Magnification Prior: A Self-supervised Method For Learning Representations On Breast Cancer Histopathological Images

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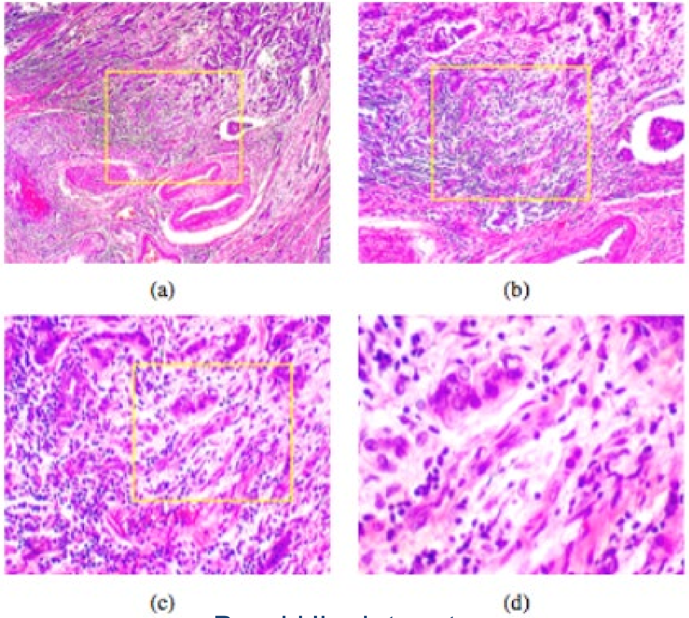
Motivation



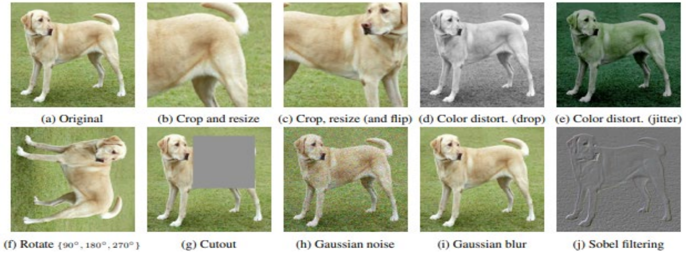
BreakHis dataset
(a) 40x, (b) 100x, (c) 200x (d) 400x

- **Human-labeled & unlabeled data in the medical image domain is in scarcity**
- **Human supervised labels are not always correct**
- **State-of-the-art self-supervised learning (SSL) methods on natural visuals are not efficiently adaptable to specialized domain**

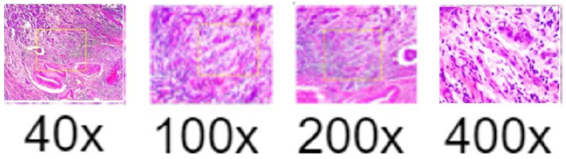
Prakash Chandra Chhipa

Hypothesis

- **Adapting contrastive self-supervised representation learning on histopathological images is possible by:**
  - ✓ Reducing human driven augmentations, and
  - ✓ Focusing on supervision signal from data i.e., magnification

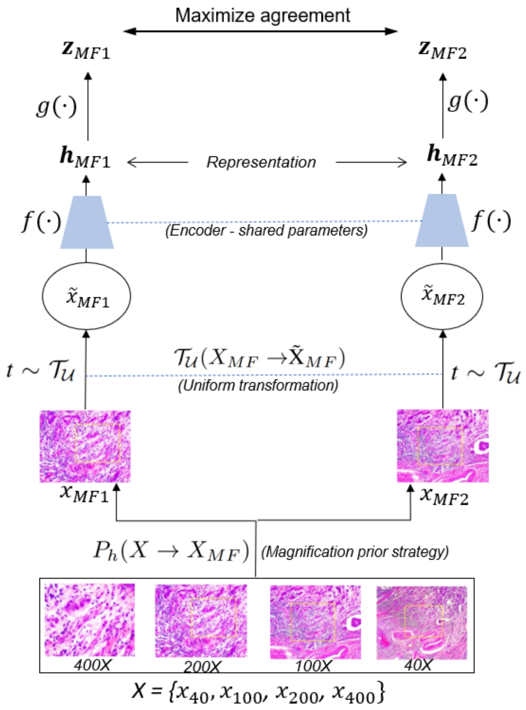


Source – Chen et al. 2020



Supervision signal – different magnifications

Magnification Prior Contrastive Similarity Method



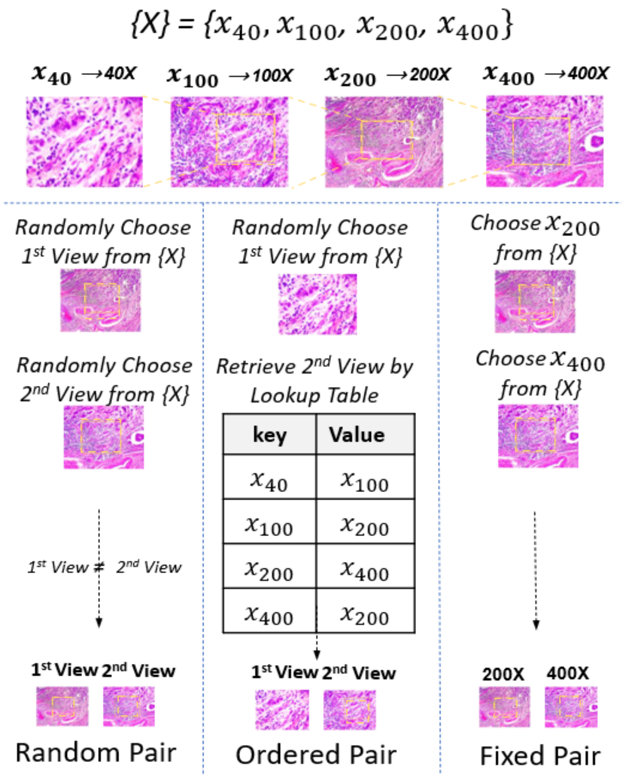
- **Input view pair is sampled out of 4 magnifications**
  - ✓ 3 different pair sampling strategy
  - ✓ No augmentation for input view
  - ✓ BreakHis breast cancer dataset

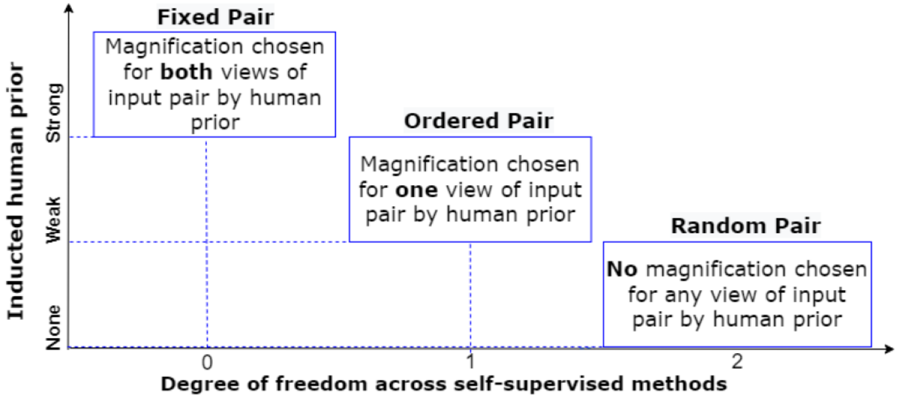
- **Similarity maximization through temperature scaled cross entry**
  (SimCLR, 2020)

$$L_{\mathrm{MF1,MF2}} = -\log \frac{\exp(sim(z_{\mathrm{MF1}}, z_{\mathrm{MF2}})/\tau)}{\sum_{k=1}^{2N} 1_{[k \neq MF1]} exp(sim(z_{\mathrm{MF1}}, z_k)/\tau)}$$

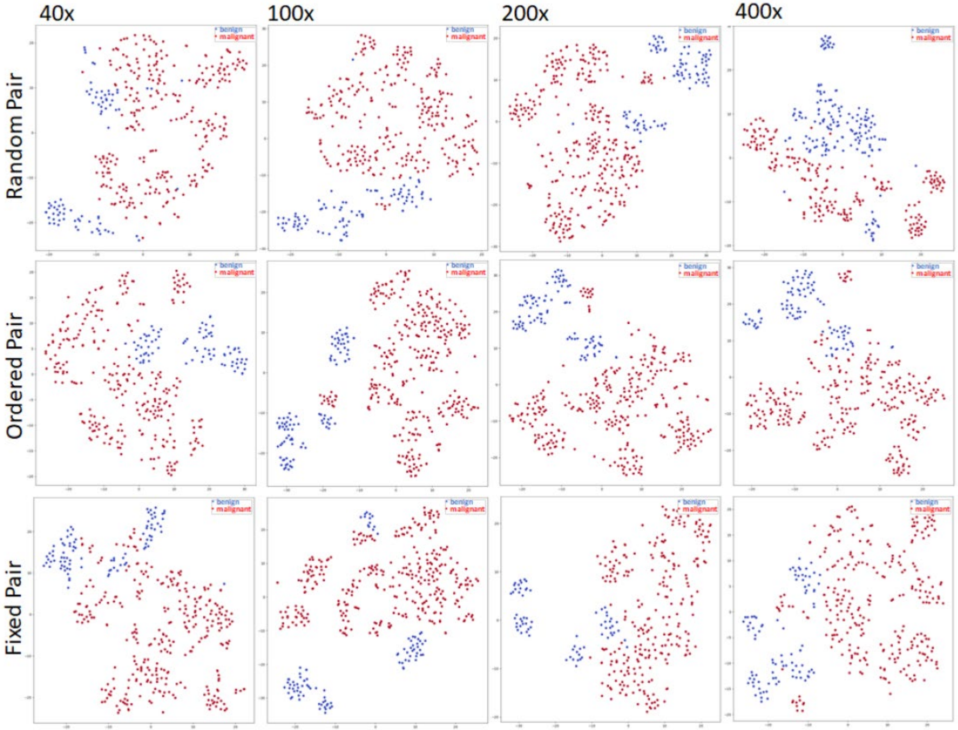
- **Encoders - Resnet50, Efficient-b2**

Pair Sampling Strategy





Self-supervised Representations



Blue(benign); red(malignant)

t-SNE visualization of the features from self-supervised MPCS pretrained encoder

- No fine-tuning
- No linear evaluation yet

Results – downstream task malignancy classification

1. BreakHis dataset

- ✓ Achieves state-of-the-art results with only 20% labels
- ✓ Outperforms over existing methods in fully supervised settings

Method	Patient Level Accuracy (RR)				Mean	Image Level Accuracy				Mean
	40X	100X	200X	400X		40X	100X	200X	400X	
Original-GLCM[51]	74.7±1.0	78.6±2.6	83.4±3.3	81.7±3.3	79.60±2.55	-	-	-	-	-
PFTAS[25]	83.80±2.0	82.10±4.9	85.10±3.1	82.30±3.8	83.33±3.45	-	-	-	-	-
MIL-NP[53]	92.1±5.9	89.1±5.2	87.2±4.3	82.7±3.0	87.77±4.6	87.8±5.6	85.6±4.3	80.8±2.8	82.9±4.1	84.28±4.20
SW[51]	88.6±5.6	84.5±2.4	85.3±3.8	81.7±4.9	85.02±4.17	89.6±6.58	85.0±4.8	84.0±3.2	80.8±3.1	84.85±4.42
MI[6]	83.08±2.08	83.17±3.51	84.63±2.72	82.10±4.42	83.25±3.18	-	-	-	-	-
Deep[50]	84.0±6.9	83.9±5.9	86.3±3.5	82.1±2.4	84.07±4.67	84.6±2.9	84.8±4.2	84.2±1.7	81.6±3.7	83.80±3.13
MILCNN[53]	86.9±5.4	85.7±4.8	85.9±3.9	83.4±5.3	85.47±4.85	86.1 ± 4.28	83.8±3.0	80.2±2.6	80.6±4.6	82.68±3.62
GLPB[3]	84.5±4.2	83.5±2.0	89.6±5.0	**88.2±4.0**	86.45±3.8	82.1±6.4	81.4±4.8	88.4±5.0	87.2±4.5	84.78±5.18
RPDB[39]*	92.02±0.9	90.21±2.40	81.94±1.70	80.09±0.70	88.06±1.4	**94.26±3.2**	92.71±0.4	83.90±2.8	82.74±1.5	88.40±1.98
SMSE[54]	87.51±4.07	89.12±2.86	90.83±3.31	87.10±3.80	88.64±3.51	-	-	-	-	-
ImageNet (Eff-net b2)	91.91±4.25	91.93±4.20	91.46±5.17	88.10±3.88	90.85±4.36	92.12±4.18	92.66±4.20	91.83±4.55	88.35±5.21	91.24±4.54
MPCS-FP (Eff-net b2)	92.23±3.50	92.72±3.68	91.94±3.80	88.40±3.26	91.33±3.56	92.23±3.80	**93.57±3.23**	92.23±2.98	88.40±3.90	91.61±3.48
MPCS-OP (Eff-net b2)	**92.45±3.25**	**93.47±2.98**	**92.44±3.30**	89.00±3.05	**91.84±3.15**	92.67±3.36	**93.63±3.38**	**92.72±2.80**	**88.74±3.90**	**91.94±3.36**
MPCS-RP (Eff-net b2)	**93.26±3.48**	**93.57± 3.36**	**92.23±3.21**	**89.57±3.79**	**92.15±3.46**	**93.45±3.55**	93.38±2.80	**92.28±3.49**	**89.81±3.15**	**92.23±3.24**
ImageNet (RN-50)	91.46±4.30	91.24±5.1	90.72±4.68	87.90±4.12	90.33±4.55	91.83±5.12	92.23±4.15	91.61±4.00	87.88±4.80	90.89±4.52
MPCS-FP (RN-50)	91.83±3.88	92.67±2.72	91.61±3.40	89.00±3.15	91.28±3.29	92.24±3.48	92.66±3.88	91.91±3.68	88.40±3.66	91.30±3.68
MPCS-OP (RN-50)	**93.00±3.66**	93.26±3.08	**92.28±2.88**	**88.74±3.60**	**91.82±3.31**	**93.26±3.40**	**93.45±2.89**	**92.45±3.77**	**89.57±2.96**	**92.18±3.26**
MPCS-RP (RN-50)	92.72±3.50	**93.57± 2.88**	92.23±3.90	88.40±3.05	91.73±3.33	92.72±3.38	92.72±4.02	91.91±3.21	88.56±3.89	91.48±3.66

Results – downstream task malignancy classification

2. BACH dataset

- ✓ largely outperforms over existing methods in multi class

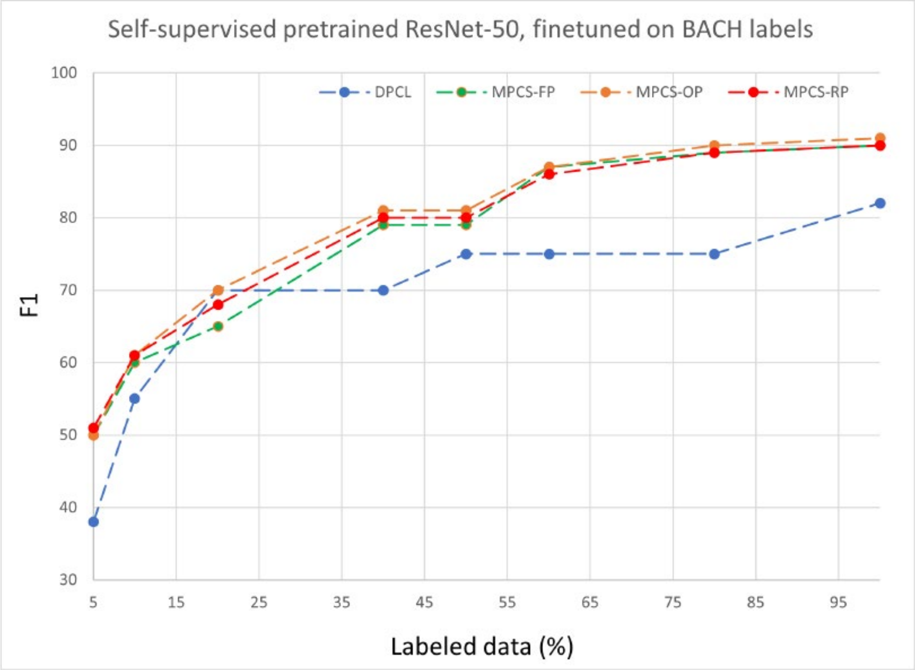
Method	Image-wise accuracy		Patch-wise accuracy	
	validation	test	validation	test
PT [44]	-	90.00	-	77.40
HN [60] (RN-50)	-	81.60	-	-
HN [60]	-	91.30	-	82.10
DPCL [14]	-	87.00	-	-
ImageNet [57] re-implement	92.40±2.04	90.50±2.10	80.56±3.06	80.00±2.64
MPCS-FP	92.50±1.90	90.55±2.05	84.25±1.88	82.79±2.05
MPCS-OP	**93.31±1.85**	**91.85±1.77**	**83.90±1.89**	**83.13±2.00**
MPCS-RP	93.00±1.88	91.00±2.32	83.78±2.09	82.90±2.10

3. Breast Cell Cancer dataset

- ✓ Outperforms existing methods in linear evaluation and finetuning

Method	Fine-tuned		
	accuracy	precision	recall
ST [43]	86.00±3.00	-	**1.0**
MATN [34]	91.70	-	-
ATN [30]	75.50±1.60	0.73±0.01	0.73±0.04
MPCS-FP	98.14±2.05	0.99±0.01	0.98±0.01
MPCS-OP	**98.18±1.80**	**0.99±0.01**	0.98±0.01
MPCS-RP	98.10±2.00	0.985±0.01	0.98±0.01

Label Efficiency on BACH dataset

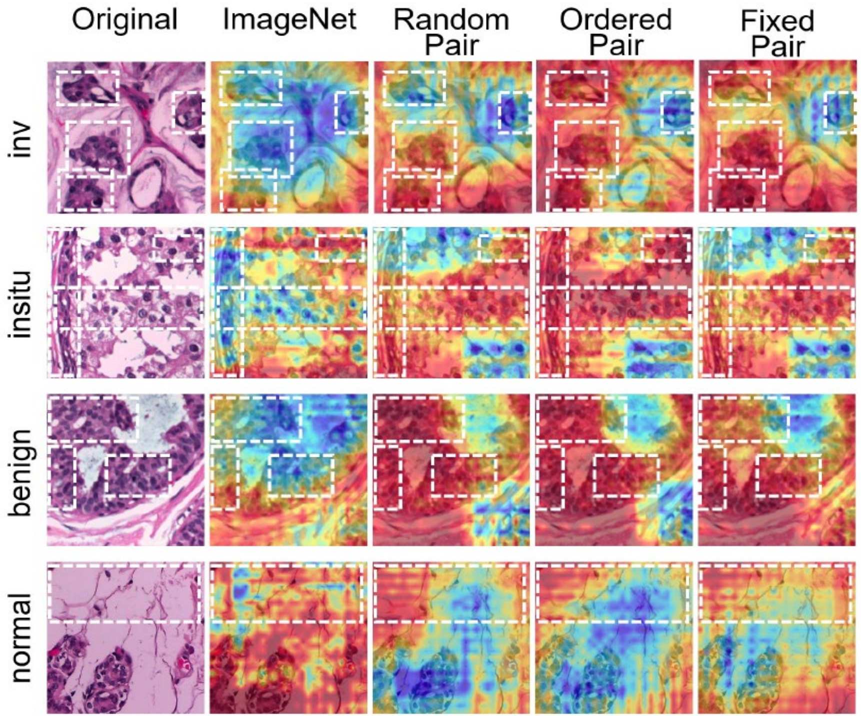


DPCL - *Ciga, O., Xu, T., & Martel, A. L. (2022). Self supervised contrastive learning for digital histopathology. Machine Learning with Applications, 7, 100198.*

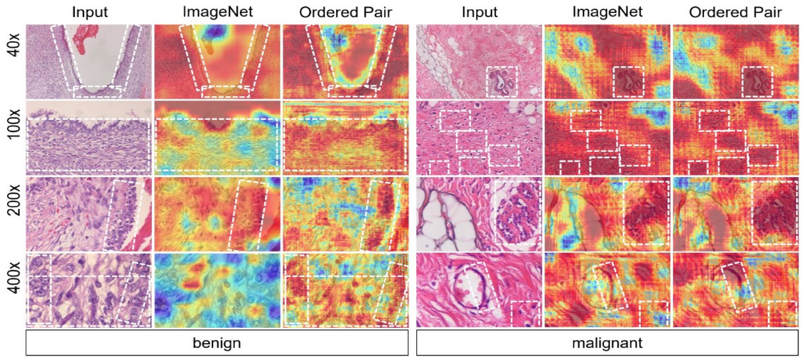
- **DPCL uses 57 datasets for pretraining**
- **MPCS consistently shows improved performance across label distribution**
  - ✓ Pretrained on single dataset
  - ✓ All three variants are consistent

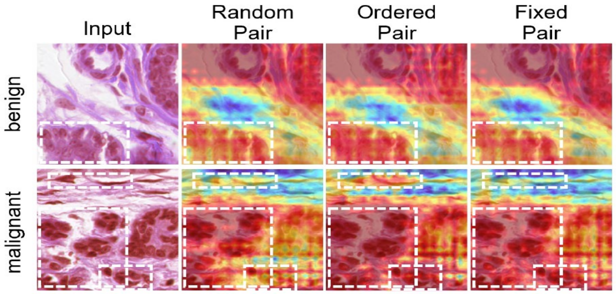
Qualitative Analysis

BACH dataset



BreakHis dataset





Breast Cancer Cell

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