





## MINING GAZE FOR CONTRASTIVE LEARNING TOWARD **COMPUTER-ASSISTED DIAGNOSIS**

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## **EYE-TRACKING**

Eye-tracking (gaze), has involved to be a low-cost and popular tool to

## **INTUITIVE FINDINGS**

a radiologist, • When read by semantically similar regions







Research Lab

NEA



Eye-tracker inside



understand and interpret reasoning and clinical decision in 2024.

Apple Vision Pro, Meta's latest Quest headset and Sony PSVR2, all have eye-trackers inside.

usually demonstrate **similar** distributions of gaze points.

Benign lesion often attracts a scattered gaze distribution, whereas malignant parts have a more centralized distribution

## METHOD



**Philosophy:** Images with similar radiologist gaze patterns are considered as positive pairs and be pulled closer in the latent space.

Gaze Similarity Evaluation: To align with radiologists' varied reading patterns for different medical images, we design three schemes for gaze similarity evaluation, distinguishing unstructured and structured images.

	RN18			RN50			RN101		
Method	M-AUC	AUC	ACC	M-AUC	AUC	ACC	M-AUC	AUC	ACC
From-scratch	71.39±3.26	73.98±4.55	76.76±4.79	68.01±2.41	71.44±4.38	75.41±4.22	69.89±2.56	67.27±3.71	73.78±2.02
ImageNet	83.43±1.98	82.38±2.84	80.38±2.34	89.73±0.89	86.17±1.23	82.97±1.08	88.90±2.98	87.50±0.89	85.63±2.26
MoCo	82.19±3.05	84.69±2.53	82.43±1.71	89.52±2.15	89.44±0.90	81.62±1.38	92.28±2.86	91.03±1.88	86.22±1.58
MoCo+McGIP	85.07±2.43	88.37±1.73	83.51±1.01	<b>92.74±1.87</b>	<b>91.44±2.08</b>	85.68±1.38	93.06±1.73	92.58±2.92	87.03±0.66
BYOL	90.42±2.31	90.59±1.48	83.78±0.85	93.84±1.72	87.96±1.71	85.95±1.83	93.82±3.44	<b>90.39±2.08</b>	86.49±0.89
BYOL+McGIP	95.83±0.63	<b>94.96±1.13</b>	<b>85.14±0.85</b>	97.07±0.75	93.80±0.79	87.57±1.01	<b>95.46±2.67</b>	90.09±3.08	<b>86.76±0.54</b>
SimSiam	91.10±3.26	91.81±1.63	83.51±1.01	93.11±2.26	86.56±2.99	86.27±1.79	92.26±1.11	<b>90.26±1.14</b>	85.68±1.08
SimSiam+McGIP	95.30±1.16	94.62±1.34	85.95±1.38	95.30±0.78	<b>89.22±0.95</b>	88.65±1.38	96.85±0.63	90.08±1.51	87.84±1.01

RESULTS

**Consistent Improvements:** McGIP acts as a plug-and-play technique for different frameworks and backbones.







**Expertise demanding** 

Lesion Representation Normal Region Representation				CONCLUSIONS				
	•		INbreast			Tufts		
•		Method	M-AUC	AUC	ACC	AUC ACC	<ul> <li>Gaze data can enhance the</li> </ul>	
BYOL	BYOL	RN18 GT Gaze	93.01±1.78 95.83±0.63	90.86±1.32 94.96±1.13	84.32±0.66 <b>85.14±0.85</b>	60.53 59.00 62.91 65.00	effectiveness of contrastive learning methods in a model-	
BYOL+Gaze	BYOL+Gaze	GT RN50 Gaze	96.02±0.88 97.07±0.75	88.96±1.61 93.80±0.79	85.14±0.85 87.57±1.01	59.29 58.00 61.35 67.50	<ul><li>agnostic manner.</li><li>Compared to ground truth</li></ul>	
		GT RN101 Gaze	94.81±2.48 <b>95.46±2.67</b>	<b>90.60±2.97</b> 90.09±3.08	85.95±1.08 86.76±0.54	59.17 63.50 61.14 64.50	labels, gaze data consistently outperforms across various	
<b>Better Spatial Sensing:</b> compared with all othe denotes more similar p	A point is selected and or points. Brighter color oints.	Better than solution between gaz revealing the	Supervised the and gr superiority	Contrastive ound-truth of gaze c	<b>e Learning</b> (GT) on data (defau	: Compariso e-hot labels It contrastiv	n effectiveness in uncovering s, visual semantics.	

learning method: BYOL)