Addressing Label Scarcity and Domain Shift in Medical Image Segmentation

1 Suruchi Kumari[1], Pravendra Singh[1]

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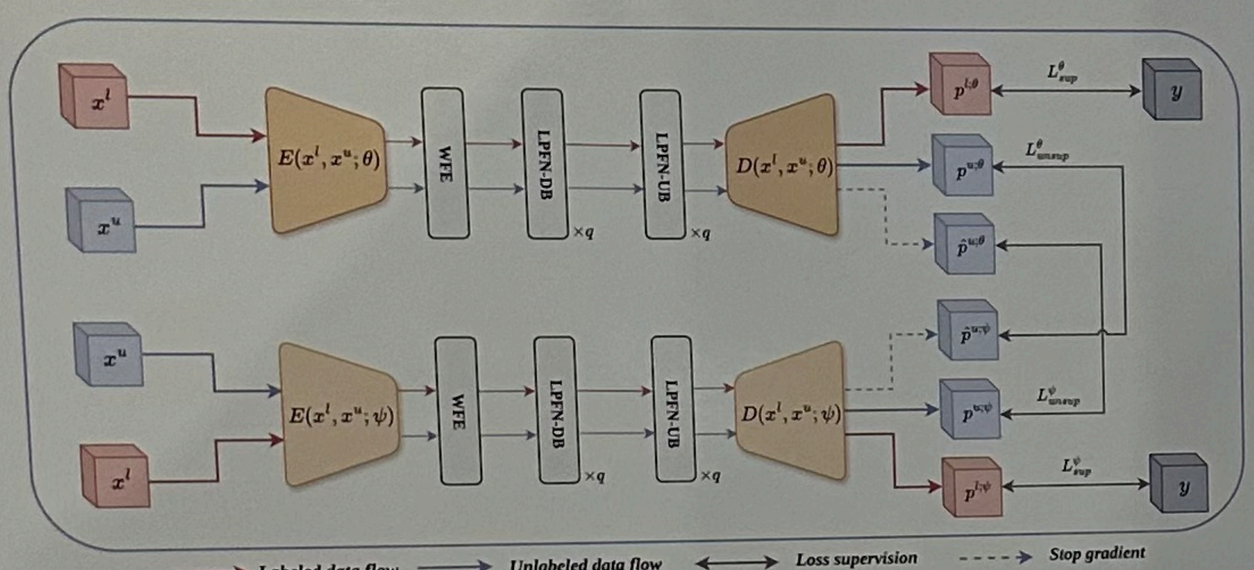
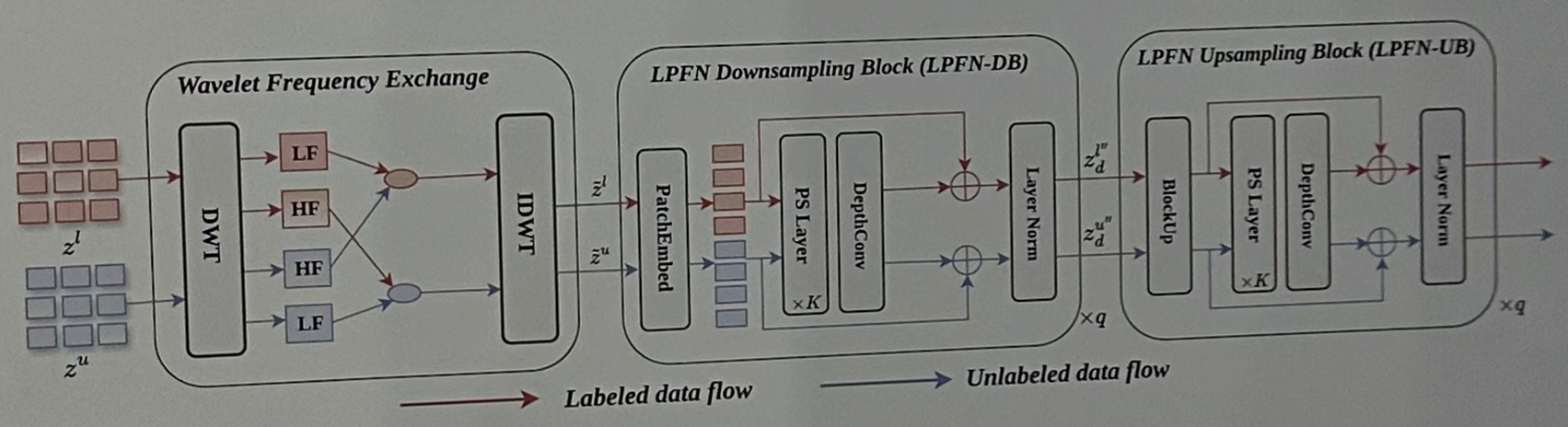
Objective

- Limited annotated datasets are a challenge for the MIA. Existing methods use SSL techniques to use abundant unlabeled data alongside the limited labeled samples to reduce annotation costs.
- Domain shift is an another challenge in medical imaging. Models trained on one modality, or population often fail on others due to variations in acquisition. Domain adaptation methods address this by learning domain-invariant features.
- We introduce a novel unified framework that addresses the challenges of limited annotations and domain shifts simultaneously, leveraging Wavelet-Frequency Exchange (WFE) and a Learnable Parametric Feature Network.

Method



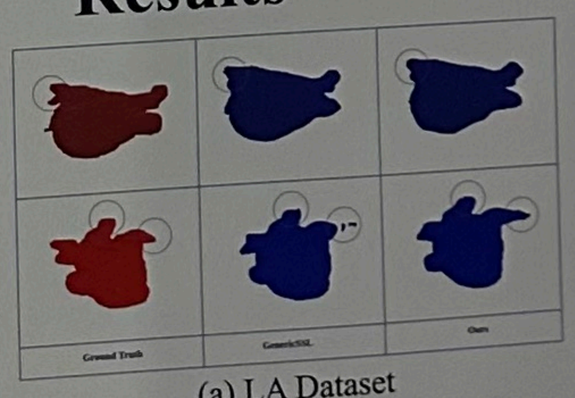
- WFE provides two main benefits: it mitigates overfitting by preventing the model from memorizing specific details from limited labeled data in SSL, and it reduces the domain gap in UDA.
- The LPFN improves feature representation by using downsampling and upsampling blocks, capturing multi-scale feature relationships with Parametric Spline layers to better model and reconstruct spatial details.



Results

Method	Scans used		Metrics				Scans used		Metrics			
	Labeled	Unlabeled	Dice↑	Jaccard↑	95HD↓	ASD↓	Labeled	Unlabeled	Dice↑	Jaccard↑	95HD↓	ASD↓
VNet	4(5%)	0	52.55	39.60	47.05	9.87	8(10%)	0	82.74	71.72	13.35	3.26
UA-MT [28]			82.26	70.98	13.71	3.82			87.79	78.39	8.68	2.12
DTC [17]			81.25	69.33	14.90	3.99			87.51	78.17	8.23	2.36
SASSNet [14]			81.60	69.63	16.16	3.58			87.54	78.05	9.84	2.59
MC-Net [25]			83.59	72.36	14.07	2.70			87.62	78.25	10.03	1.82
SS-Net [24]			86.33	76.15	9.97	2.31			88.55	79.62	7.49	1.90
BCP [1]	4(5%)	76(95%)	88.02	78.72	7.90	2.15	8(10%)	72(90%)	89.62	81.31	6.81	1.76
MLRPL [19]			-	-	-	-			89.86	81.68	6.91	1.85
VCLIPSeg [13]			88.51	79.49	10.48	2.28			90.59	82.87	6.22	1.61
Genericssl [23]			89.93	81.82	5.25	1.86			90.31	82.40	5.55	1.64
Ours			90.62	82.63	5.16	1.64			91.53	84.40	4.82	1.63

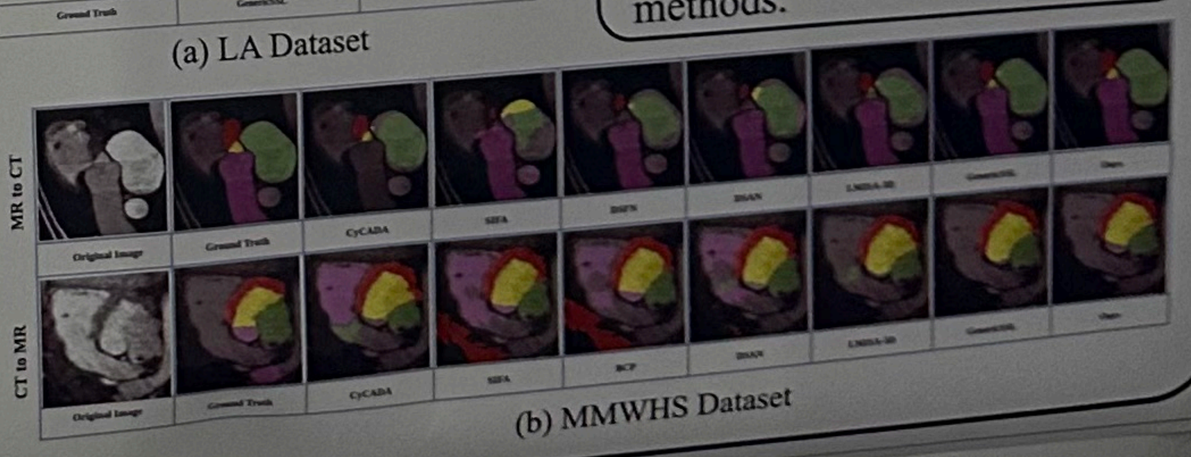
(a) LA Dataset



(a) LA Dataset

Method	MR To CT						CT To MR					
	Dice ↑					ASD ↓	Dice ↑					ASD ↓
	AA	LAC	LVC	MYO	Avg	Avg	AA	LAC	LVC	MYO	Avg	Avg
PnP-AdaNet [6]	74.0	68.9	61.9	50.8	63.9	12.8	43.7	68.9	61.9	50.8	63.9	8.9
AdaOutput [22]	65.2	76.6	54.4	43.6	59.9	9.6	60.8	39.8	71.5	35.5	51.9	5.7
CycleGAN [29]	73.8	75.7	52.3	28.7	57.6	10.8	64.3	30.7	65.0	43.0	50.7	6.6
CyCADA [8]	72.9	77.0	62.4	45.3	64.4	9.4	60.5	44.0	77.6	47.9	57.5	7.9
SIFA [3]	81.3	79.5	73.8	61.6	74.1	7.0	65.3	62.3	78.9	47.3	63.4	5.7
DSAN [7]	79.9	84.8	82.8	66.5	78.5	5.9	71.3	66.2	76.2	52.1	66.5	5.4
LMISA-3D [9]	84.5	82.8	88.6	70.1	81.5	2.3	60.7	72.4	86.2	64.1	70.8	3.6
Genericssl [23]	93.2	89.5	91.7	86.2	90.1	1.7	62.8	87.4	61.3	74.1	71.4	7.9
Ours	92.3	93.5	91.7	92.6	92.5	1.4	69.8	77.3	73.9	76.6	74.4	6.1

(b) MMWHS Dataset



(b) MMWHS Dataset

Conclusion

- Our method uses a single framework to address both limited annotated data and domain shift problems.
- It performs better than existing methods.