PMRNet: Physics-informed Multi-scale Refinement Network for Medical Image Segmentation

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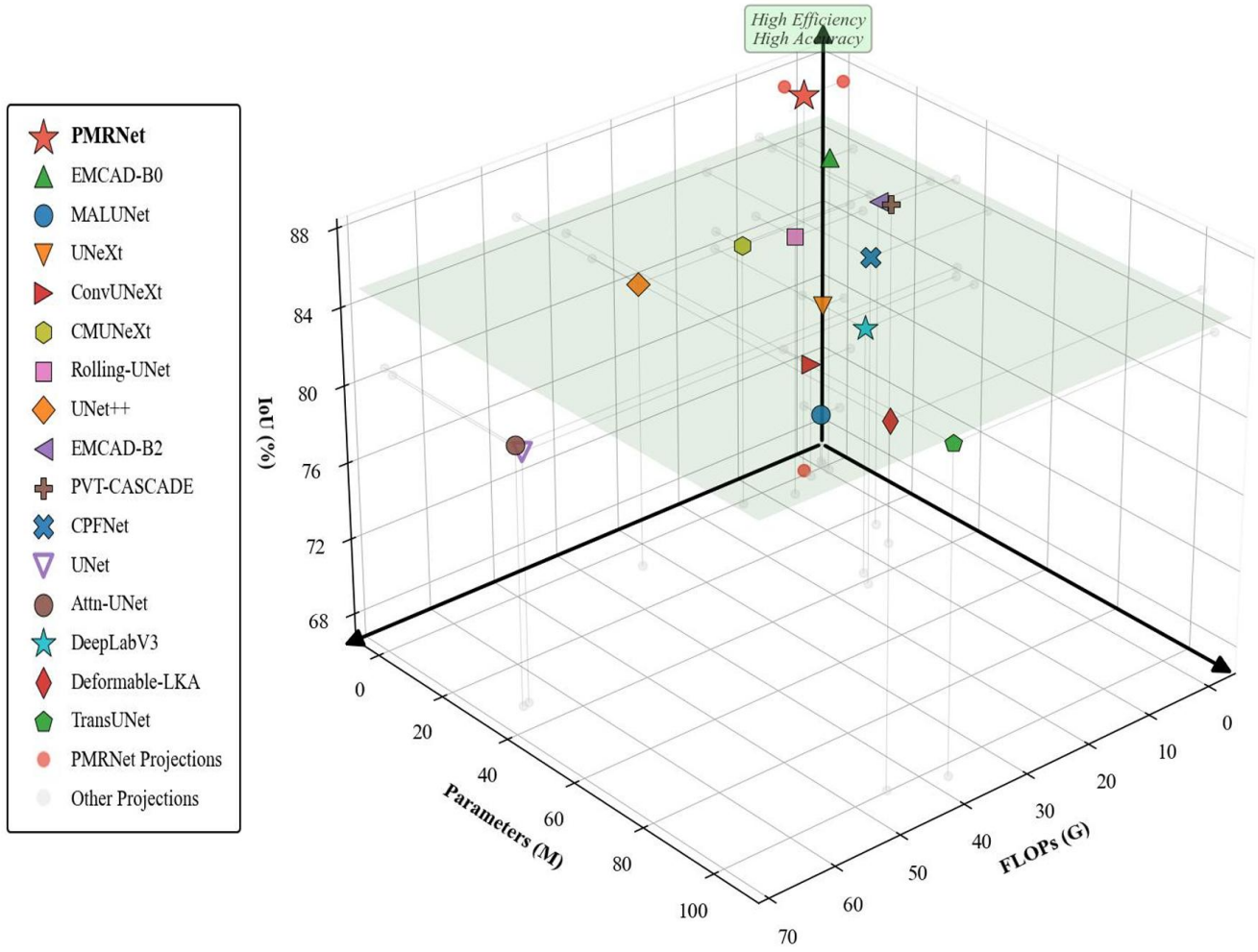
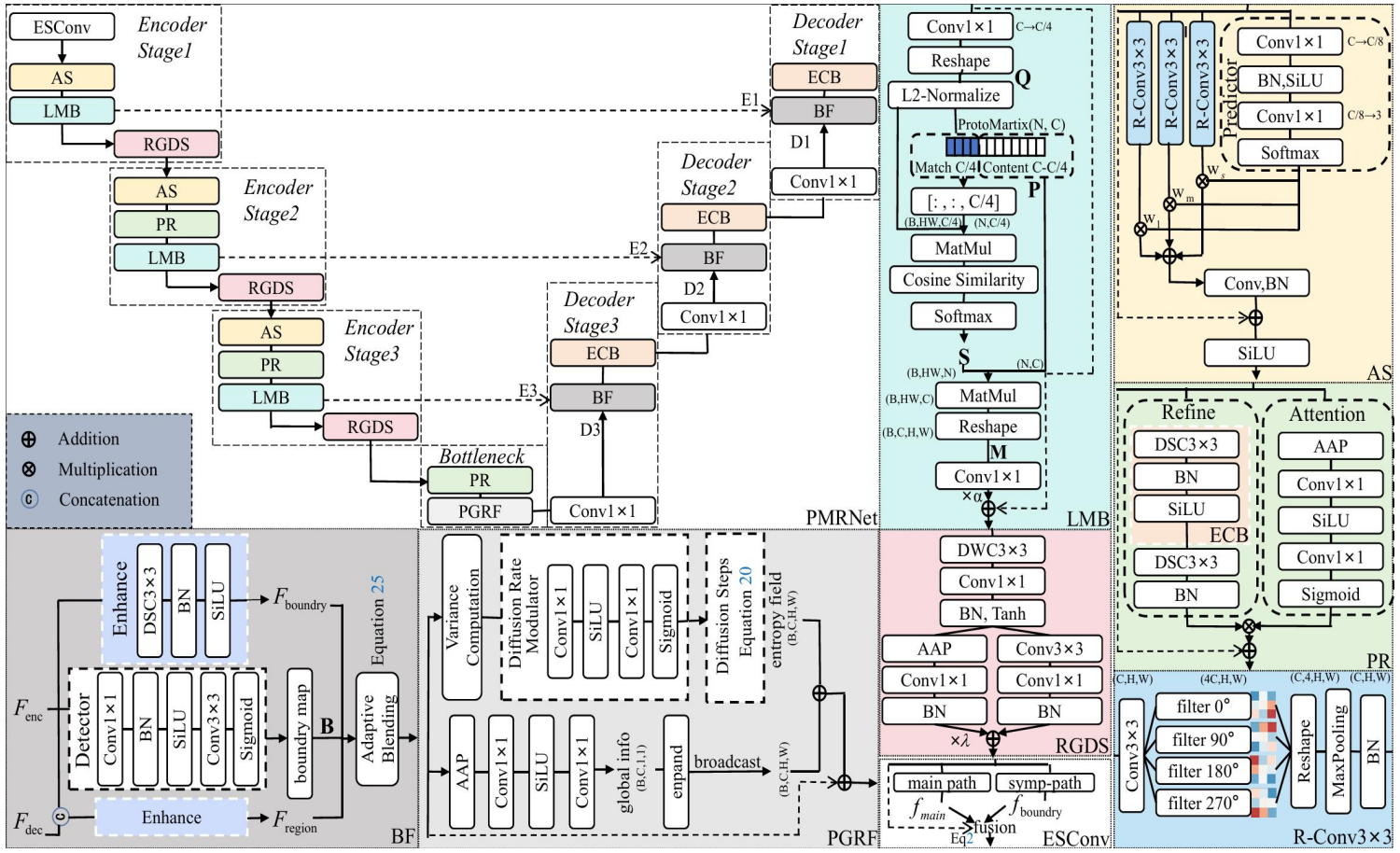
Background & Motivation

- Clinical Need: Point-of-care medical image segmentation requires both high accuracy and computational efficiency.
- The Dilemma:
- CNNs lack global context.
- Transformers are too computationally expensive.
- Existing lightweight models sacrifice accuracy on complex structures.
- Our Goal: Achieve SOTA accuracy with <1M parameters.



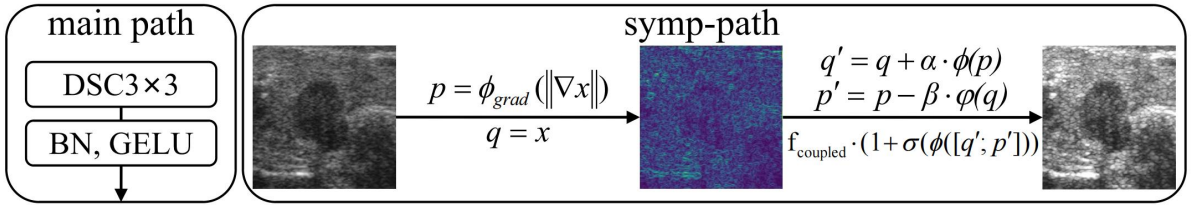
Proposed Solution: PMRNet Overview

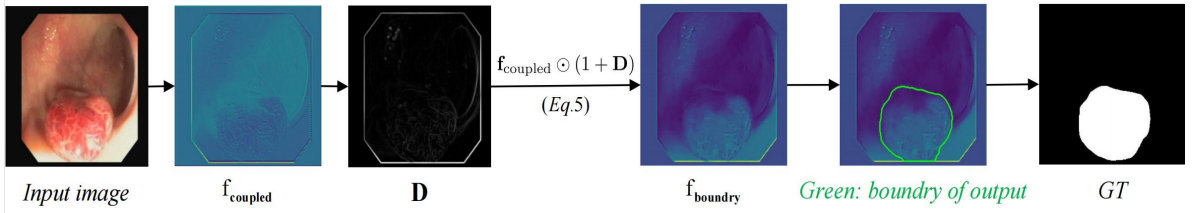
- Instead of scaling up parameters, we scale up inductive bias using physics principles.
- Three Key Innovations:
- 1. Physics-informed Encoder
- 2. Efficient Global Context (Entropy-driven Diffusion)
- 3. Boundary-aware Decoder



Innovation: Enhanced Symplectic Convolution

- Problem: Standard convolutions treat boundaries and interiors identically.
- Solution: Inspired by Hamiltonian mechanics.
- Feature maps = Position (q)
- Spatial gradients = Momentum (p)
- Mechanism: Couples spatial features with derivatives in a joint update step.
- Result: Preserves boundary signals without heavy attention mechanisms.

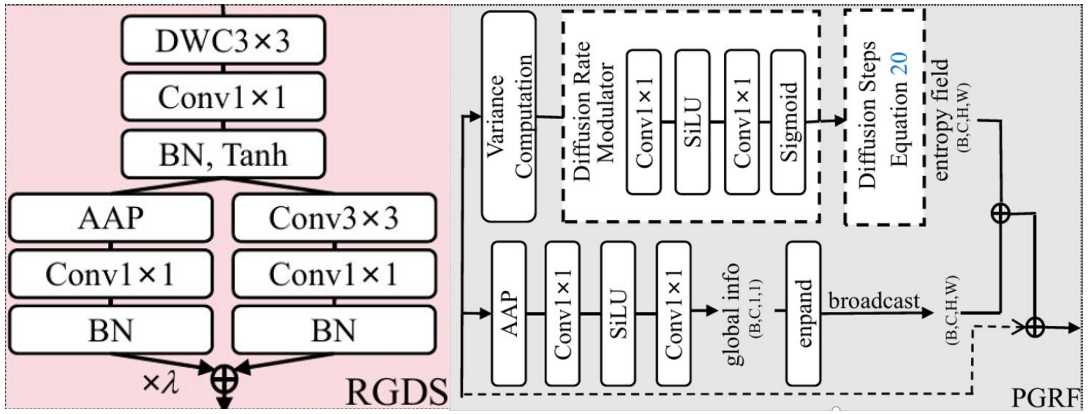


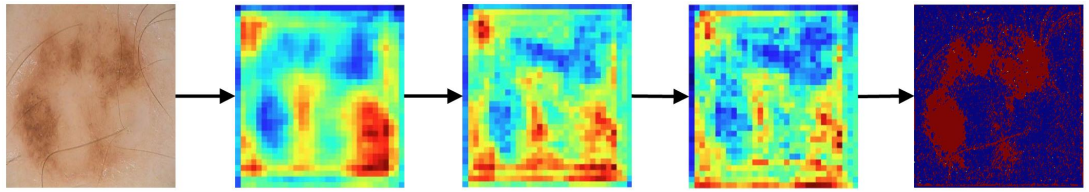


$$\begin{bmatrix} \mathbf{q}' \\ \mathbf{p}' \end{bmatrix} = \begin{bmatrix} \mathbf{q} \\ \mathbf{p} \end{bmatrix} + \epsilon \cdot \tanh\left(\mathrm{BN}(\mathrm{Conv}_{1\times1}([\mathbf{p}; -\mathbf{q}]))\right)$$

Innovation: PGRF & RGDS

- Pseudo-Global Receptive Field (PGRF):
- Replaces $O(N^2)$ self-attention with $O(N)$ heat equation diffusion.
- Information flows adaptively from high-certainty to uncertain areas.
- Renormalization Group Downsampling (RGDS):
- Folds fine-scale structures into channels before halving resolution.
- Prevents loss of small object information.



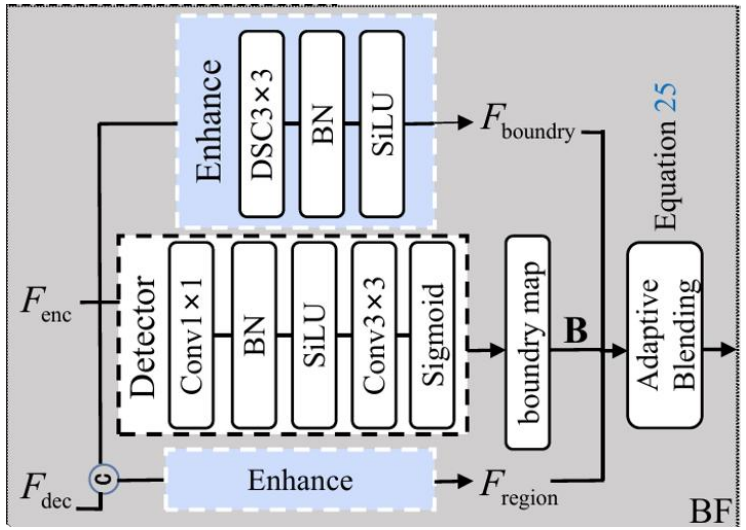


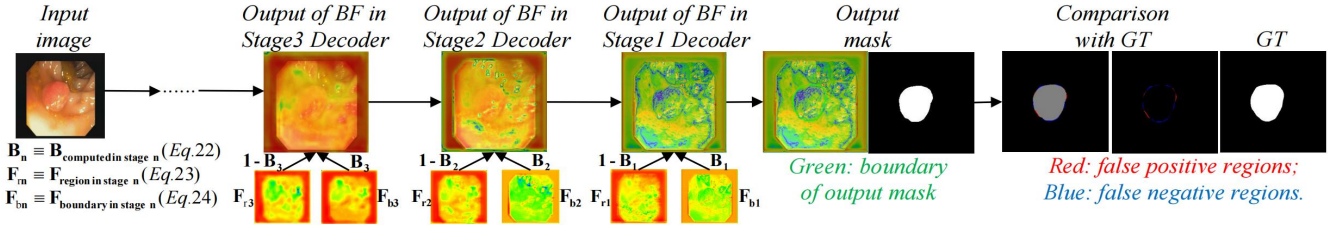
$$\mathbf{x}_{\text{enhanced}} = \mathbf{x} + \alpha \cdot \big(\boldsymbol{\beta}(\mathbf{x}) + \boldsymbol{\gamma}(\mathbf{x}) \odot \mathbf{x}\big)$$

$$\mathbf{u}^{(k+1)} = \mathbf{u}^{(k)} + D(\mathbf{x}) \odot \mathcal{L}(\mathbf{u}^{(k)}) \cdot (0.5)^k + 0.1 \cdot \mathbf{g}$$

Innovation: Boundary-aware Decoder

- Concept: Not all skip connections are equally useful.
- Boundary-aware Fusion (BF) Module:
- Gates skip connections based on learned local boundary strength.
- Region path & Boundary path processed separately.
- Result: Keeps the decoder spatially precise with minimal parameters.





Results: Computational Efficiency

- Ultra-lightweight footprint:
- Parameters: 0.87M (100x smaller than TransUNet)
- Computations: 3.43 GFLOPs
- Real-time Inference:
- Achieves 152.03 FPS on a single RTX 4090.
- Outperforms heavier models while maintaining strict computational budgets.

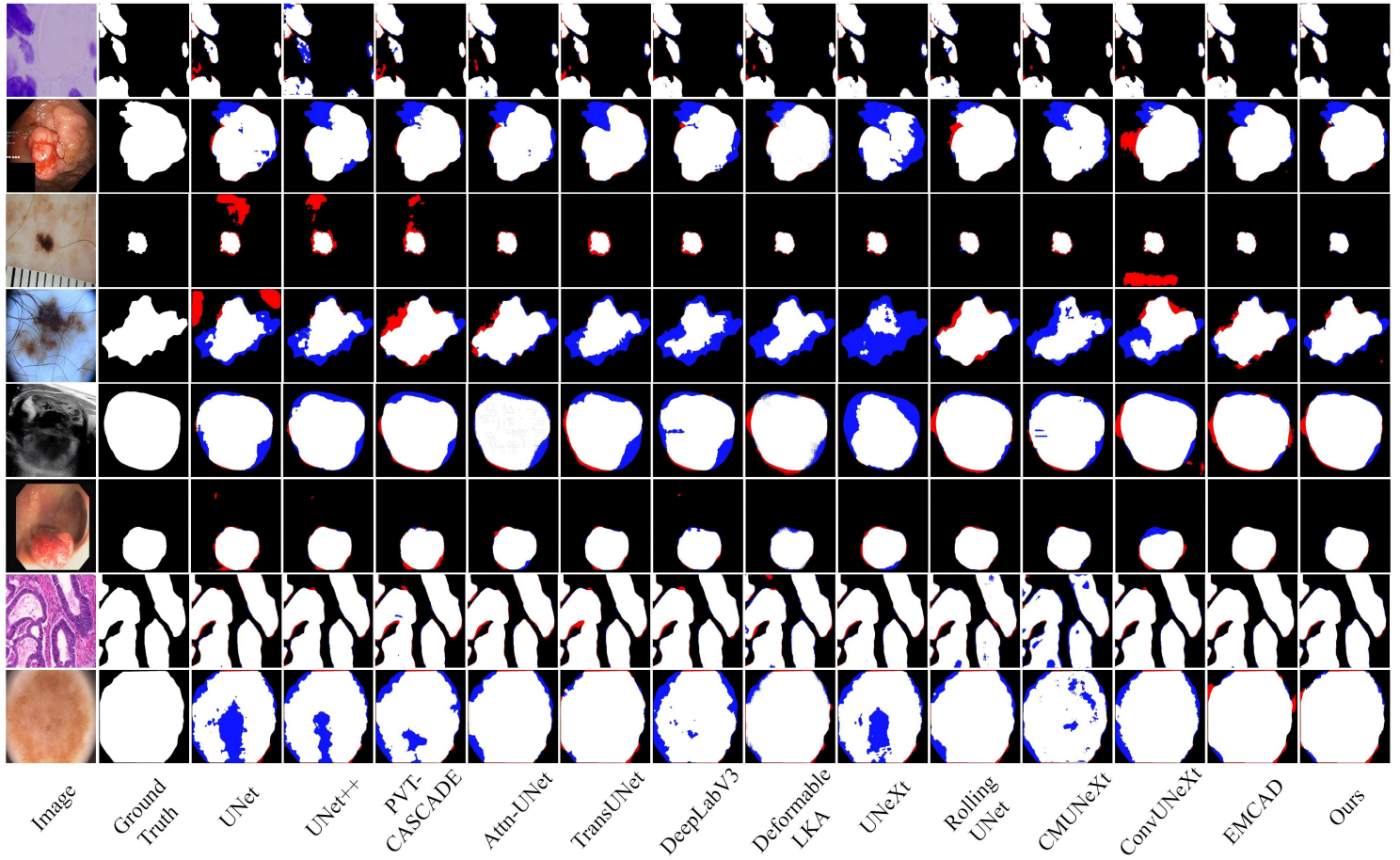
Method	Params(M)	FLOPs(G)	TG3K								Clinic							
			IoU↑	Dice↑	HD95↓	ASD↓	SE↑	PC↑	SP↑	ACC↑	IoU↑	Dice↑	HD95↓	ASD↓	SE↑	PC↑	SP↑	ACC↑
UNet [51]	34.53	65.53	71.20	80.90	23.19	7.81	83.81	83.63	98.83	97.43	80.00	87.26	21.61	6.63	87.33	91.16	99.11	98.21
UNet++ [74]	9.16	34.65	72.47	81.55	20.14	7.58	83.94	85.07	98.94	97.57	82.05	88.84	23.85	5.86	90.74	89.41	99.01	98.33
TransUNet [9]	105.32	38.52	73.22	82.24	20.97	7.07	84.69	84.94	98.72	97.46	83.87	90.35	16.72	4.27	91.14	91.48	99.25	98.50
UNeXt [61]	1.47	0.57	70.64	80.06	19.19	7.19	84.44	82.16	98.56	97.45	75.75	84.40	29.48	6.84	85.99	87.09	98.94	97.92
Rolling-UNet [40]	7.10	8.28	72.09	81.20	18.10	6.71	83.84	83.69	98.81	97.49	80.98	87.82	19.55	5.63	88.75	89.63	99.15	98.43
PVT-CASCADE [49]	34.12	7.62	73.77	82.75	17.34	5.93	86.32	83.97	98.67	97.44	85.09	91.07	14.94	4.38	91.10	92.03	99.34	98.77
Attn-UNet [45]	34.88	66.64	73.29	82.11	19.01	7.40	83.66	86.20	**99.01**	97.56	80.52	87.46	23.03	7.17	88.43	90.21	99.06	98.18
Deformable-LKA [3]	101.64	46.12	73.04	82.25	17.94	5.99	85.30	83.30	98.64	97.60	85.65	91.60	13.90	3.57	92.19	92.15	99.18	98.70
DeepLabV3 [10]	39.76	14.92	66.21	76.92	19.93	7.76	79.09	81.30	98.74	97.12	80.09	87.50	19.48	6.47	89.17	87.63	99.00	98.30
CPFNet [19]	43.27	16.15	73.89	83.02	16.10	5.67	85.43	84.90	98.76	97.60	84.26	90.70	16.24	4.02	91.72	91.26	99.16	98.58
EMCAD-B2 [50]	26.76	5.60	74.88	83.56	15.49	5.75	**86.35**	84.59	98.75	97.83	84.30	90.47	14.47	4.31	90.61	92.35	99.35	98.71
CMUNeXt [60]	3.15	14.84	69.48	79.13	19.91	8.05	82.28	83.20	98.61	97.17	80.97	87.92	21.16	6.72	89.07	89.95	98.90	98.19
EMCAD-B0 [50]	3.92	0.84	70.83	80.43	20.01	7.08	82.87	84.34	98.75	97.18	83.98	90.52	16.35	4.45	90.39	91.80	99.36	98.68
MALUNet [52]	0.18	0.17	66.67	77.00	20.63	7.66	81.18	79.11	98.24	96.78	69.59	79.69	29.20	8.94	82.52	81.18	98.52	97.18
ConvUNeXt [23]	3.54	3.69	64.76	74.93	22.72	8.76	78.15	79.62	98.58	96.82	73.20	81.50	26.12	9.10	82.14	85.07	98.82	97.78
PMRNet **(Ours)**	0.87	3.43	**76.19**	**84.73**	**14.96**	**5.51**	86.03	**87.61**	98.97	**97.85**	**87.25**	**92.56**	**13.13**	**3.54**	**93.40**	**92.50**	**99.38**	**98.98**

Method	Breast			BUSI			DDTI			DSB18			GlaS		
	IoU↑	Dice↑	HD95↓	IoU↑	Dice↑	HD95↓	IoU↑	Dice↑	HD95↓	IoU↑	Dice↑	HD95↓	IoU↑	Dice↑	HD95↓
UNet	60.53	71.55	40.35	64.74	74.24	36.76	80.18	88.64	20.48	85.83	92.07	3.68	82.73	90.13	25.91
UNet++	61.70	72.48	38.11	67.89	76.91	35.52	80.30	88.75	19.21	85.15	91.59	3.98	84.79	91.46	21.18
TransUNet	62.64	72.67	29.52	69.06	78.22	28.67	80.80	89.11	19.63	86.25	92.26	3.40	83.98	90.83	24.37
Rolling-UNet	63.64	73.65	31.82	71.55	80.78	26.64	79.06	87.94	20.34	84.84	91.42	4.04	84.59	91.29	23.25
EMCAD-B2	64.72	74.82	30.38	72.03	80.61	22.69	82.27	90.02	16.98	85.33	91.71	3.83	85.39	91.79	21.44
Deformable-LKA	38.27	51.09	67.32	71.83	80.63	23.33	**82.81**	90.30	16.07	85.86	92.00	3.94	83.84	90.94	25.51
DeepLabV3	56.98	68.69	32.48	71.56	80.60	23.34	82.80	**90.32**	**15.90**	66.57	78.66	8.56	79.84	88.37	21.84
PMRNet **(Ours)**	**64.73**	**75.51**	**26.03**	**73.56**	**81.88**	**22.58**	82.52	90.17	16.70	**86.87**	**92.74**	**3.36**	**85.70**	**92.03**	**19.58**

Method	ISIC2017			ISIC2018			Kvasir-SEG			PH^2			TN3K		
	IoU↑	Dice↑	HD95↓	IoU↑	Dice↑	HD95↓	IoU↑	Dice↑	HD95↓	IoU↑	Dice↑	HD95↓	IoU↑	Dice↑	HD95↓
UNet	81.68	88.57	16.70	80.73	88.03	20.23	71.68	80.37	45.10	88.07	93.47	18.52	68.68	78.63	30.37
UNet++	81.05	87.98	16.81	81.65	88.81	18.41	76.41	84.02	37.76	89.70	94.46	14.82	70.13	79.71	29.99
TransUNet	82.06	88.85	15.70	80.68	87.90	19.01	78.36	85.64	30.98	89.69	94.39	18.86	70.63	80.20	27.55
Rolling-UNet	82.14	88.82	14.12	81.67	88.76	17.70	76.11	83.88	32.55	89.08	94.08	17.86	70.13	79.77	27.81
EMCAD-B2	81.49	88.29	15.27	81.78	88.74	16.58	78.62	85.85	29.71	89.92	94.58	14.68	72.72	82.02	24.34
Deformable-LKA	78.76	86.02	18.98	82.47	89.26	**15.78**	77.31	84.37	31.32	90.45	94.90	14.60	67.04	77.69	32.16
DeepLabV3	81.28	88.44	15.56	81.14	88.43	18.04	73.62	81.92	33.04	88.86	93.99	15.05	67.01	77.62	27.59
PMRNet **(Ours)**	**83.14**	**89.69**	**13.73**	**82.51**	**89.32**	15.79	**81.21**	**87.67**	**26.68**	**91.07**	**95.24**	**14.13**	**73.50**	**82.50**	**23.03**

Results: Accuracy & Visualization

- Evaluated on 12 diverse medical imaging datasets.
- Highlights (Clinic Dataset):
- 87.25% IoU and 92.56% Dice.
- Qualitative Results:
- Superior boundary delineation.
- Robust handling of small objects and ambiguous edges.
- Significant reduction in false positive/negative regions.



Conclusion

- Summary: PMRNet demonstrates that physical inductive biases can effectively replace brute-force parameter scaling.
- Impact: Enables high-accuracy medical image segmentation on resource-constrained devices.
- Open Source: Code is available on GitHub.
- Thank You!