0061**	0.9742 ± 0.0012	4.013 ± 0.179	2.732 ± 0.110	4.249 ± 0.193
	softDice [26] + Graph Decoder + Morph Module	**0.6687 ± 0.0092**	/	0.9742 ± 0.0014	**0.665 ± 0.049**	**1.207 ± 0.070**	**0.858 ± 0.059**
STARE	softDice [26]	0.7119 ± 0.0392	0.9290 ± 0.0283	0.9889 ± 0.0012	1.874 ± 0.139	1.209 ± 0.112	2.063 ± 0.162
	Pointscatter [40]	0.7224 ± 0.0414	0.9494 ± 0.0179	0.9896 ± 0.0012	2.080 ± 0.149	1.365 ± 0.116	2.213 ± 0.166
	softDice [26] + Graph Decoder	**0.7298 ± 0.0428**	**0.9506 ± 0.0208**	**0.9898 ± 0.0011**	1.467 ± 0.113	1.074 ± 0.104	1.654 ± 0.132
	softDice [26] + Graph Decoder + Morph Module	0.7291 ± 0.0387	/	0.9894 ± 0.0011	**0.482 ± 0.042**	**0.799 ± 0.077**	**0.653 ± 0.059**
MassRoad	softDice [26]	0.6339 ± 0.0169	0.9718 ± 0.0047	**0.9942 ± 0.0009**	1.672 ± 0.056	1.627 ± 0.087	1.968 ± 0.097
	Pointscatter [40]	**0.6405 ± 0.0149**	0.9694 ± 0.0042	**0.9942 ± 0.0009**	3.333 ± 0.124	1.553 ± 0.086	3.429 ± 0.149
	softDice [26] + Graph Decoder	0.6289 ± 0.0175	**0.9731 ± 0.0045**	0.9941 ± 0.0009	1.933 ± 0.065	1.729 ± 0.088	2.229 ± 0.105
	softDice [26] + Graph Decoder + Morph Module	0.6388 ± 0.0168	/	**0.9942 ± 0.0009**	**0.620 ± 0.021**	**1.355 ± 0.083**	**1.122 ± 0.075**

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Centerline extraction

- ***Graph Decoder*** *during training enables the network to learn branch-level features, leading to enhanced performance in both volumetric and topological metrics.*
- *The combined use of* ***Graph Decoder*** *and* ***Morph Module*** *showcases the ability to preserve the crucial topological characteristics.*

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Experimental Results

Tubular structure segmentation

- ***GraphMorph*** *achieves best results across all methods thanks to the utilization of branch-level features.*

Table 3: Comparison with SOTA methods on the segmentation task. Best results are in bold; second-best are underlined. Our approach secures all leading scores and most secondary peaks.

Dataset	Backbone	Method	Volumetric metrics (↑)			Distribution metrics		Topological metrics (↓)		
			Dice	clDice	ACC	ARI(↑)	VOI(↓)	β_0 error	β_1 error	χ error
DRIVE	UNet	softDice [26]	0.8148 ± 0.0093	0.8128 ± 0.0169	0.9535 ± 0.0023	0.767 ± 0.011	0.348 ± 0.012	1.191 ± 0.069	1.078 ± 0.074	1.467 ± 0.083
	UNet	clDice [37]	0.8150 ± 0.0078	<u>0.8322 ± 0.0163</u>	0.9520 ± 0.0021	0.765 ± 0.009	0.357 ± 0.012	0.910 ± 0.056	0.998 ± 0.070	1.181 ± 0.071
	UNet	Pointscatter [40]	0.8155 ± 0.0081	0.8277 ± 0.0179	0.9525 ± 0.0020	0.766 ± 0.009	0.353 ± 0.010	1.360 ± 0.080	1.276 ± 0.083	1.663 ± 0.094
	UNet	TopoLoss [14]	<u>0.8187 ± 0.0075</u>	0.8194 ± 0.0160	<u>0.9540 ± 0.0020</u>	<u>0.771 ± 0.009</u>	0.345 ± 0.010	0.821 ± 0.050	0.997 ± 0.072	1.100 ± 0.067
	DSCNet [33]	softDice	0.8118 ± 0.0083	0.8107 ± 0.0172	0.9527 ± 0.0021	0.763 ± 0.010	0.352 ± 0.011	1.267 ± 0.075	1.110 ± 0.076	1.550 ± 0.087
	TransUNet [4]	softDice	0.8153 ± 0.0094	0.8139 ± 0.0182	0.9538 ± 0.0020	0.768 ± 0.010	<u>0.344 ± 0.009</u>	1.125 ± 0.066	1.184 ± 0.082	1.420 ± 0.082
	DC-UNet [22]	softDice	0.8086 ± 0.0103	0.8018 ± 0.0163	0.9526 ± 0.0024	0.760 ± 0.012	0.351 ± 0.011	1.227 ± 0.074	1.061 ± 0.074	1.499 ± 0.087
	UNet	softDice+Ours	**0.8238 ± 0.0091**	0.8278 ± 0.0166	**0.9557 ± 0.0023**	**0.778 ± 0.011**	**0.336 ± 0.012**	<u>0.692 ± 0.047</u>	<u>0.932 ± 0.068</u>	<u>0.951 ± 0.062</u>
	UNet	clDice+Ours	0.8168 ± 0.0076	**0.8467 ± 0.0146**	0.9520 ± 0.0021	0.767 ± 0.009	0.357 ± 0.012	**0.619 ± 0.043**	**0.924 ± 0.065**	**0.857 ± 0.056**
ISBI12	UNet	softDice [26]	0.8043 ± 0.0092	0.9295 ± 0.0078	0.9146 ± 0.0060	0.653 ± 0.018	0.785 ± 0.040	0.569 ± 0.046	0.616 ± 0.047	0.738 ± 0.052
	UNet	clDice [37]	0.8103 ± 0.0099	0.9353 ± 0.0084	0.9163 ± 0.0064	0.660 ± 0.020	0.775 ± 0.042	0.422 ± 0.038	0.563 ± 0.045	0.576 ± 0.043
	UNet	Pointscatter [40]	0.8192 ± 0.0101	0.9406 ± 0.0077	0.9189 ± 0.0063	0.672 ± 0.020	0.758 ± 0.042	0.456 ± 0.041	0.568 ± 0.046	0.587 ± 0.047
	UNet	TopoLoss [14]	0.8104 ± 0.0090	0.9324 ± 0.0074	0.9167 ± 0.0058	0.661 ± 0.017	0.773 ± 0.039	0.516 ± 0.041	0.642 ± 0.052	0.669 ± 0.049
	DSCNet [33]	softDice	0.8152 ± 0.0087	0.9366 ± 0.0078	0.9191 ± 0.0054	0.669 ± 0.016	0.757 ± 0.037	0.450 ± 0.040	0.567 ± 0.045	0.581 ± 0.044
	TransUNet [4]	softDice	0.8056 ± 0.0080	0.9289 ± 0.0075	0.9148 ± 0.0055	0.654 ± 0.016	0.784 ± 0.037	0.636 ± 0.049	0.576 ± 0.047	0.757 ± 0.053
	DC-UNet [22]	softDice	0.8150 ± 0.0089	0.9366 ± 0.0084	0.9196 ± 0.0063	0.671 ± 0.019	0.753 ± 0.043	0.511 ± 0.043	0.586 ± 0.046	0.652 ± 0.047
	UNet	softDice+Ours	<u>0.8216 ± 0.0091</u>	<u>0.9449 ± 0.0069</u>	<u>0.9211 ± 0.0057</u>	<u>0.678 ± 0.018</u>	<u>0.745 ± 0.039</u>	<u>0.361 ± 0.034</u>	**0.520 ± 0.043**	<u>0.488 ± 0.041</u>
	UNet	clDice+Ours	**0.8223 ± 0.0086**	**0.9459 ± 0.0066**	**0.9213 ± 0.0056**	**0.679 ± 0.017**	**0.744 ± 0.038**	**0.353 ± 0.034**	<u>0.539 ± 0.043</u>	**0.482 ± 0.040**
STARE	UNet	softDice [26]	0.8170 ± 0.0402	0.8526 ± 0.0306	0.9749 ± 0.0044	0.781 ± 0.042	0.276 ± 0.033	0.786 ± 0.064	0.653 ± 0.072	0.960 ± 0.079
	UNet	clDice [37]	0.8212 ± 0.0386	0.8579 ± 0.0319	0.9752 ± 0.0041	0.785 ± 0.040	0.276 ± 0.032	0.571 ± 0.049	0.629 ± 0.069	0.743 ± 0.065
	UNet	Pointscatter [40]	0.8171 ± 0.0395	0.8533 ± 0.0331	0.9743 ± 0.0041	0.780 ± 0.041	0.285 ± 0.031	0.844 ± 0.070	0.781 ± 0.080	0.997 ± 0.086
	UNet	TopoLoss [14]	0.8175 ± 0.0449	0.8506 ± 0.0339	0.9750 ± 0.0045	0.781 ± 0.047	0.276 ± 0.033	0.659 ± 0.056	<u>0.615 ± 0.068</u>	0.806 ± 0.069
	DSCNet [33]	softDice	0.7988 ± 0.0420	0.8341 ± 0.0348	0.9723 ± 0.0052	0.759 ± 0.045	0.296 ± 0.037	0.823 ± 0.068	0.707 ± 0.072	0.988 ± 0.080
	TransUNet [4]	softDice	0.8046 ± 0.0474	0.8428 ± 0.0370	0.9737 ± 0.0047	0.767 ± 0.049	0.284 ± 0.034	0.728 ± 0.061	0.723 ± 0.076	0.884 ± 0.078
	DC-UNet [22]	softDice	0.7936 ± 0.0547	0.8300 ± 0.0426	0.9728 ± 0.0052	0.755 ± 0.057	0.288 ± 0.034	0.834 ± 0.071	0.721 ± 0.075	0.975 ± 0.082
	UNet	softDice+Ours	<u>0.8210 ± 0.0464</u>	<u>0.8578 ± 0.0372</u>	<u>0.9756 ± 0.0045</u>	<u>0.786 ± 0.049</u>	**0.271 ± 0.033**	<u>0.545 ± 0.046</u>	0.618 ± 0.067	<u>0.691 ± 0.059</u>
	UNet	clDice+Ours	**0.8283 ± 0.0371**	**0.8747 ± 0.0284**	**0.9757 ± 0.0040**	**0.792 ± 0.039**	<u>0.274 ± 0.032</u>	**0.450 ± 0.042**	**0.582 ± 0.065**	**0.598 ± 0.055**
MassRoad	UNet	softDice [26]	0.7808 ± 0.0146	0.8768 ± 0.0159	0.9780 ± 0.0036	0.750 ± 0.017	0.239 ± 0.033	0.479 ± 0.020	0.798 ± 0.076	0.777 ± 0.072
	UNet	clDice [37]	0.7788 ± 0.0143	0.8773 ± 0.0156	0.9775 ± 0.0037	0.747 ± 0.016	0.244 ± 0.033	0.512 ± 0.022	0.964 ± 0.090	0.962 ± 0.086
	UNet	Pointscatter [40]	0.7787 ± 0.0142	0.8750 ± 0.0156	0.9778 ± 0.0035	0.748 ± 0.016	0.242 ± 0.033	0.620 ± 0.027	0.800 ± 0.076	0.908 ± 0.074
	UNet	TopoLoss [14]	0.7797 ± 0.0150	0.8758 ± 0.0164	<u>0.9781 ± 0.0035</u>	0.749 ± 0.017	<u>0.238 ± 0.032</u>	0.439 ± 0.018	0.780 ± 0.076	<u>0.727 ± 0.071</u>
	TransUNet [4]	softDice	0.7620 ± 0.0169	0.8588 ± 0.0182	0.9766 ± 0.0038	0.730 ± 0.019	0.248 ± 0.034	0.734 ± 0.027	0.933 ± 0.079	1.017 ± 0.075
	LinkNet34 [3]	softDice	0.7752 ± 0.0151	0.8747 ± 0.0161	0.9775 ± 0.0036	0.744 ± 0.017	0.243 ± 0.033	0.489 ± 0.021	0.773 ± 0.076	0.771 ± 0.072
	D-Linknet34 [48]	softDice	0.7752 ± 0.0149	0.8743 ± 0.0161	0.9775 ± 0.0036	0.744 ± 0.017	0.244 ± 0.033	0.504 ± 0.022	<u>0.765 ± 0.075</u>	0.777 ± 0.072
	UNet	softDice+Ours	**0.7849 ± 0.0139**	<u>0.8816 ± 0.0151</u>	**0.9783 ± 0.0035**	**0.754 ± 0.016**	**0.237 ± 0.033**	**0.386 ± 0.016**	**0.754 ± 0.076**	**0.672 ± 0.070**
	UNet	clDice+Ours	<u>0.7851 ± 0.0137</u>	**0.8844 ± 0.0148**	0.9779 ± 0.0036	<u>0.754 ± 0.016</u>	0.241 ± 0.033	<u>0.393 ± 0.018</u>	0.879 ± 0.085	0.784 ± 0.082

Experimental Results

Visulization

- *GraphMorph reduces false negatives, false positives and topological errors on both tasks.*