Self Supervised Learning in Medical Images

Dr. Jalil Ghavidel

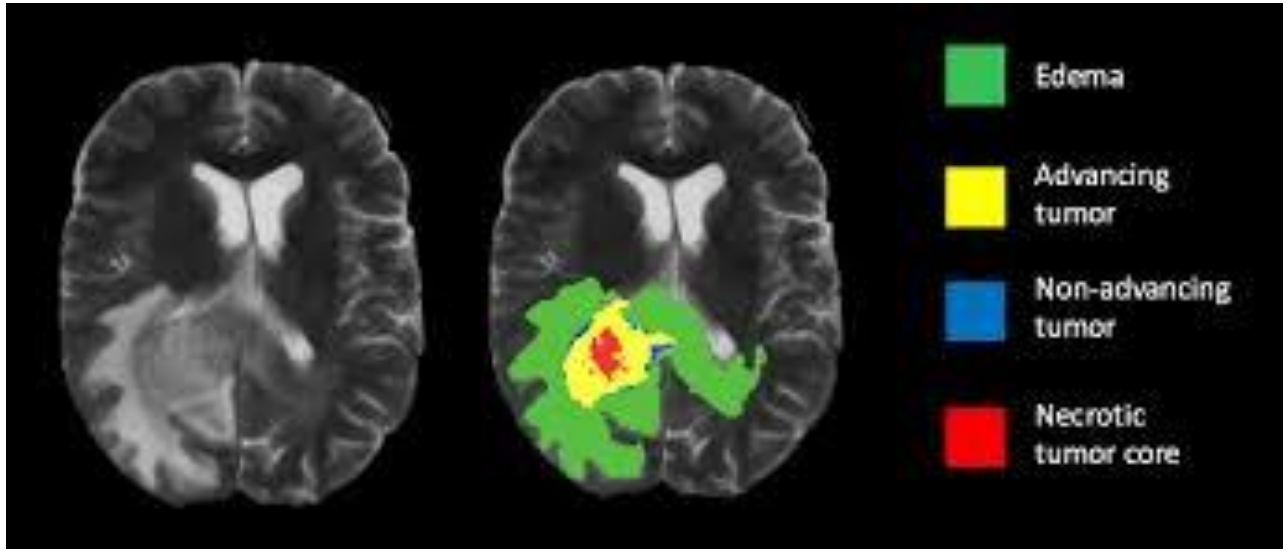
- Growing volume of medical imaging data

- Millions of medical images are generated each year

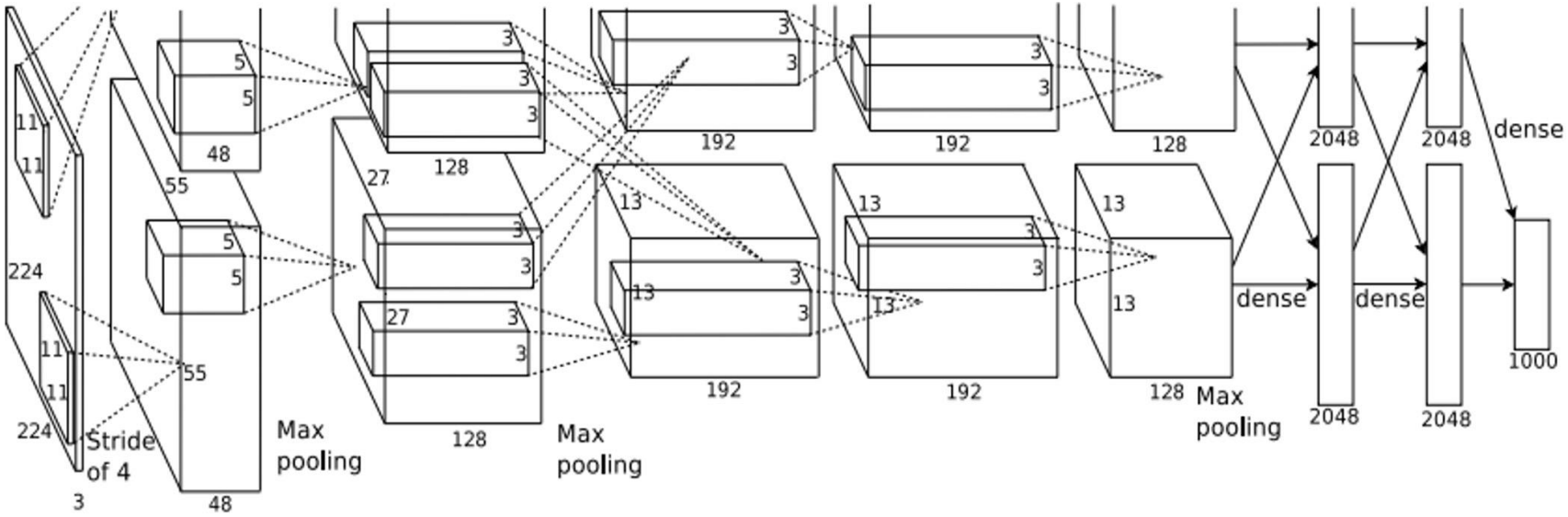
- Scarcity of expert annotations

- Less than 0.01% of the generated data is annotated

- High costs and time involved in manual labeling
- Demand for improved diagnostic accuracy

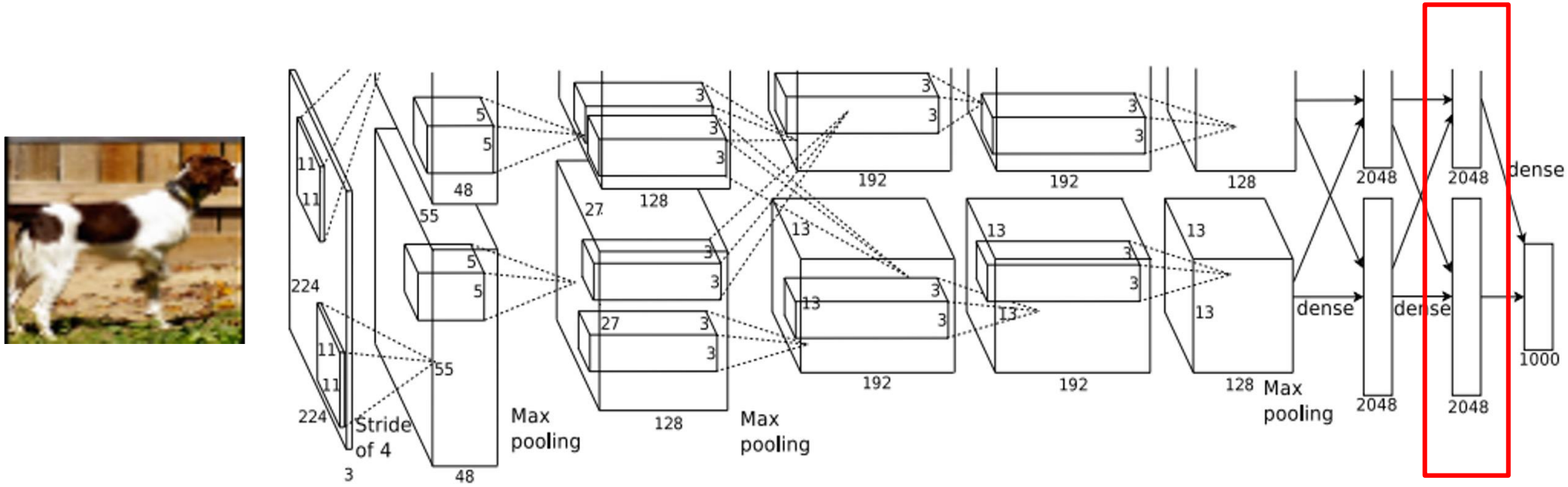


Supervised Learning

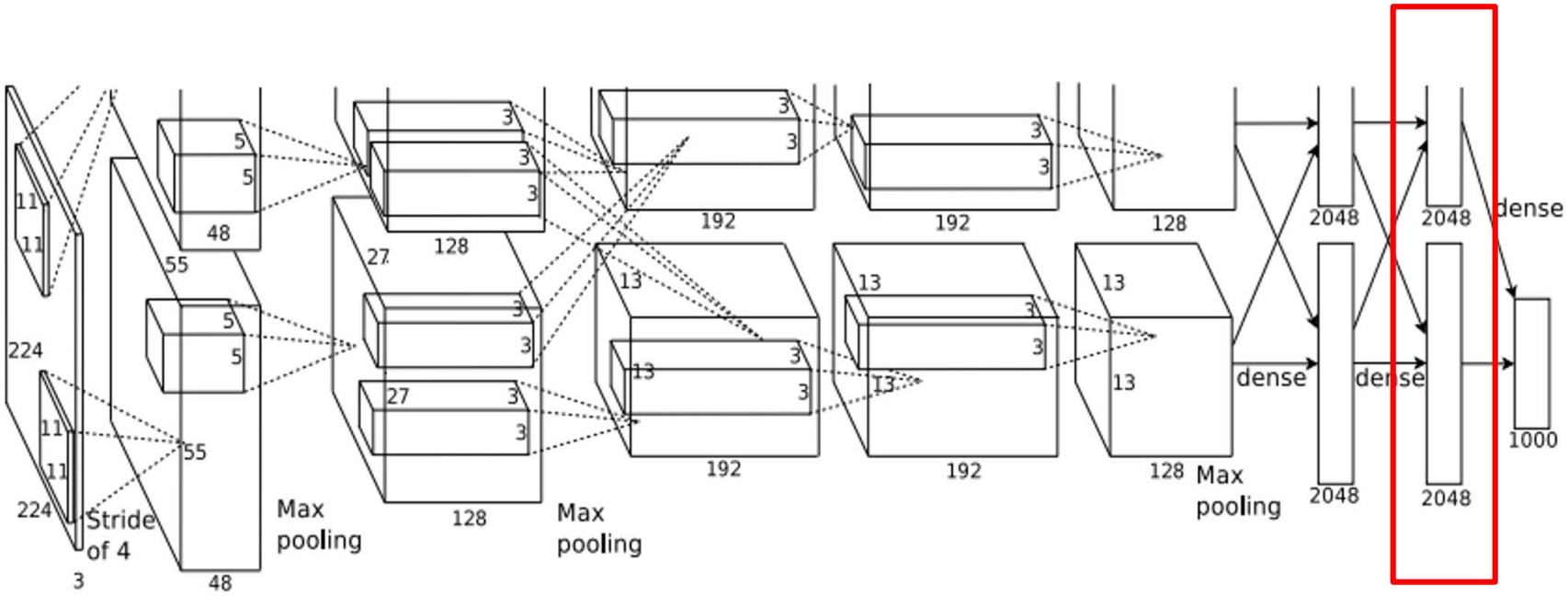


DOG

Supervised Learning



Transfer Learning



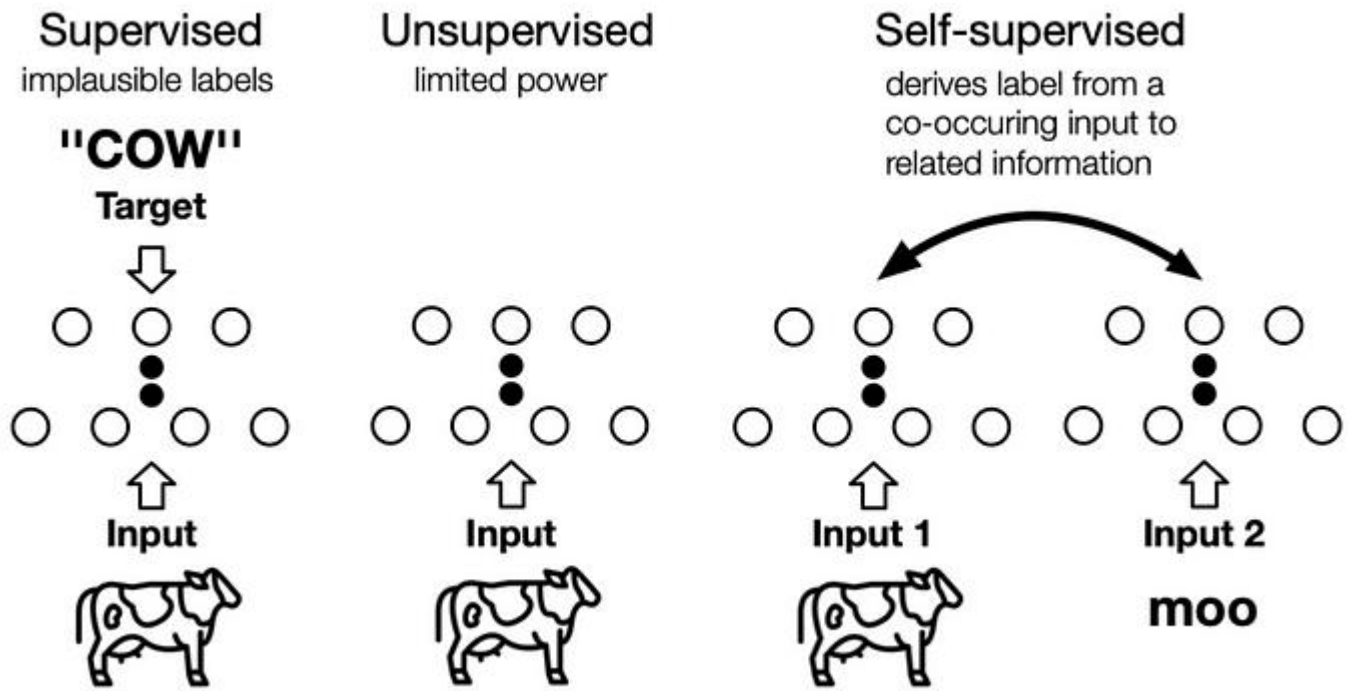
Covid-19

The Challenge with Supervised Learning

- Requires large labeled datasets
  - ImageNet with 14M images took 22 human years.
- Expert annotation bottleneck
- Overfitting to limited data
- Difficulty in capturing subtle features
  - Data Imbalance

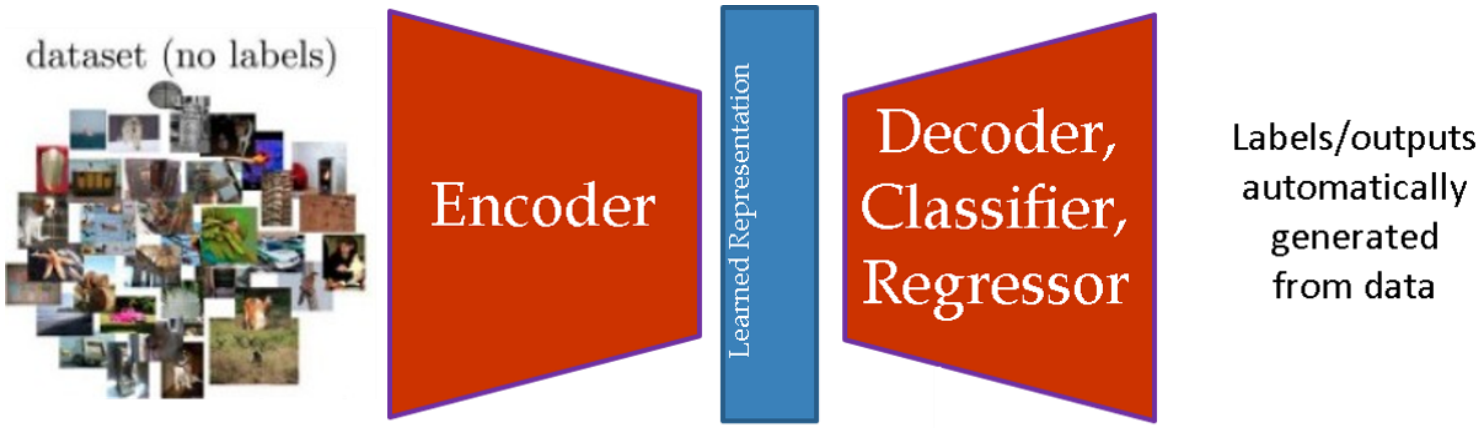
Self-Supervised Learning (SSL)

- Definition: Learning representations from unlabeled data
- Self-generated supervision signals (pretext tasks)



What is "self" supervision?

- Obtain "labels" from the data itself by using a "semi-automatic" process
- Predict part of the data from other parts



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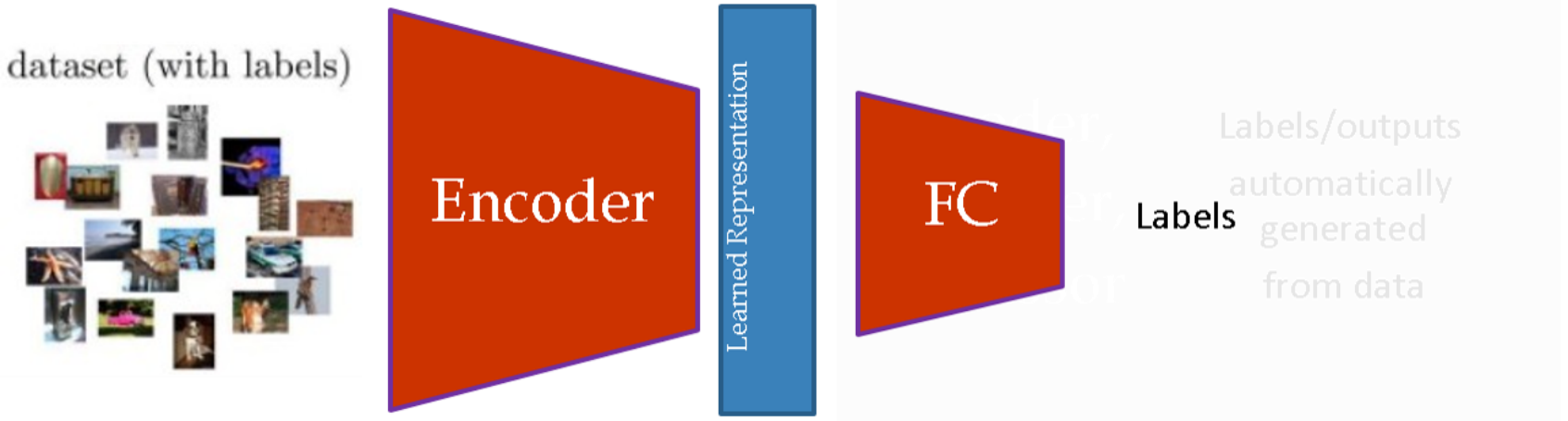
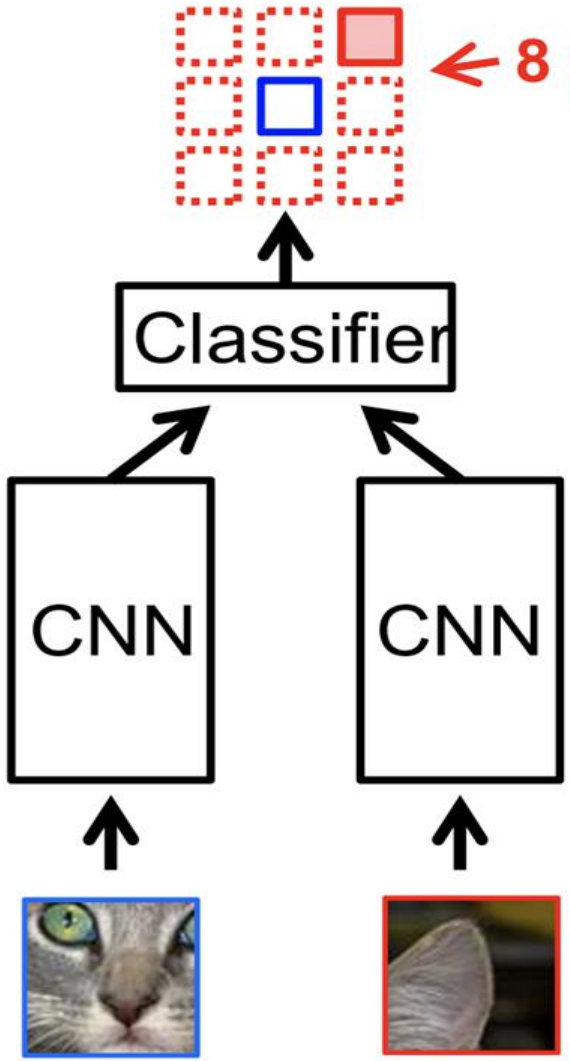
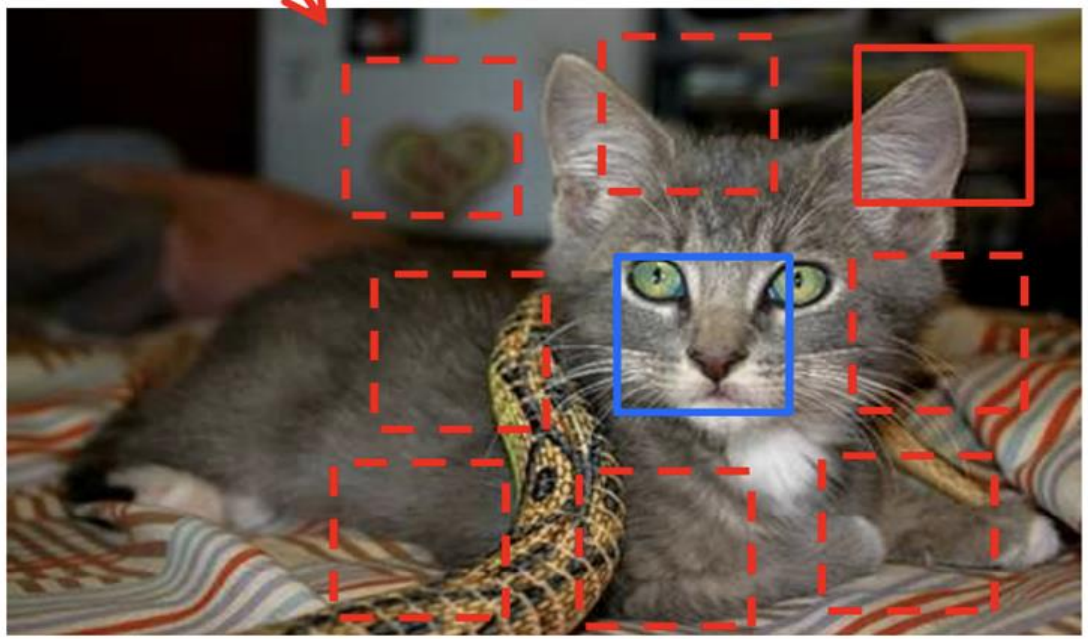


Why SSL is Ideal for Medical Imaging

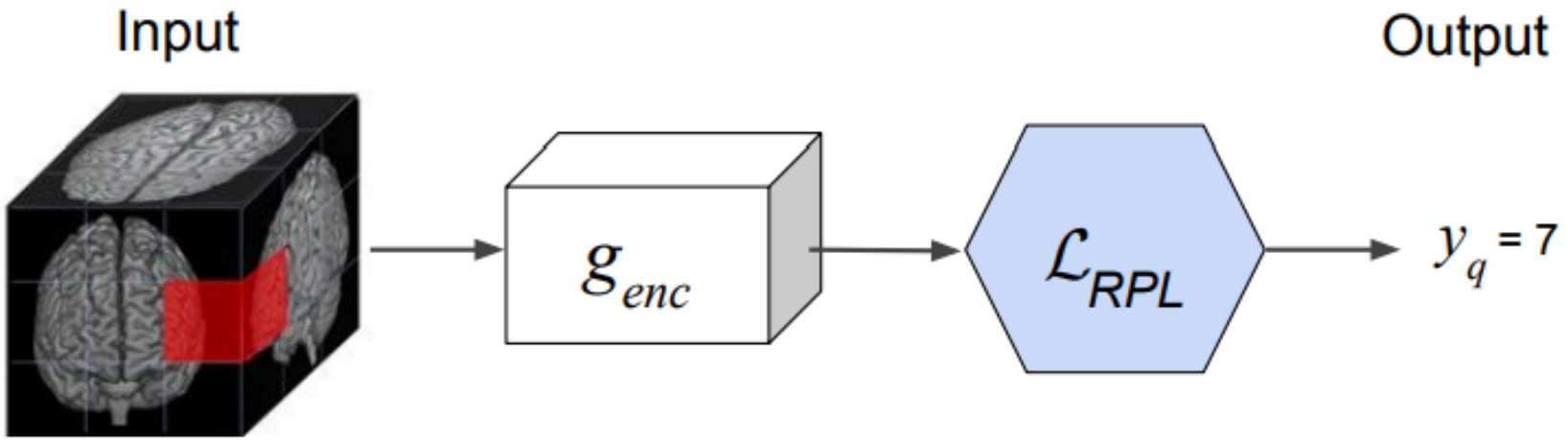
- Abundance of unlabeled medical images
- SSL pretraining improves downstream task performance
- Reduces reliance on costly manual annotations

Relative Position of patches

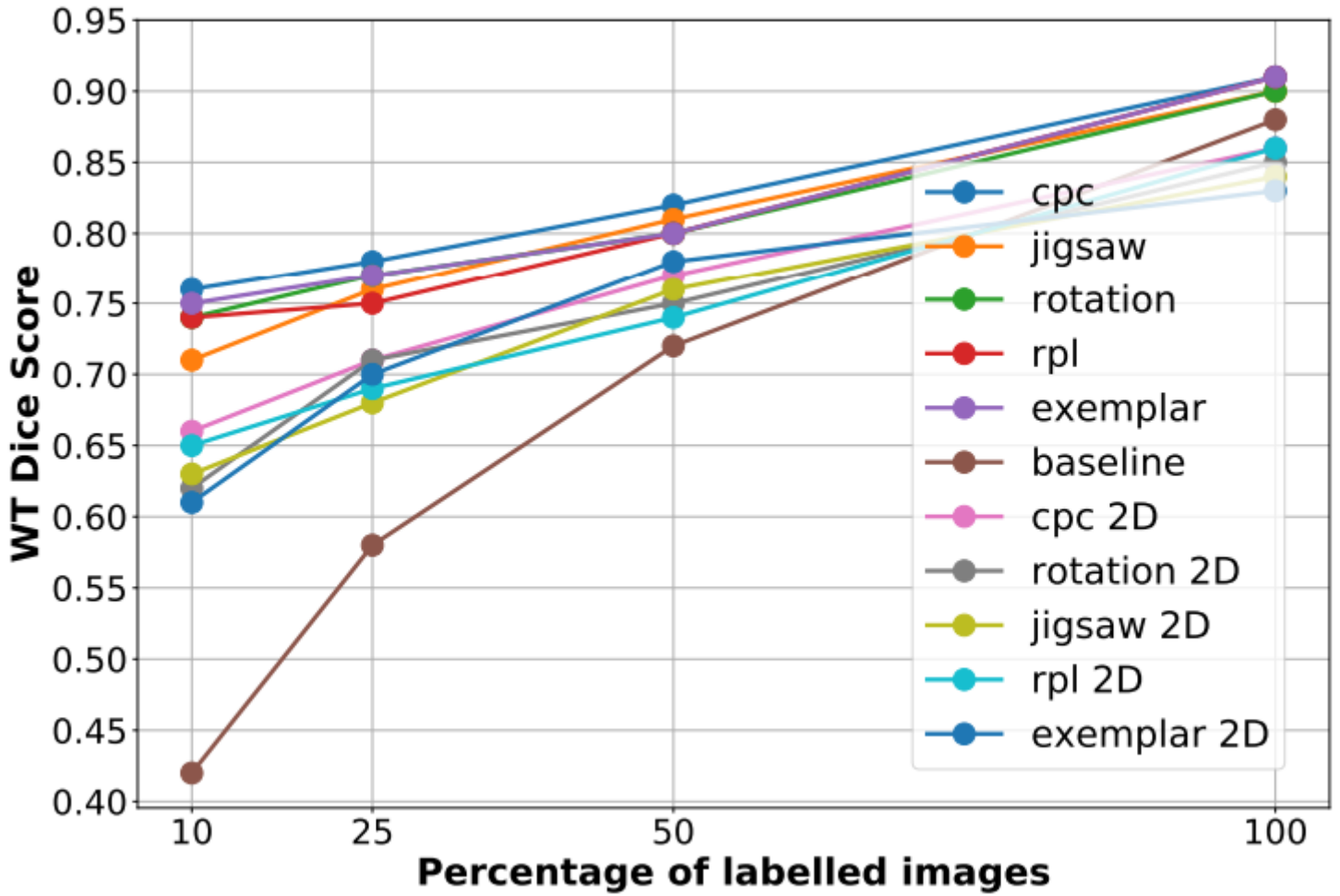




Randomly Sample Patch
Sample Second Patch



Taleb, Aiham, et al. "3d self-supervised methods for medical imaging." *Advances in neural information processing systems* 33 (2020): 18158-18172.



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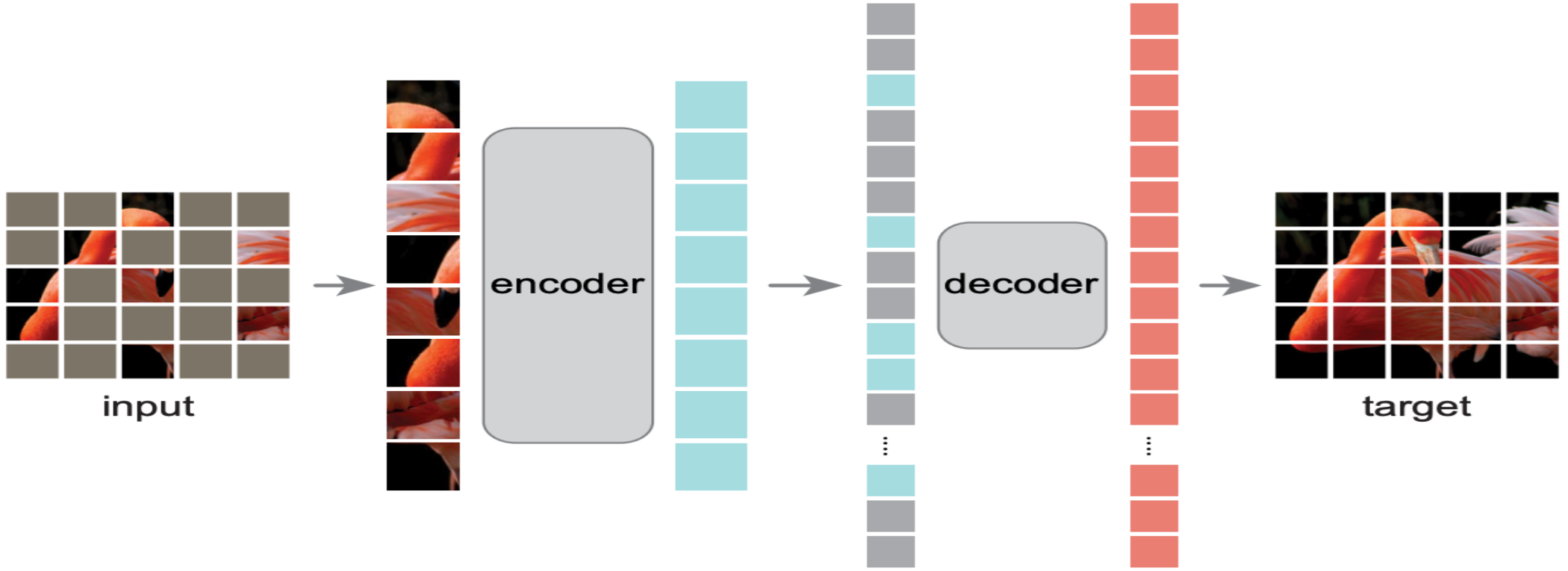
Masked Auto Encoder (MAE)



The **First** *(TvAI)* ***Skyroom***
International Virtual Congress on the practical Application of Artificial Intelligence in Medical Sciences
Date & Time: 1–5 February 2025 (09:00 Am - 12:00)

تاریخ و زمان برگزاری: ۱۳ تا ۱۷ بهمن ۱۴۰۳ (۹:۰۰ - ۱۲:۰۰ صبح)
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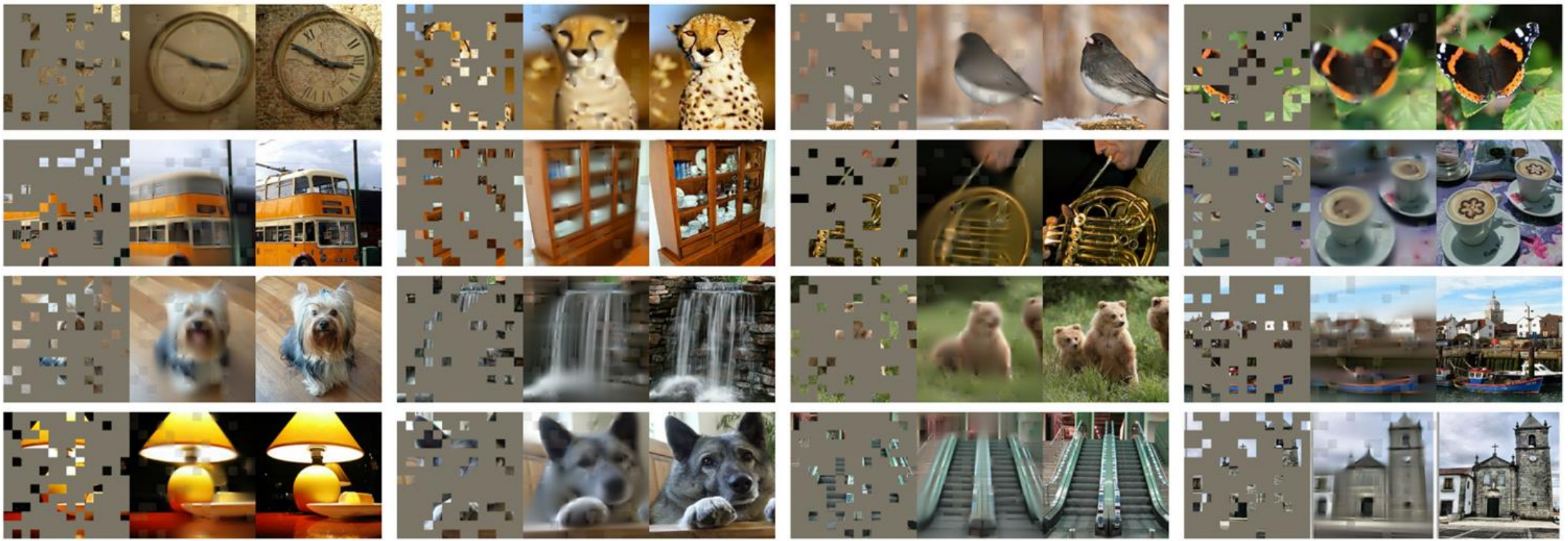
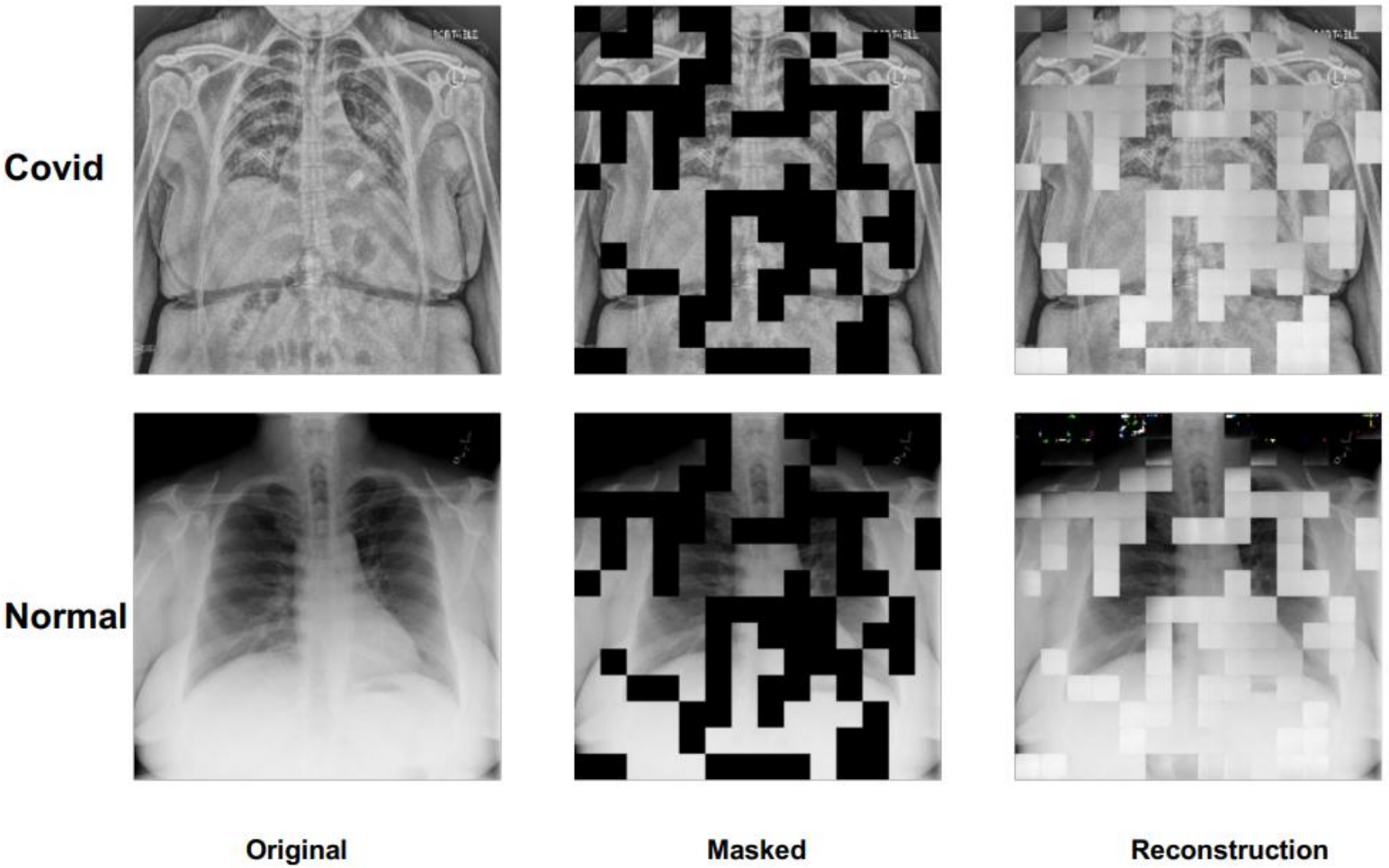
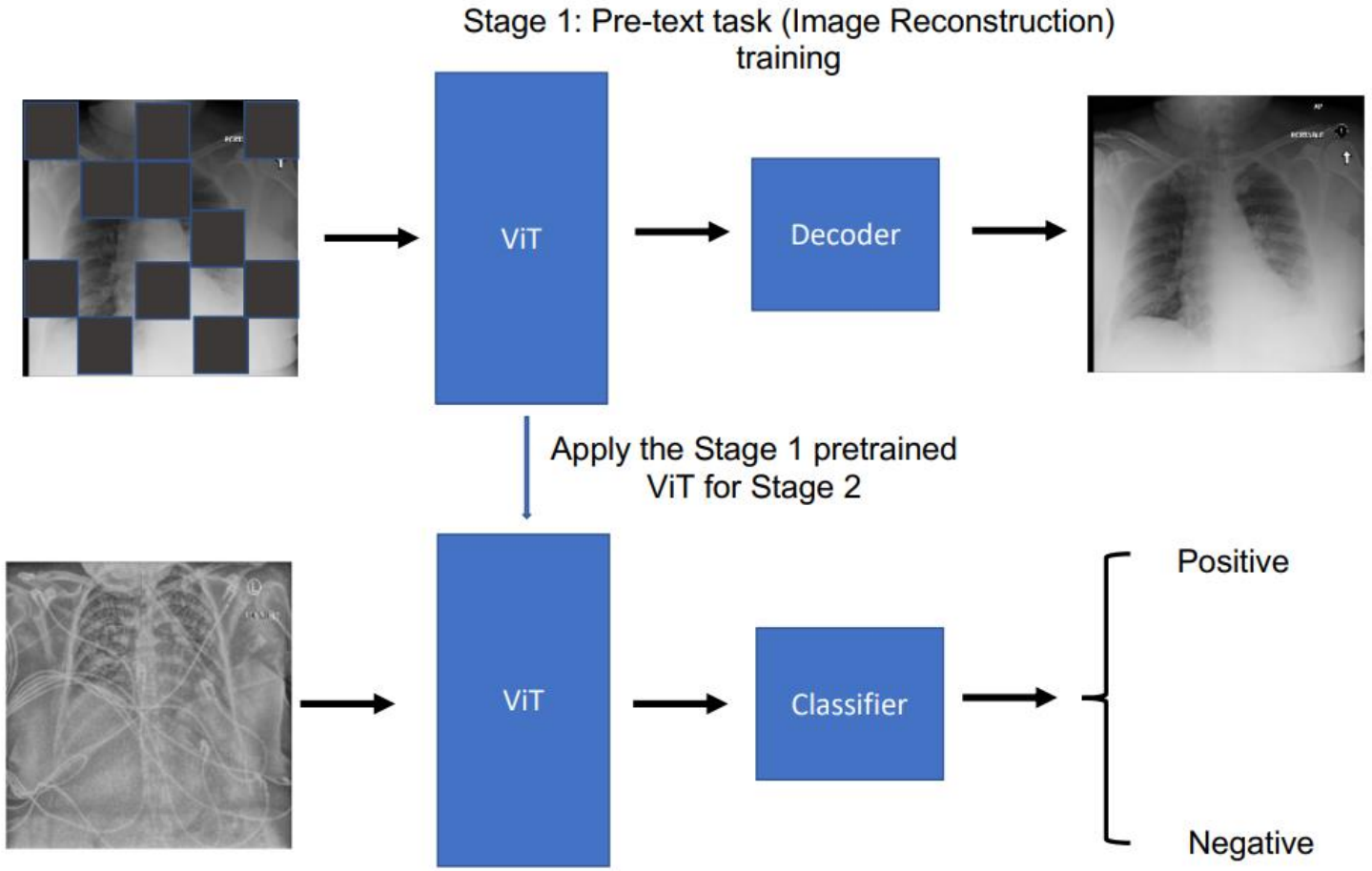
کاربرد هوش مصنوعی
در علوم پزشکی





Xing, Xin, et al. "Self-supervised learning application on COVID-19 chest X-ray image classification using masked autoencoder." *Bioengineering* 10.8 (2023): 901.



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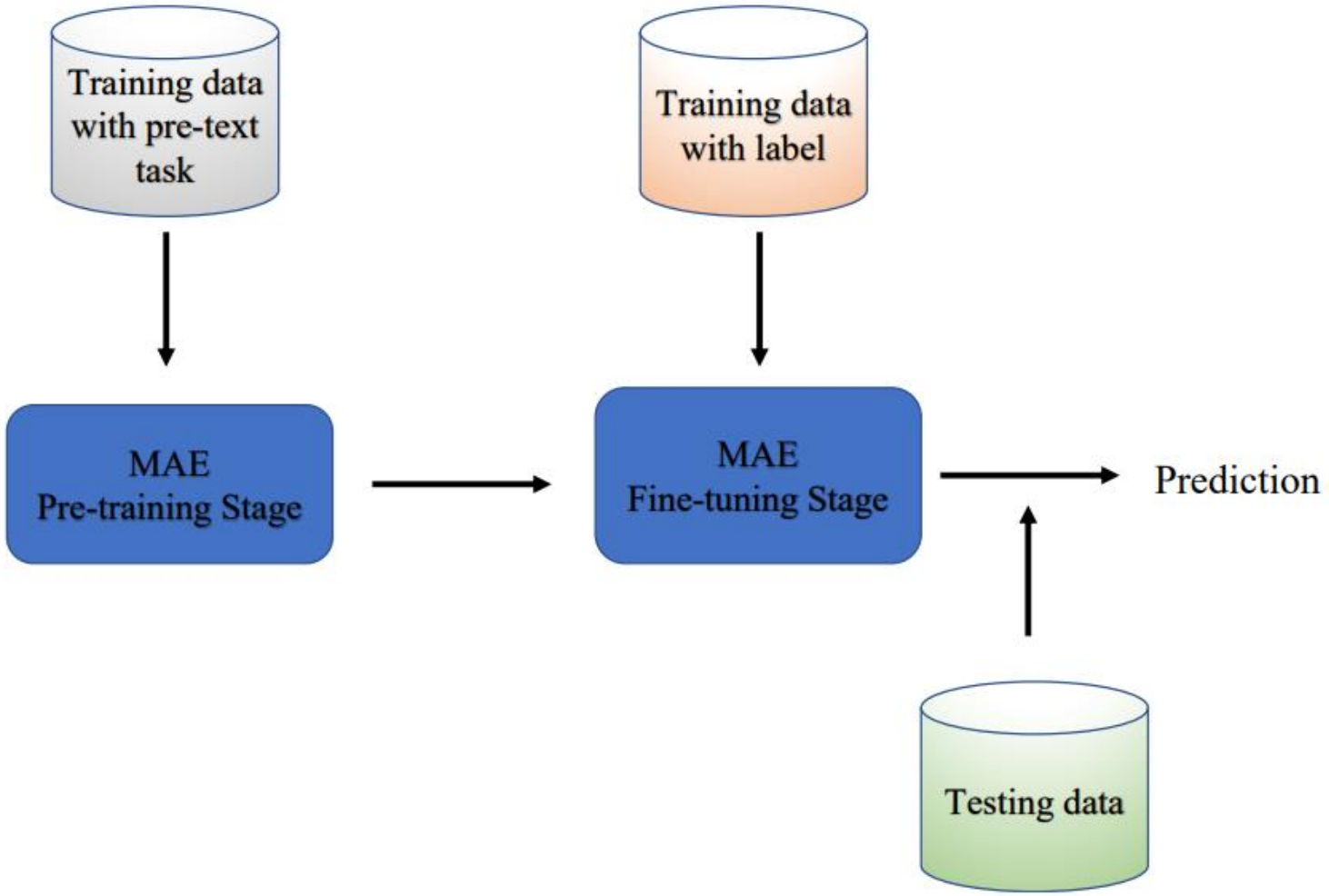

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Type	Acc	AUC	F1	Precision	Recall	AP
DenseNet121	0.9775	**0.9970**	0.9771	0.9948	0.96	0.9750
ResNet50	0.9650	0.9969	0.9641	0.9894	0.94	0.9601
ViT-scratch	0.7075	0.7808	0.7082	0.7065	0.7100	0.6466
ViT-pretrain	0.9350	0.9783	0.9340	0.9484	0.9200	0.9125
ViT-MAE	**0.9850**	0.9957	**0.9850**	**0.9950**	**0.9850**	**0.9859**

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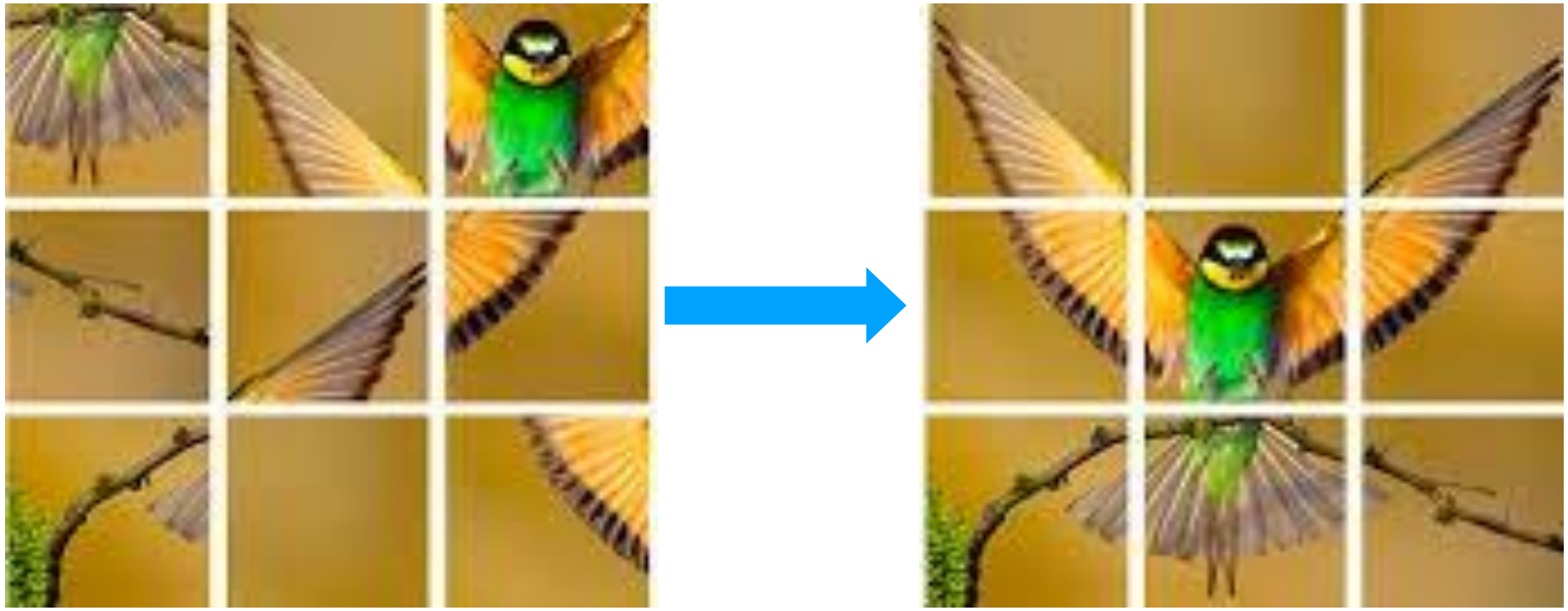
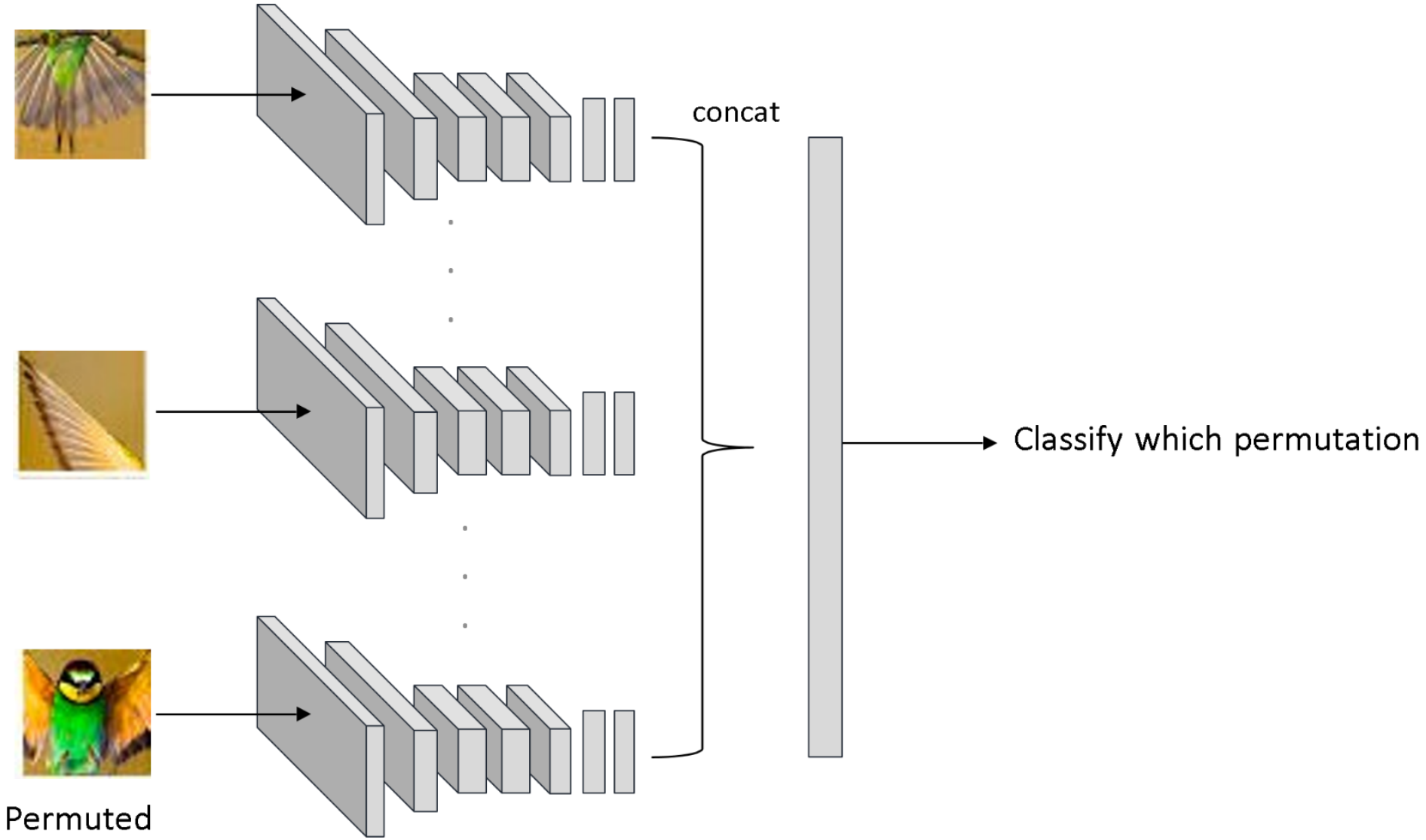
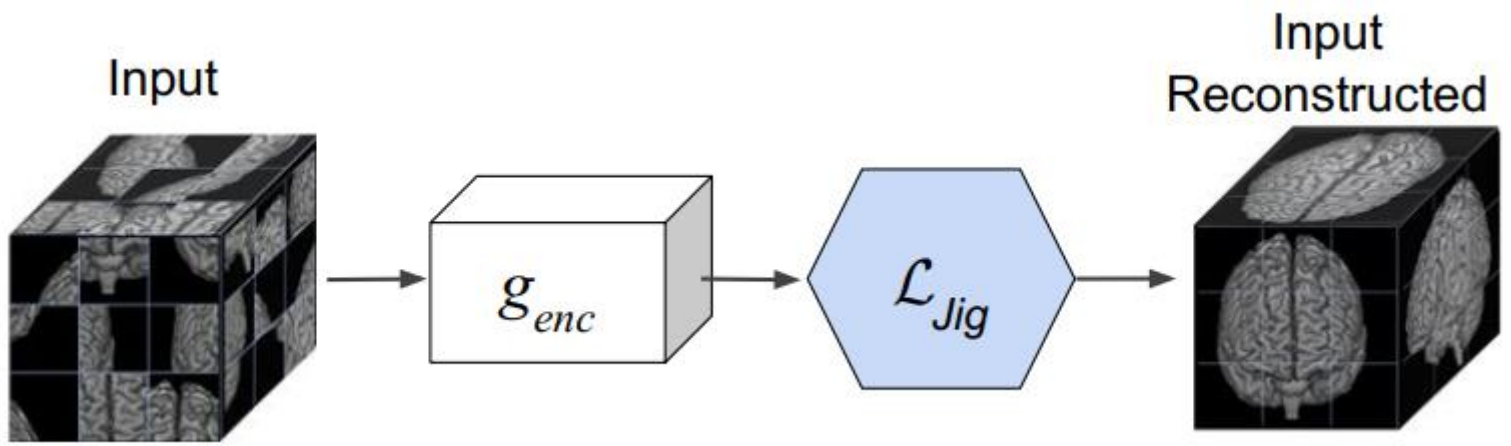
Jigsaw Puzzles




concat
Classify which permutation
Permuted
image patches



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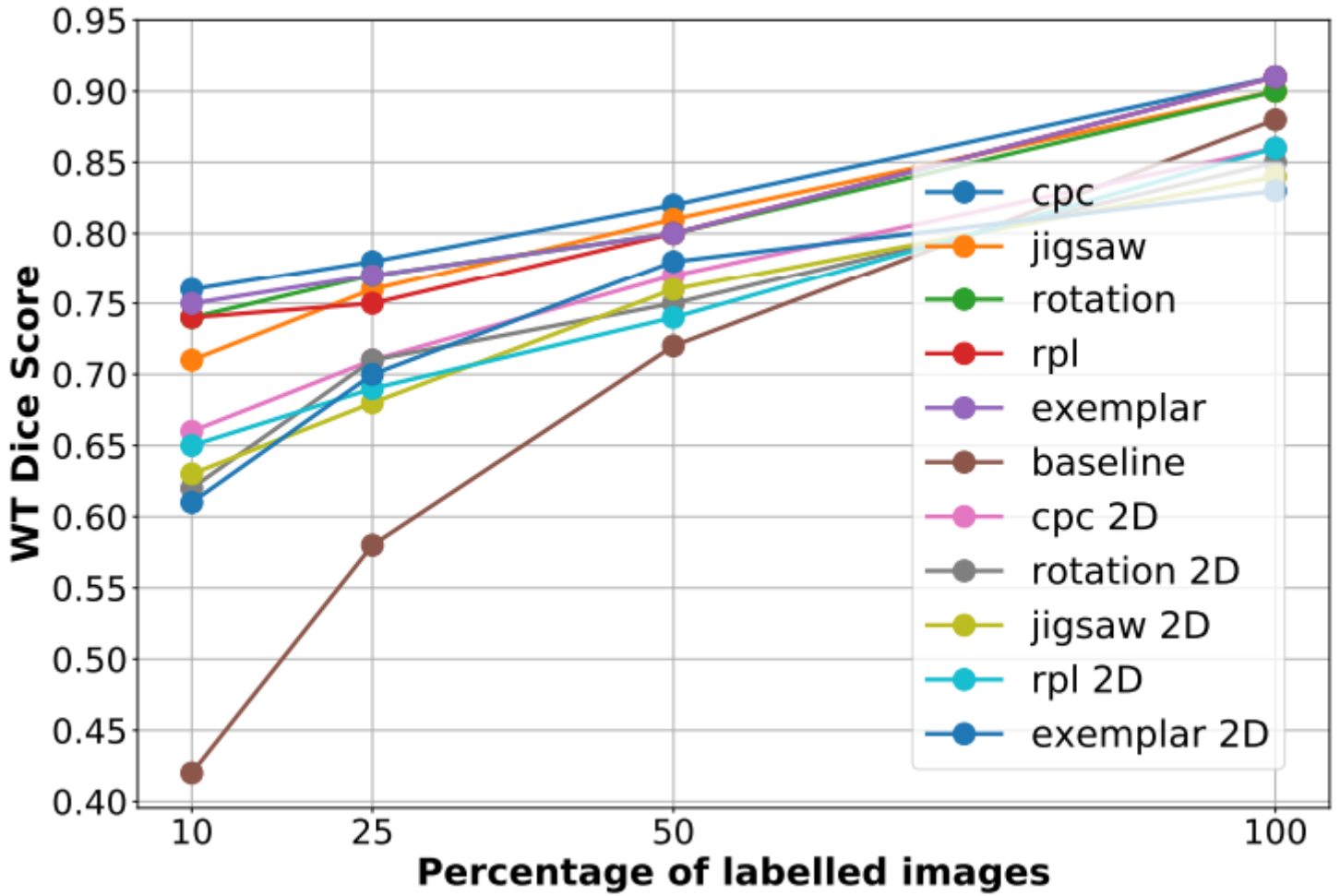

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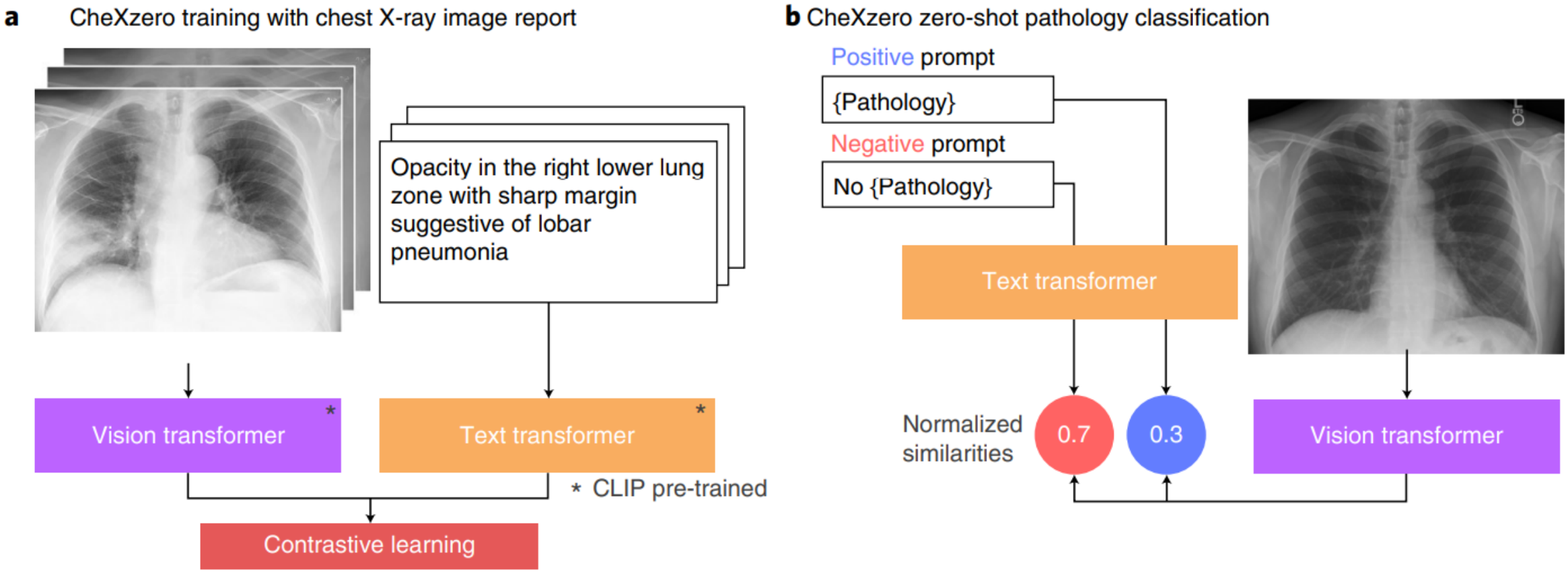
Contrastive

attract

repel

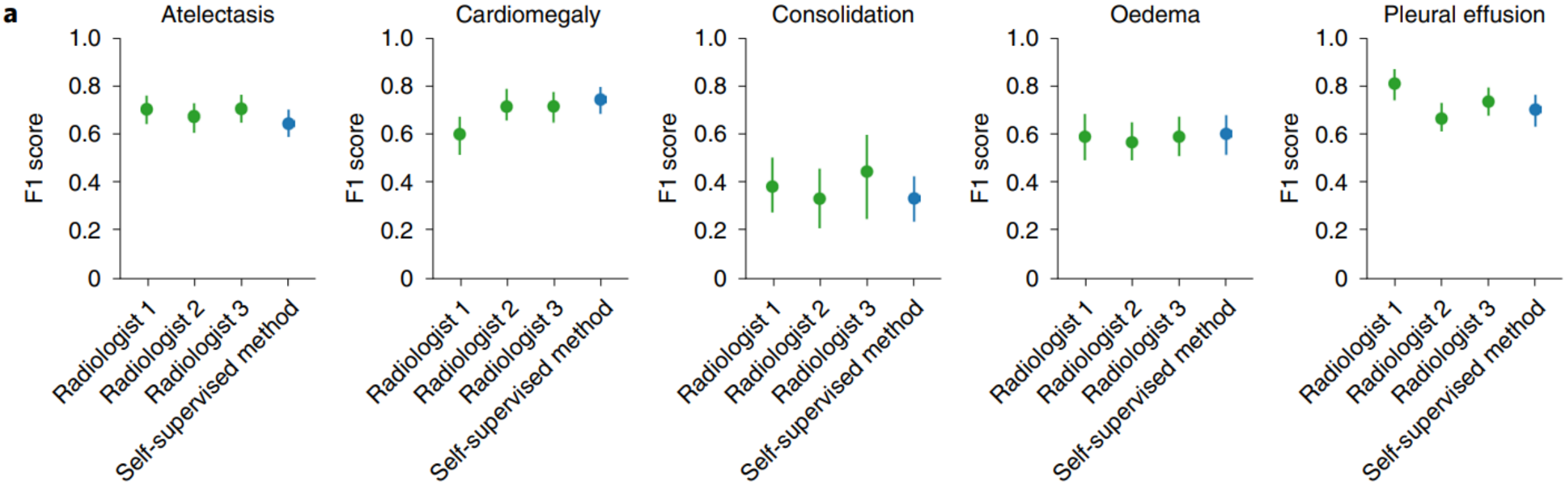
Contrastive Language-Image Pre-training



Tiu, Ekin, et al. "Expert-level detection of pathologies from unannotated chest X-ray images via self-supervised learning." *Nature Biomedical Engineering* 6.12 (2022): 1399-1406.

	Model	Mean AUC
Supervised	DAM	0.931
	DenseNet-121	0.902
Self-supervised	GLoRIA[a]	0.534
	ConVIRT- ResNet-50—1%	0.870
	ConVIRT- ResNet-50—10%	0.881
	ConVIRT-ResNet-50—100%	0.881
	ConVIRT-ViT—1%[b]	0.725
	ConVIRT-ViT—10%[b]	0.809
	ConVIRT-ViT—100%[b]	0.856
	MedAug—1%	0.810
	MoCo-CXR—1%	0.802
	MoCo-CXR—10%	0.850
	MoCo-CXR—100%	0.884
	CheXzero—0%	**0.889**

Tiu, Ekin, et a X-ray images via self-supervised learning. *Nature Biomedical Engineering* 6.12 (2022): 1399-1406.



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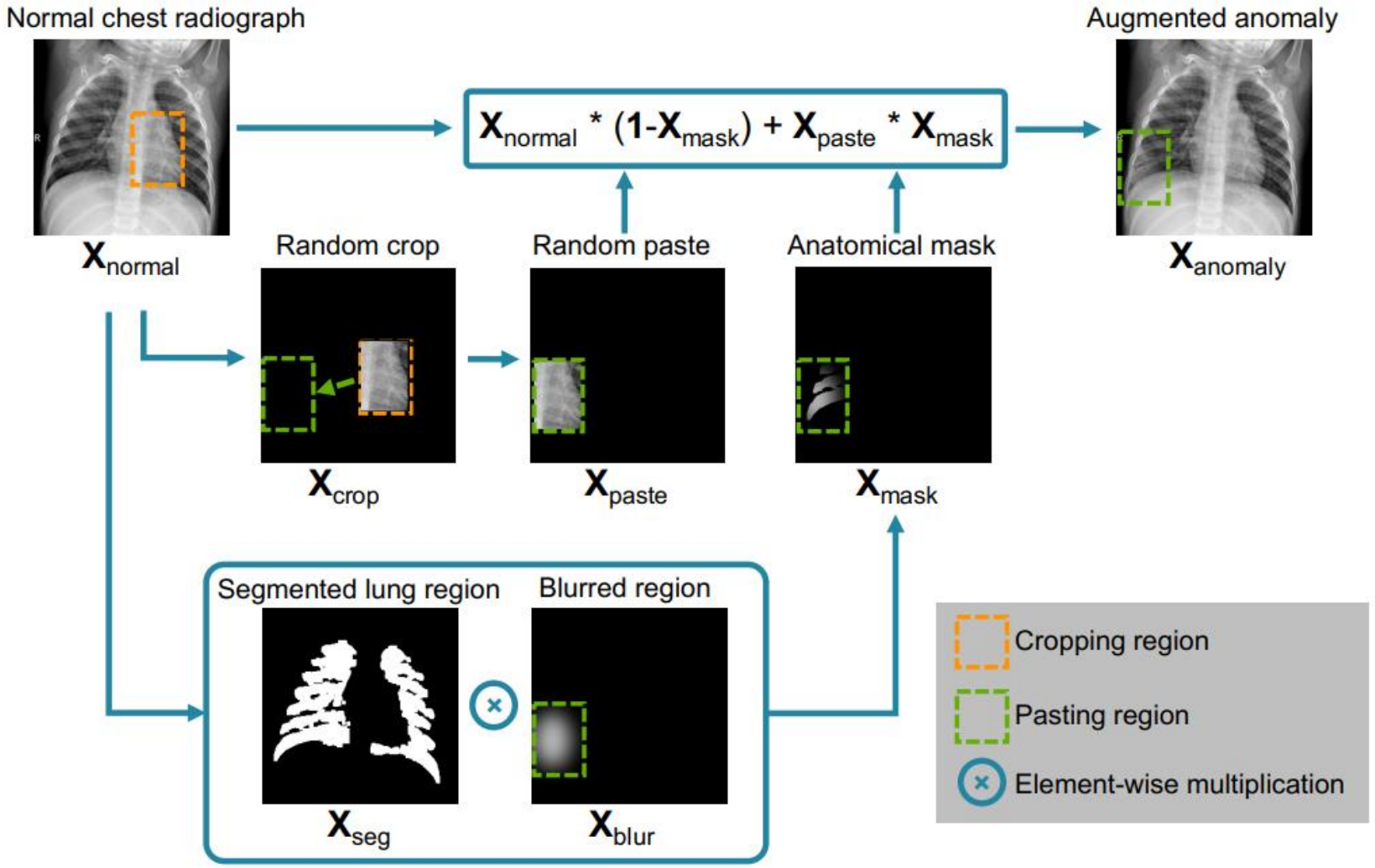
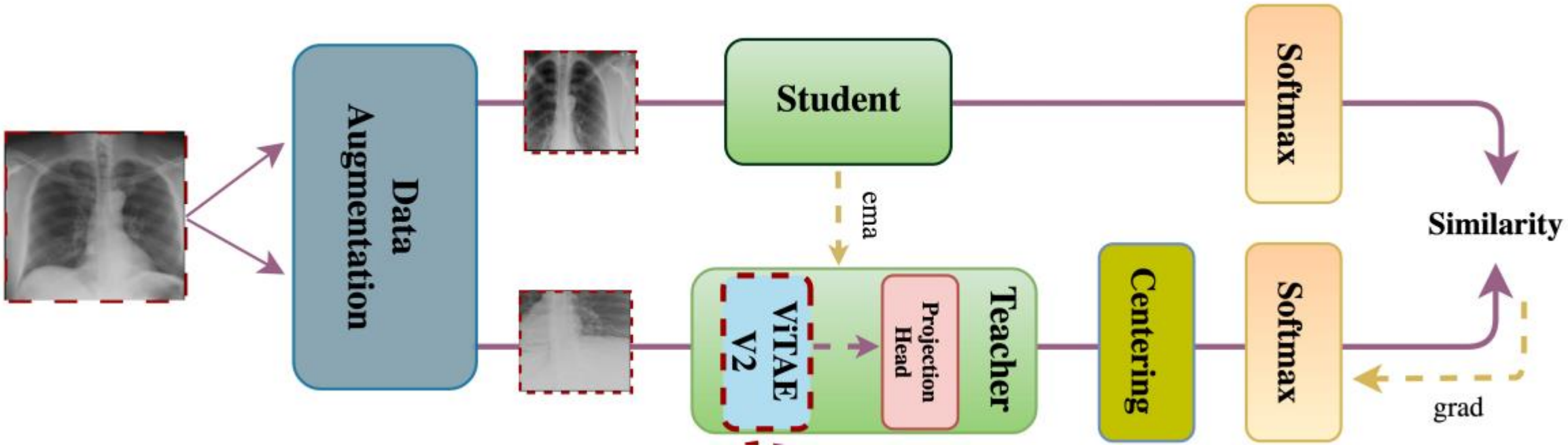


Sato, Junya, et al. "Anatomy-aware self-supervised learning for anomaly detection in chest radiographs." *Iscience* 26.7 (2023).


Data Augmentation
Student
Softmax
ema
Similarity
ViTAE V2
Projection Head
Teacher
Centering
Softmax
grad

		Non-COVID-19		COVID-19		
Method	ACC	F1-Score	Precision	F1-Score	Precision	Recall
COVIDNet-CXR [29]	67.82±6.11	73.31±3.79	3.36±6.15	56.94±5.05	81.65±6.02	46.82±17.59
COVID-CAPS [1]	65.34±3.26	65.15±5.02	65.62±3.98	64.87±4.42	66.07±4.49	64.93±9.71
COVID-SDNet [26]	76.18±2.70	76.94±2.82	74.74±3.89	75.71±3.35	78.67±4.70	72.59±6.77
Panetta et. al [24]	75.11±1.76	75.86±2.11	74.75±3.61	74.02±3.15	76.41±7.38	72.65±6.83
DINO-CXR	**76.47±3.53**	78.03±1.96	73.49±5.5	72.86±7.13	79.93±1.94	66.93±11.72

Discussion: The Future of SSL in Medicine

- Trends: increasing use of transformer-based SSL, multi-modal approaches
- Potential for personalized medicine
- Emerging research directions
  - Self-supervised reinforcement learning
  - RL agent can dynamically adjust imaging parameters (such as exposure, resolution, or even modality-specific settings) in real time

Future Research Directions

- Combining SSL with federated learning for privacy
- Multi-modal SSL: Integrating imaging with genomic and clinical data
- Adaptive SSL models that update with new data continuously
- Explainablity
- Hardware Limitations

Open Challenges and Opportunities

- Overcoming computational demands of SSL
- Lack of large, diverse datasets in medicine
- Ensuring robustness across diverse populations
- Scaling up from research to clinical practice

Final Thoughts

- SSL is transforming medical imaging by reducing annotation needs and boosting performance
- Collaboration between research and clinical practice is key
- Exciting future ahead with AI

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