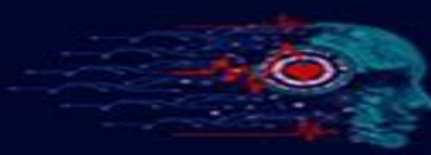


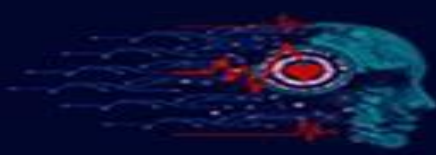
Self Supervised Learning in Medical Images



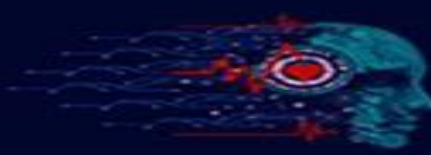
Dr. Jalil Ghavidel



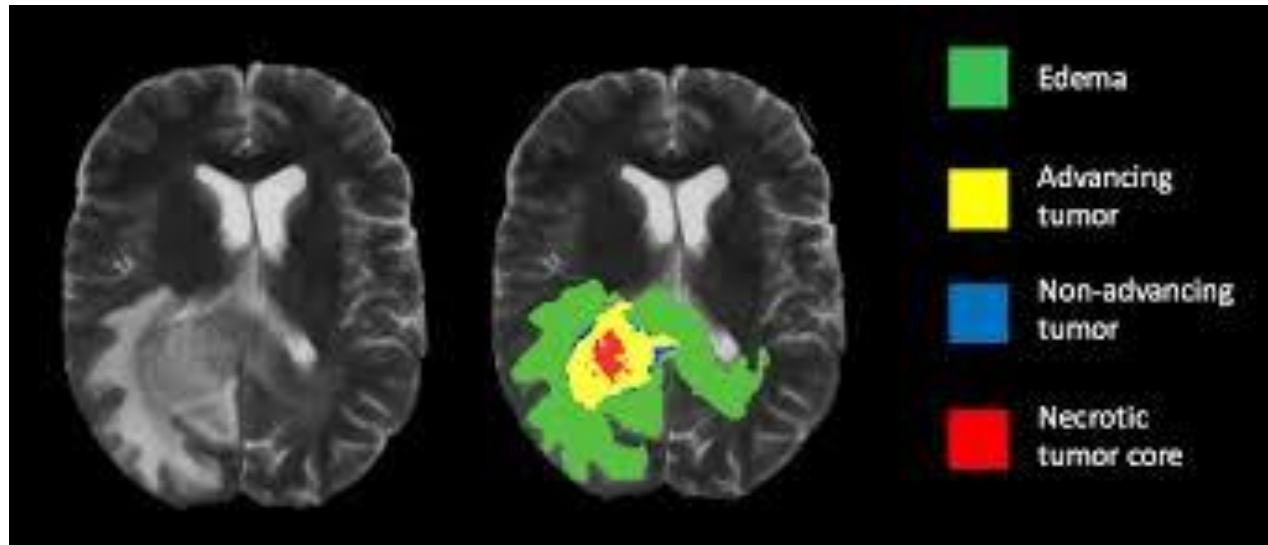
- Growing volume of medical imaging data
- Millions of medical images are generated each year

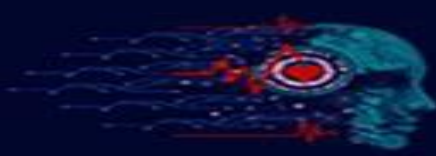


- Scarcity of expert annotations
- Less than 0.01% of the generated data is annotated

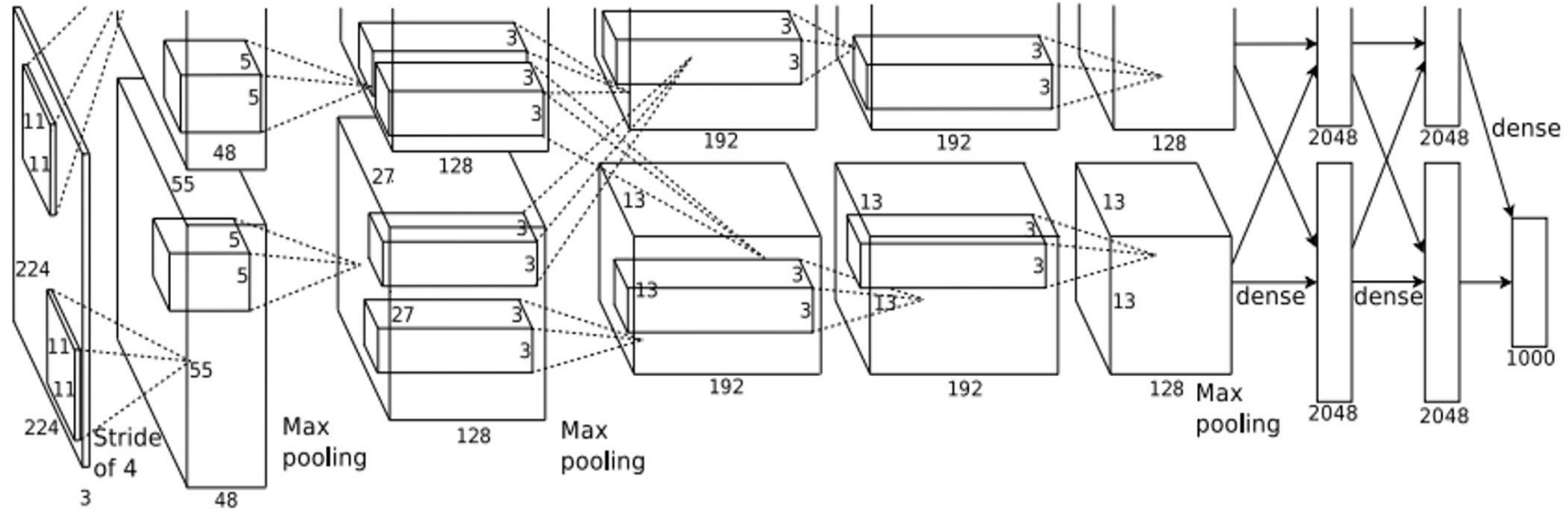


- High costs and time involved in manual labeling
- Demand for improved diagnostic accuracy

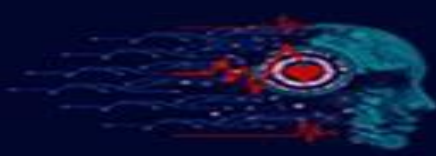




Supervised Learning

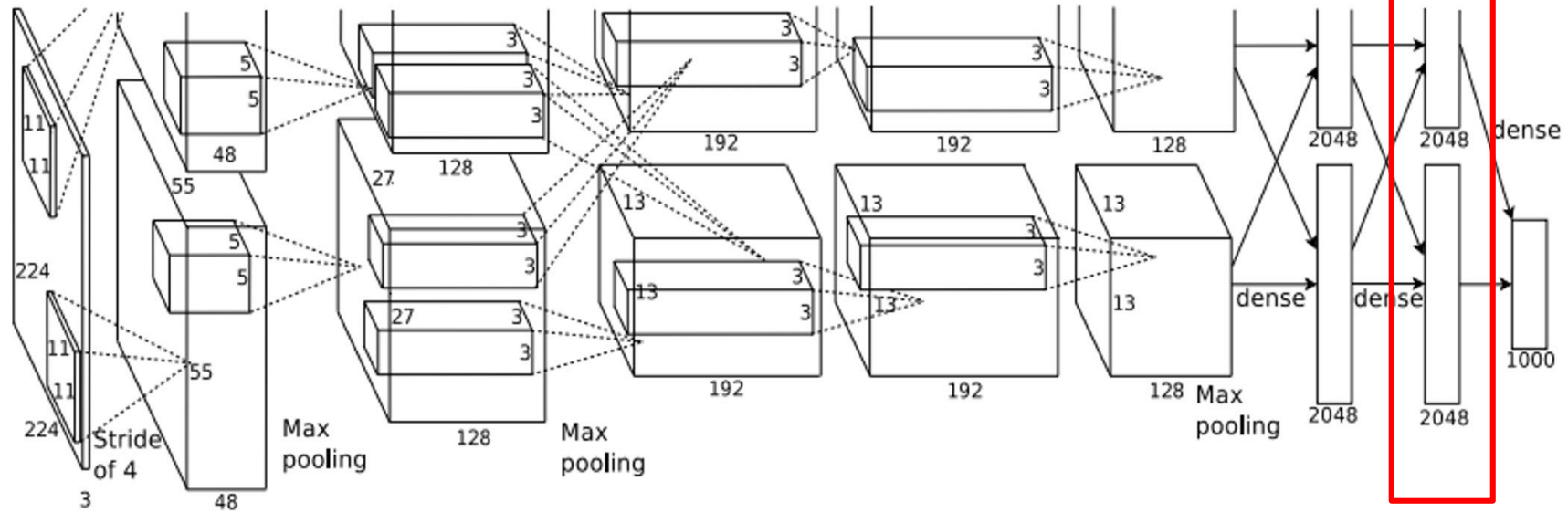


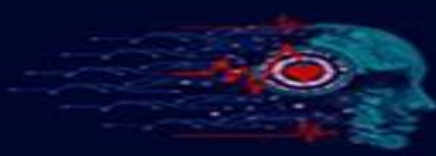
DOG



Supervised Learning

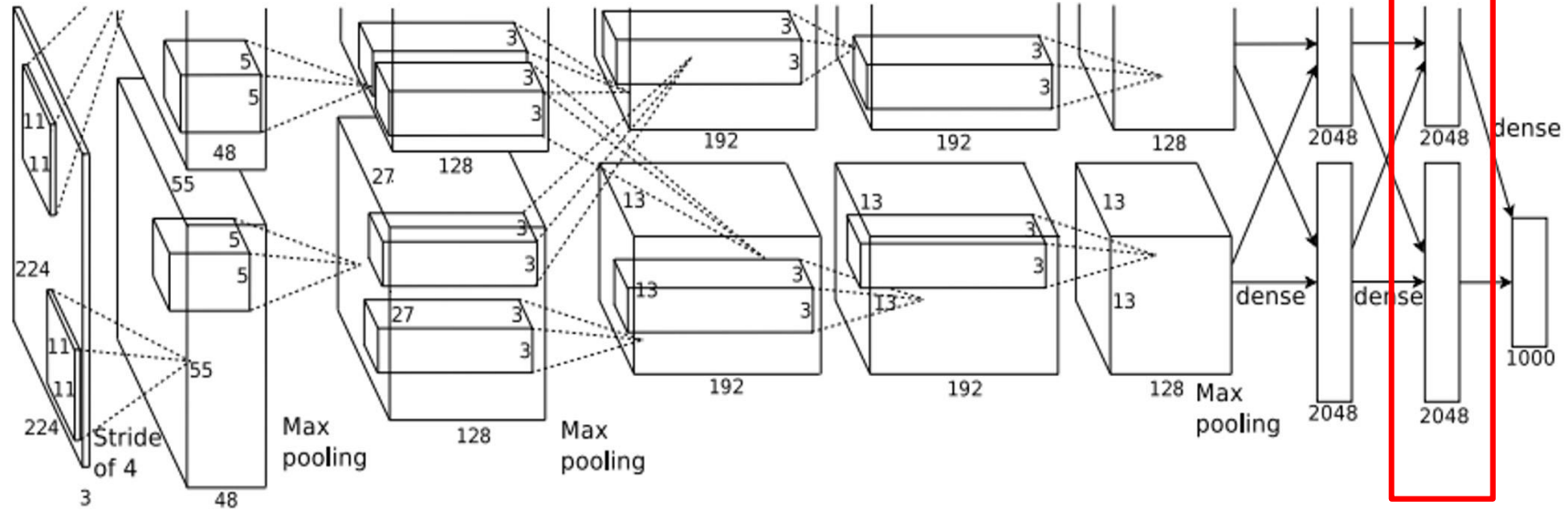
4096-dim vector

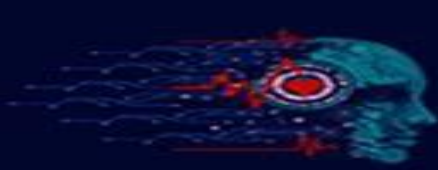




Transfer Learning

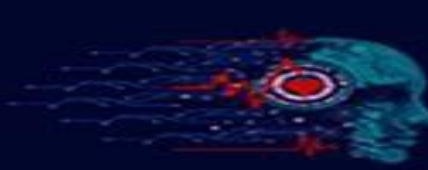
4096-dim vector





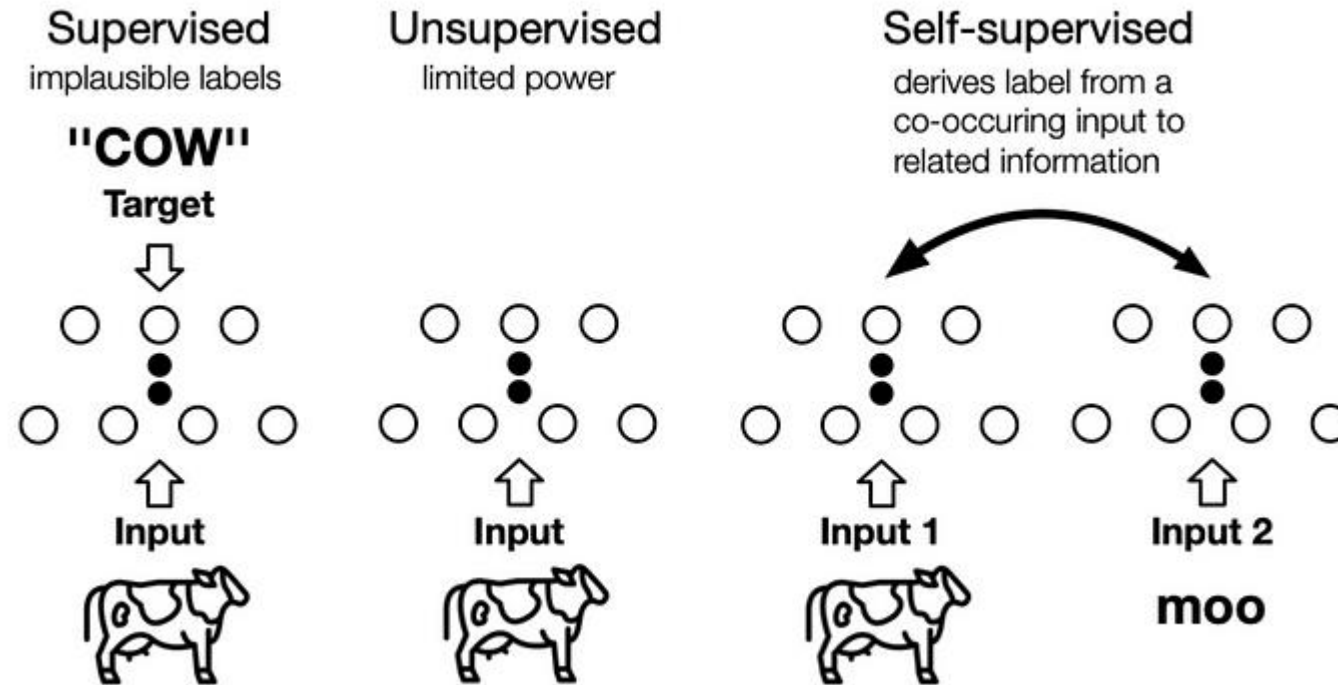
The Challenge with Supervised Learning

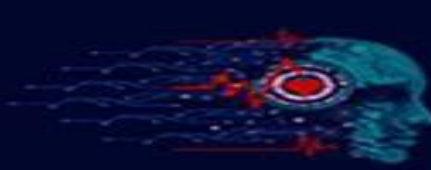
- Requires large labeled datasets
 - ImageNet with 14M images took 22 human years.
- Expert annotation bottleneck
- Overfitting to limited data
- Difficulty in capturing subtle features
 - Data Imbalance



Self-Supervised Learning (SSL)

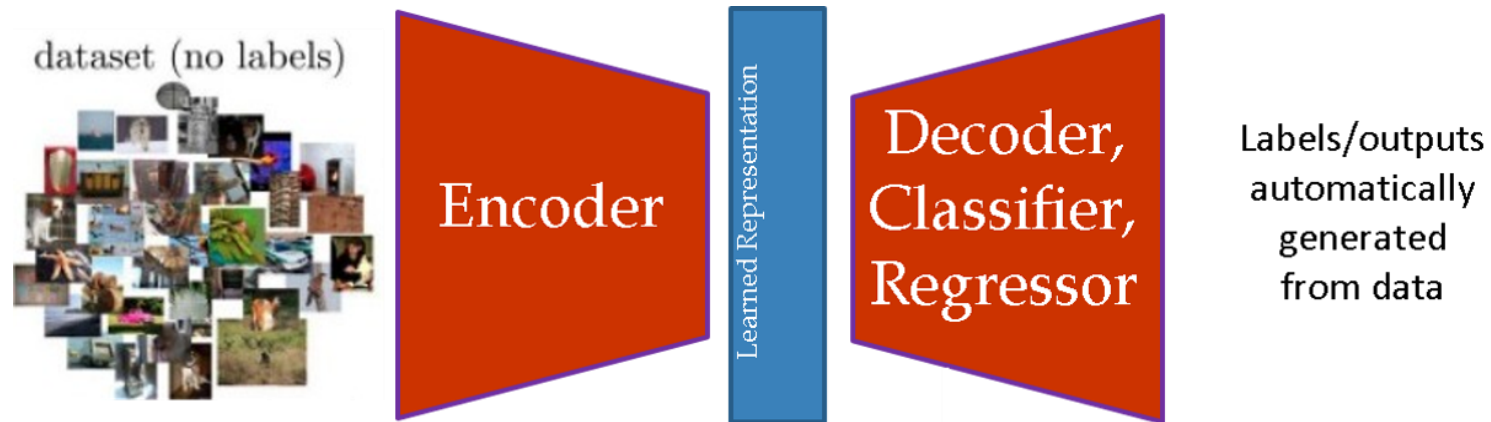
- Definition: Learning representations from unlabeled data
- Self-generated supervision signals (pretext tasks)

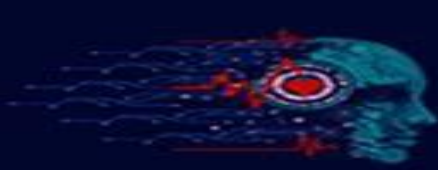




What is "self" supervision?

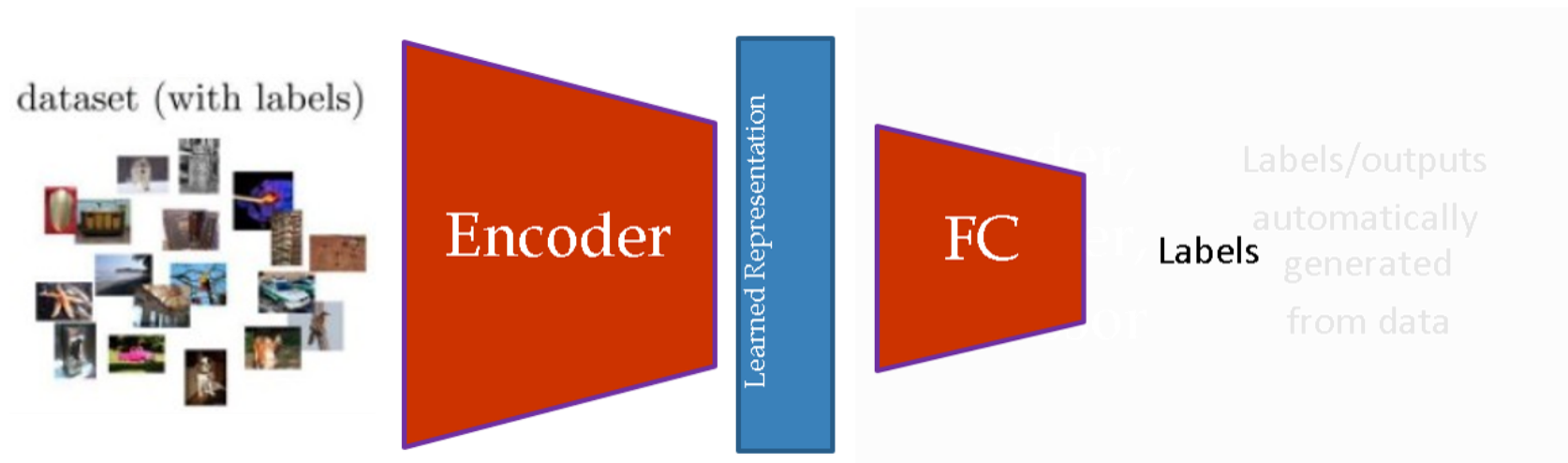
- Obtain "labels" from the data itself by using a "semi-automatic" process
- Predict part of the data from other parts

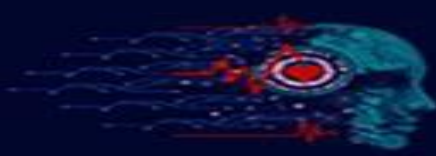




What is "self" supervision?

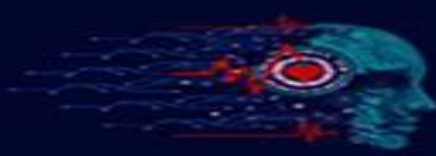
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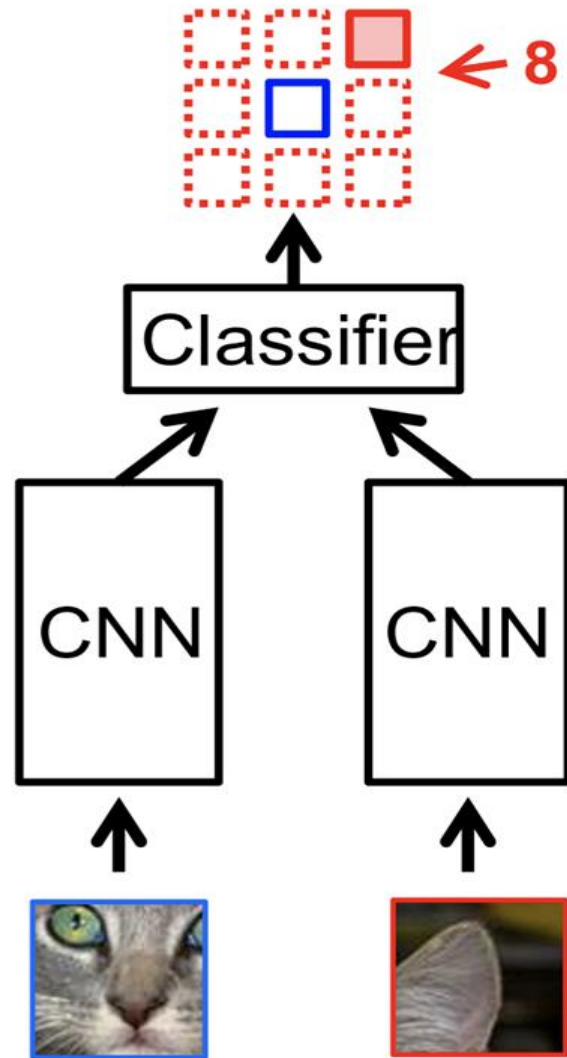


Why SSL is Ideal for Medical Imaging

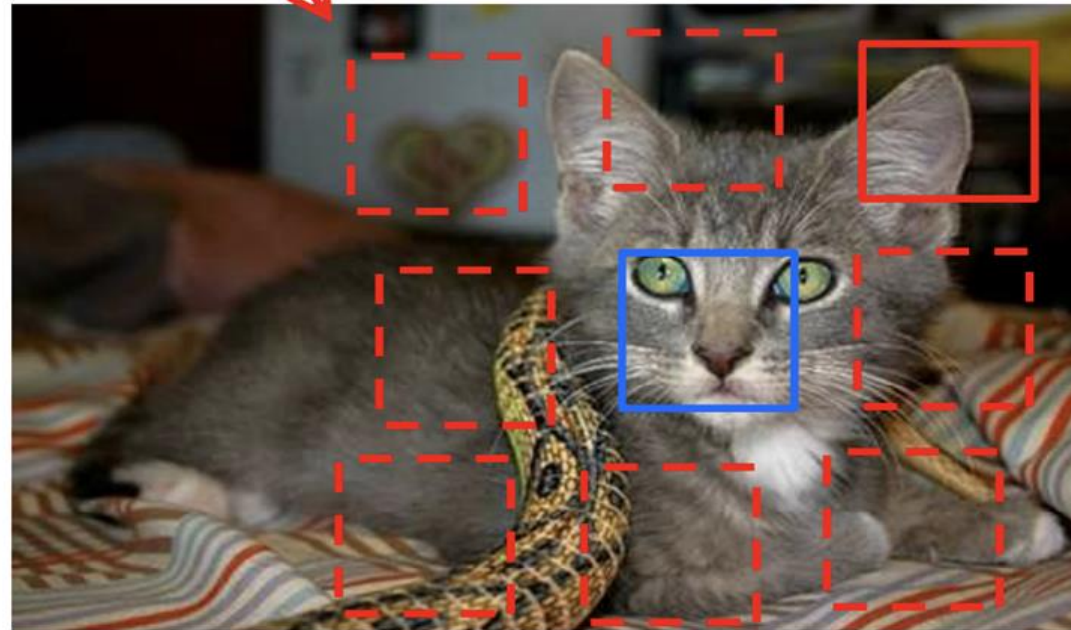
- Abundance of unlabeled medical images
- SSL pretraining improves downstream task performance
- Reduces reliance on costly manual annotations



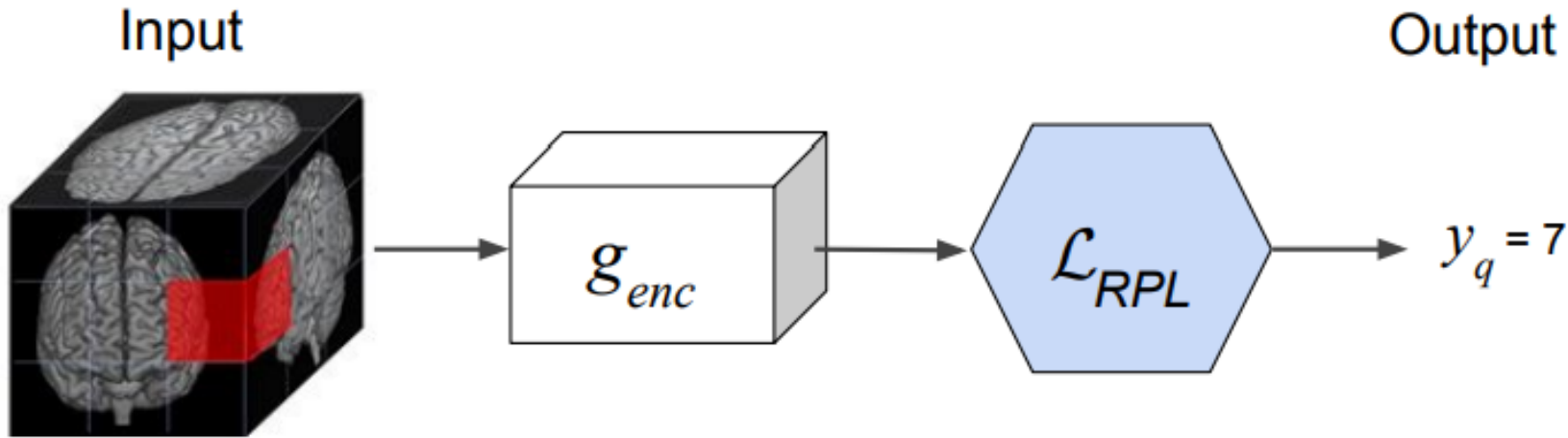
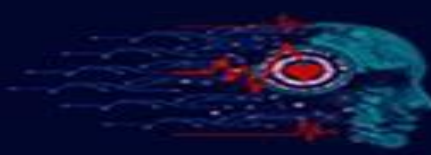
Relative Position of patches



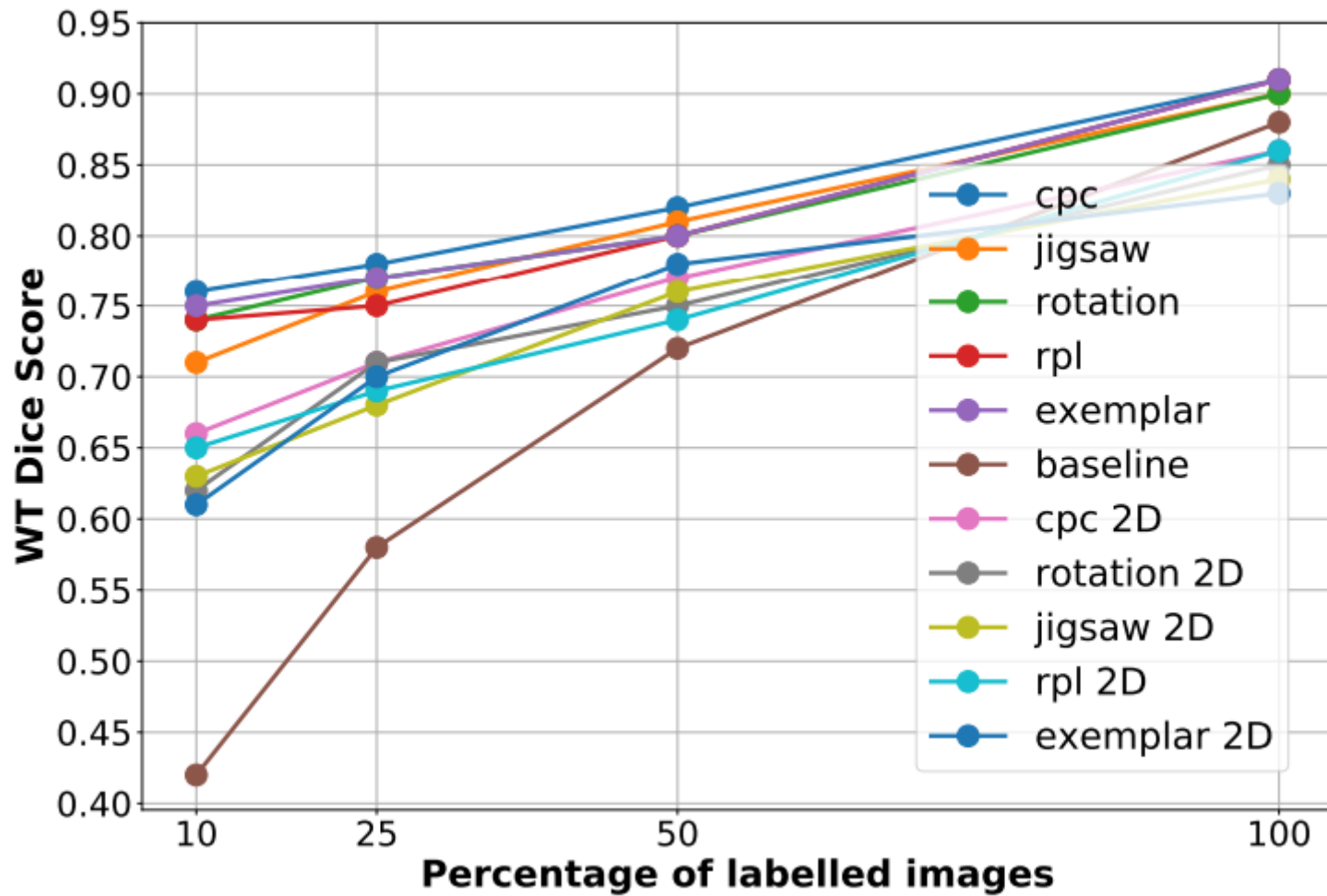
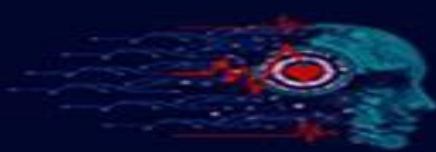
← 8 possible locations



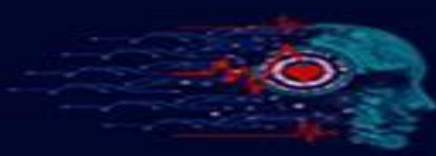
Randomly Sample Patch
Sample Second Patch



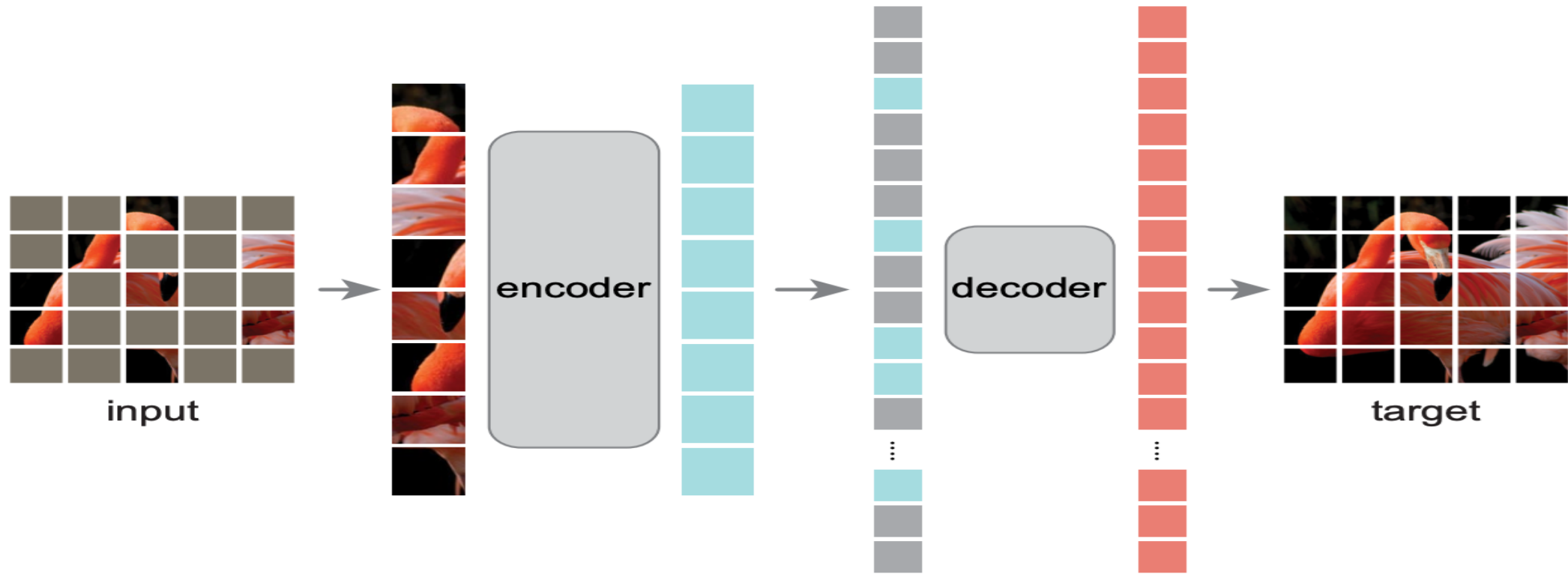
Taleb, Aiham, et al. "3d self-supervised methods for medical imaging." *Advances in neural information processing systems* 33 (2020): 18158-18172.

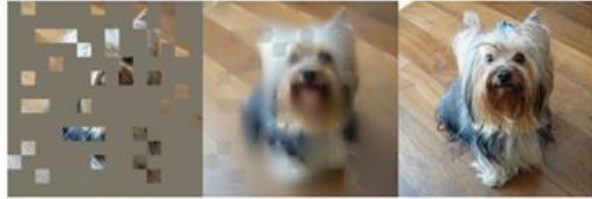
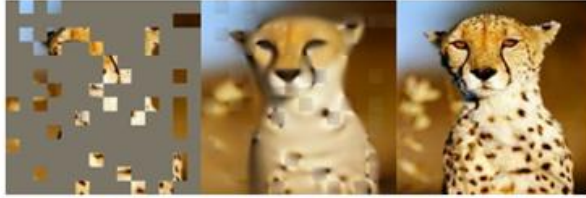
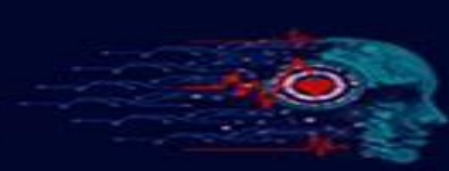


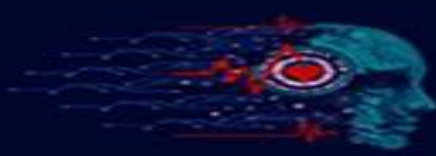
Taleb, Aiham, et al. "3d self-supervised methods for medical imaging." *Advances in neural information processing systems* 33 (2020): 18158-18172.



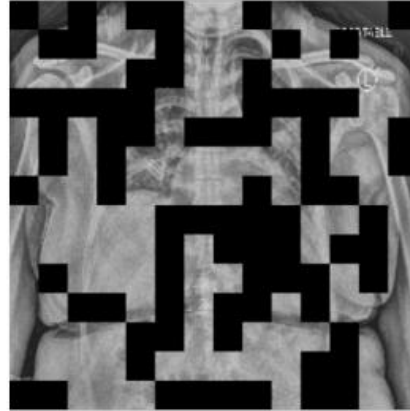
Masked Auto Encoder (MAE)



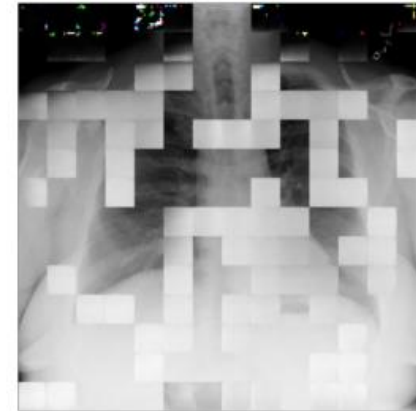




Covid



Normal

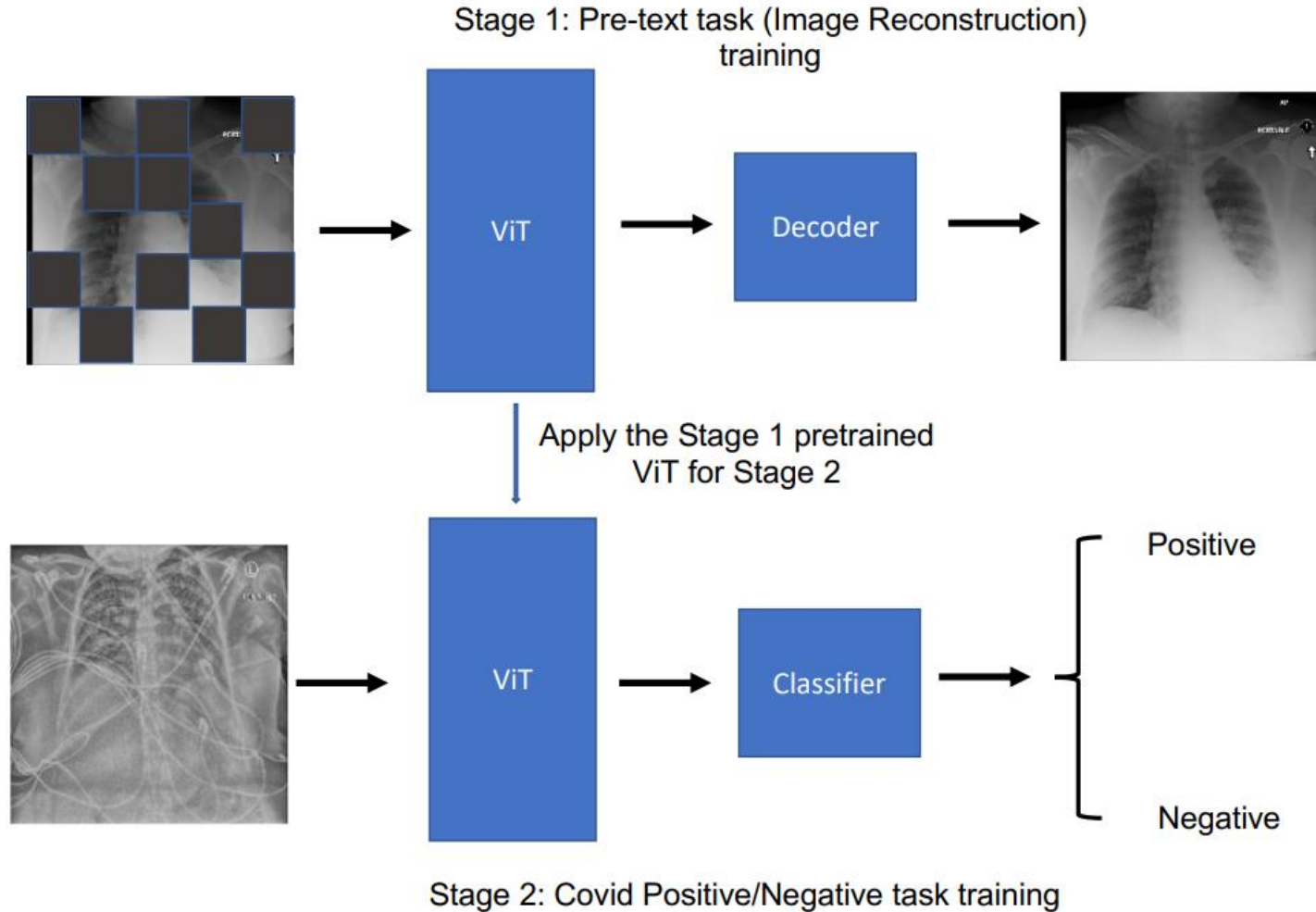
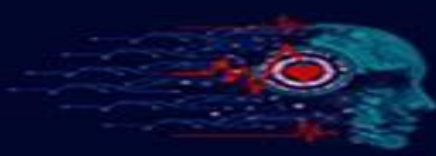


Original

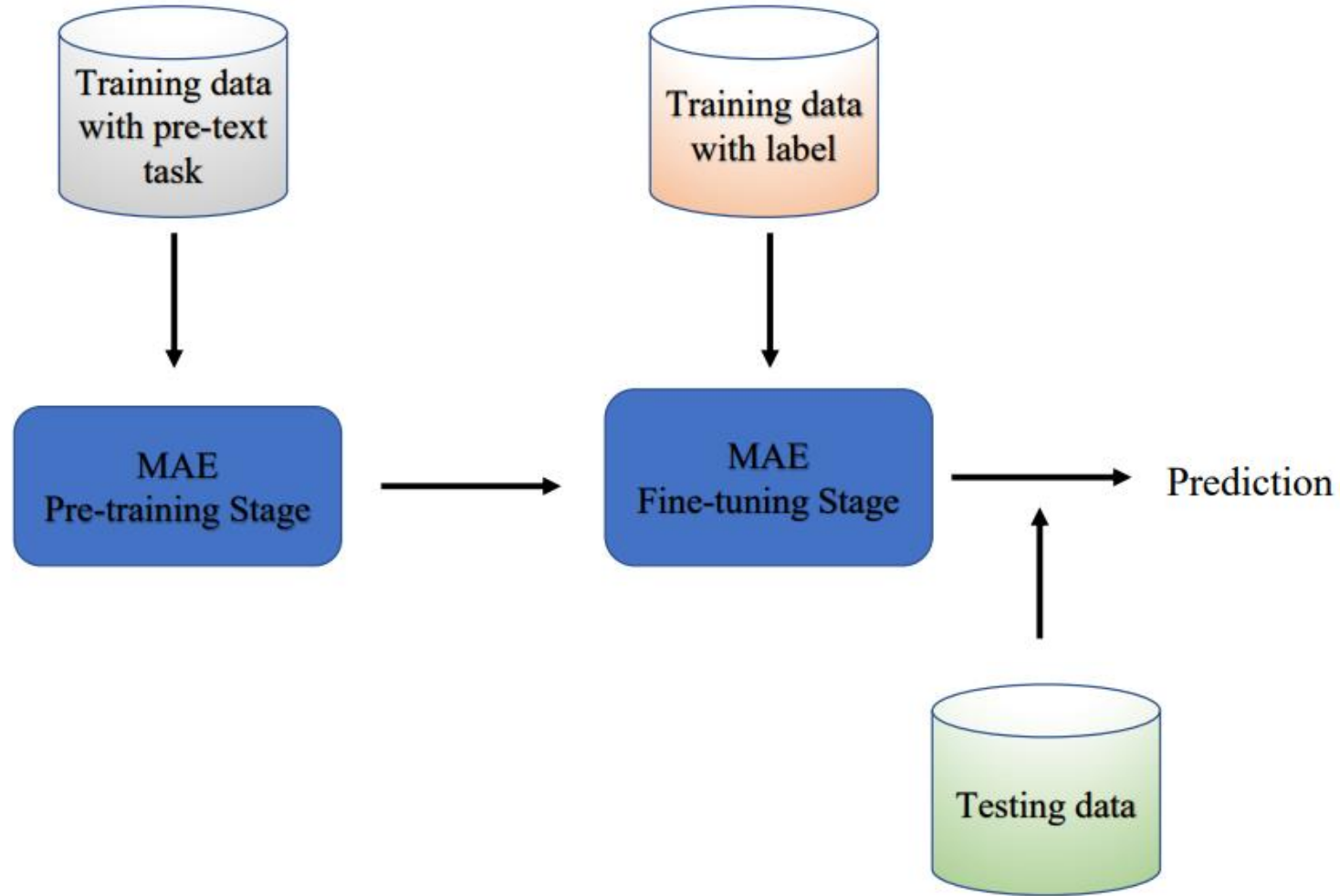
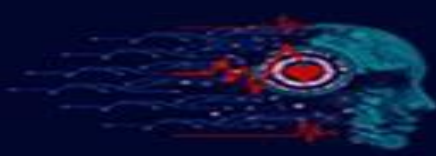
Masked

Reconstruction

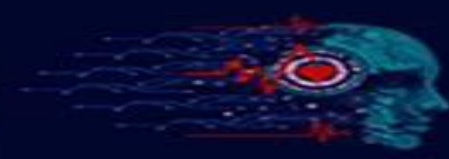
Xing, Xin, et al. "Self-supervised learning application on COVID-19 chest X-ray image classification using masked autoencoder." *Bioengineering* 10.8 (2023): 901.



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

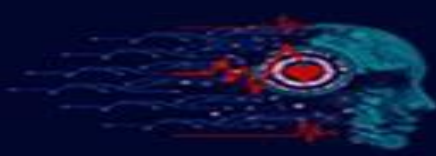


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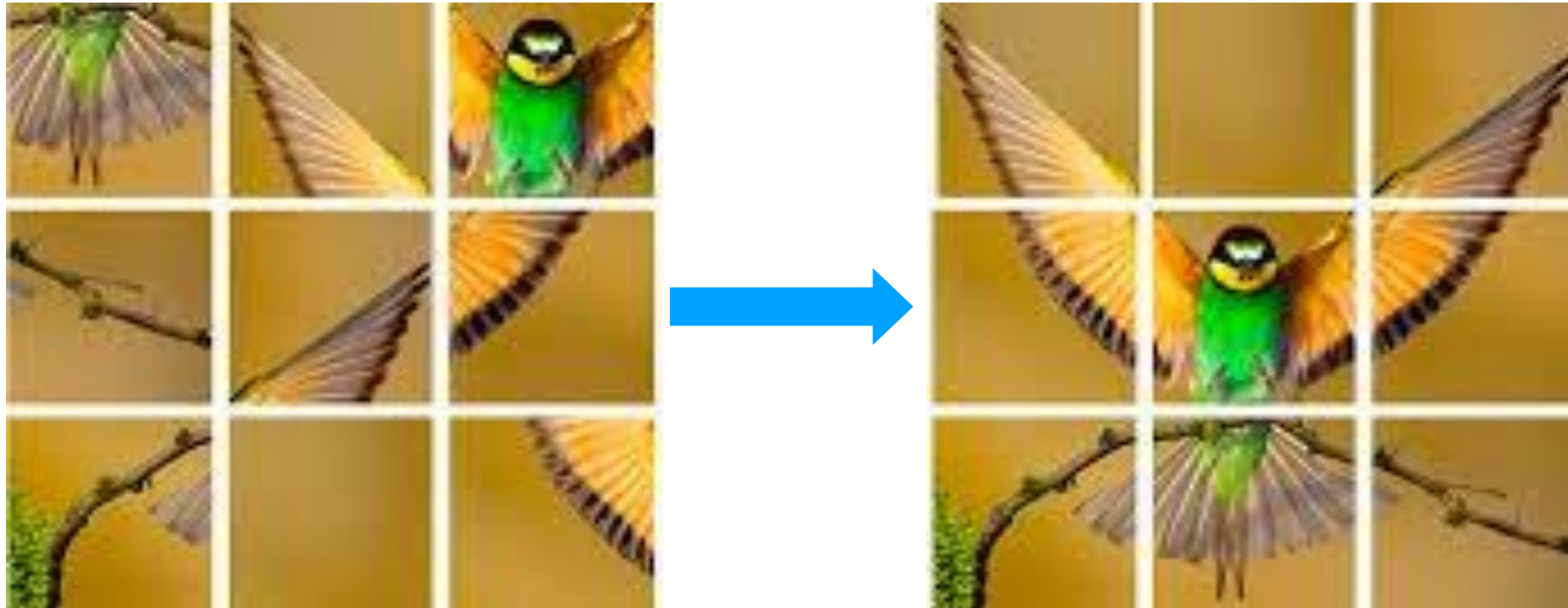


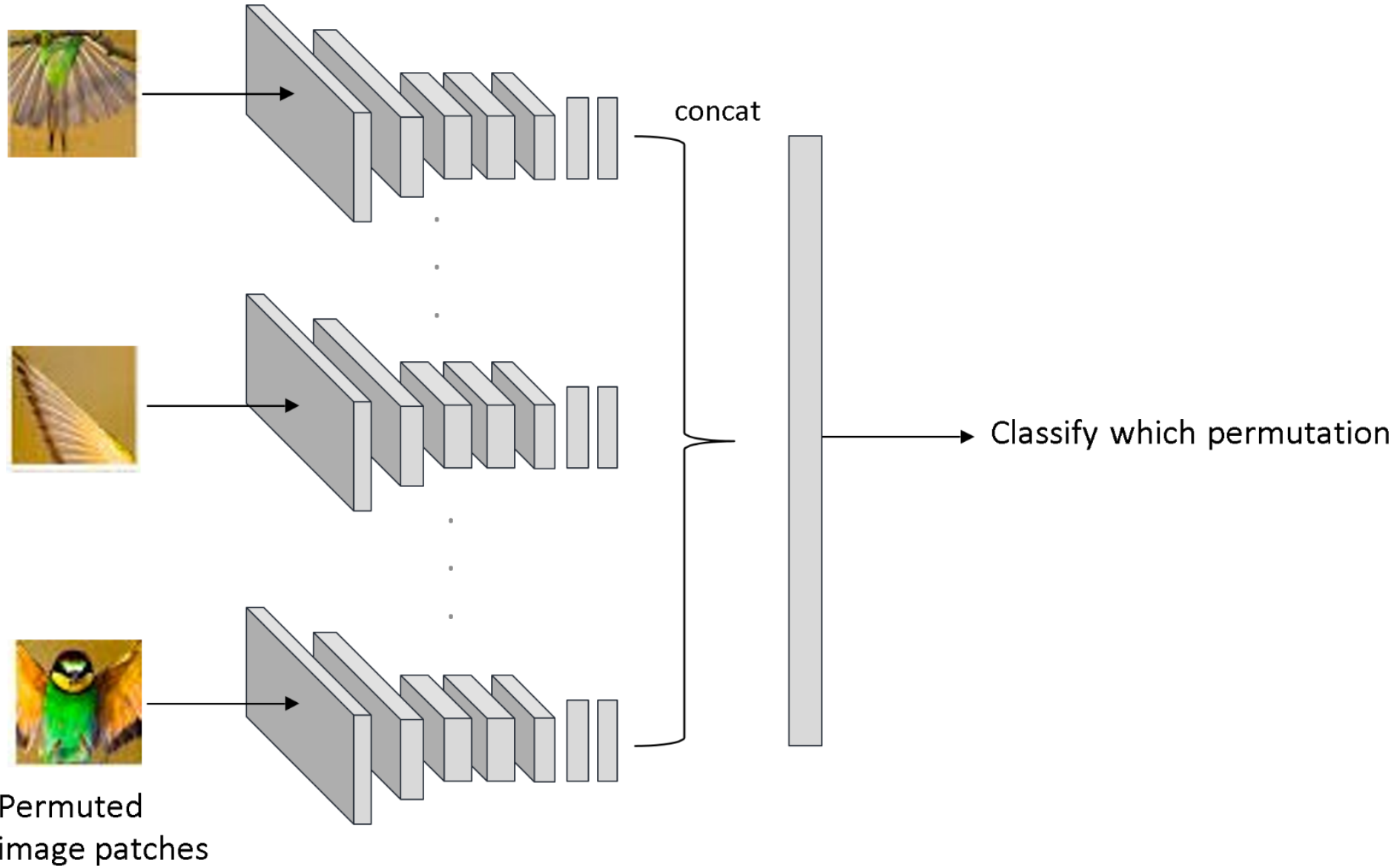
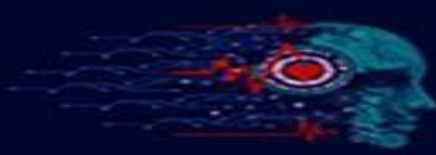
Type	Acc	AUC	F1	Precision	Recall	AP
DenseNet121	0.9775	0.9970	0.9771	0.9948	0.96	0.9750
ResNet50	0.9650	0.9969	0.9641	0.9894	0.94	0.9601
ViT-scratch	0.7075	0.7808	0.7082	0.7065	0.7100	0.6466
ViT-pretrain	0.9350	0.9783	0.9340	0.9484	0.9200	0.9125
ViT-MAE	0.9850	0.9957	0.9850	0.9950	0.9850	0.9859

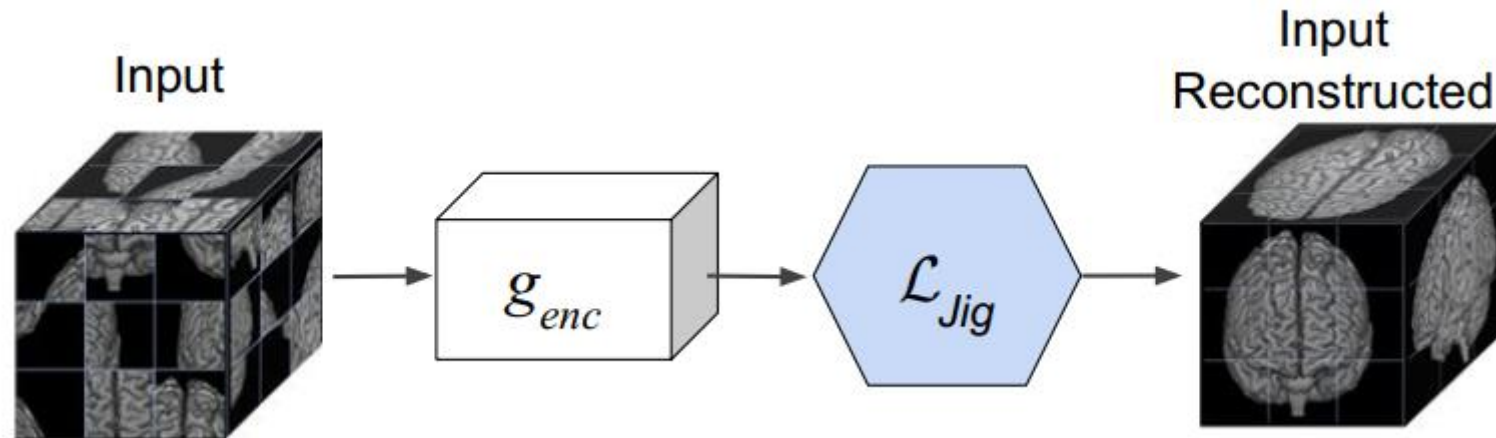
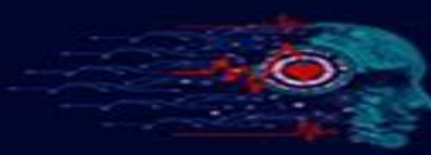
Xing, Xin, et al. "Self-supervised learning application on COVID-19 chest X-ray image classification using masked autoencoder." *Bioengineering* 10.8 (2023): 901.



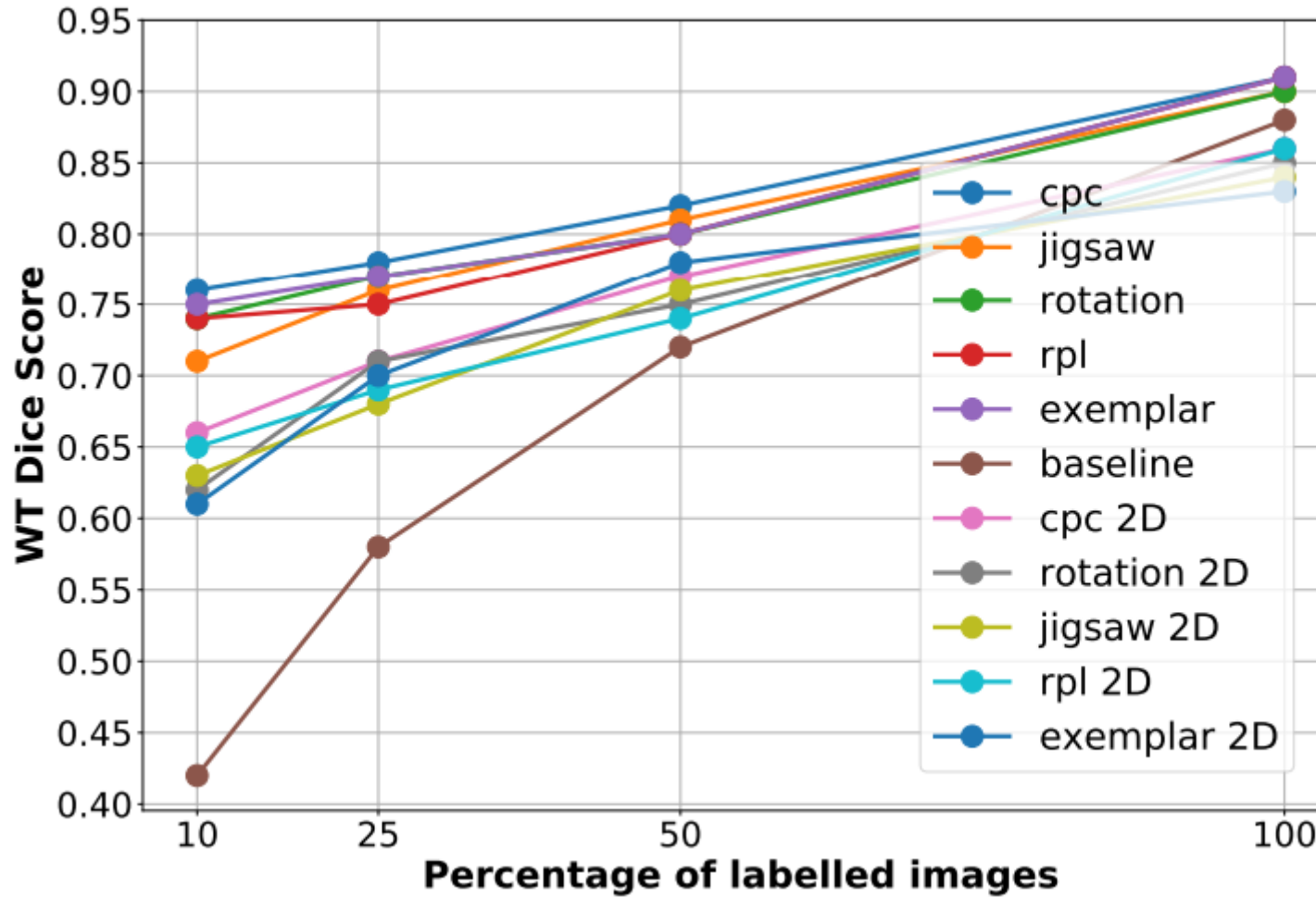
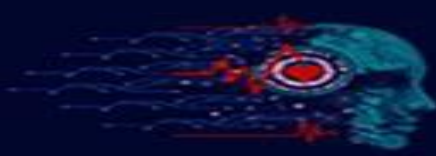
Jigsaw Puzzles



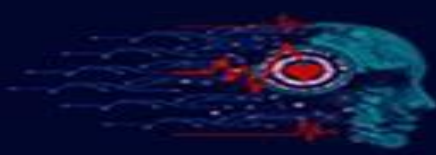




Taleb, Aiham, et al. "3d self-supervised methods for medical imaging." *Advances in neural information processing systems* 33 (2020): 18158-18172.

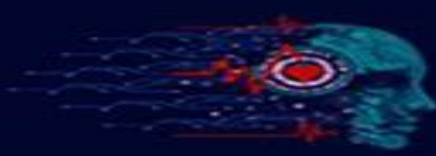


Taleb, Aiham, et al. "3d self-supervised methods for medical imaging." *Advances in neural information processing systems* 33 (2020): 18158-18172.



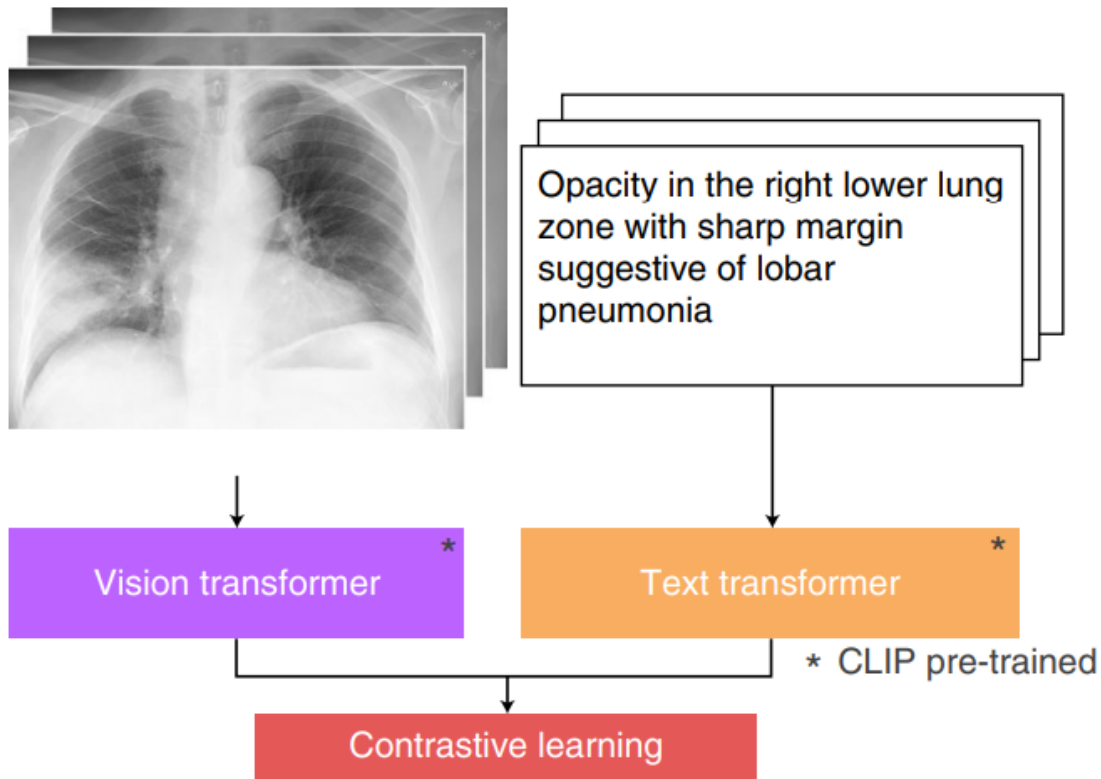
Contrastive



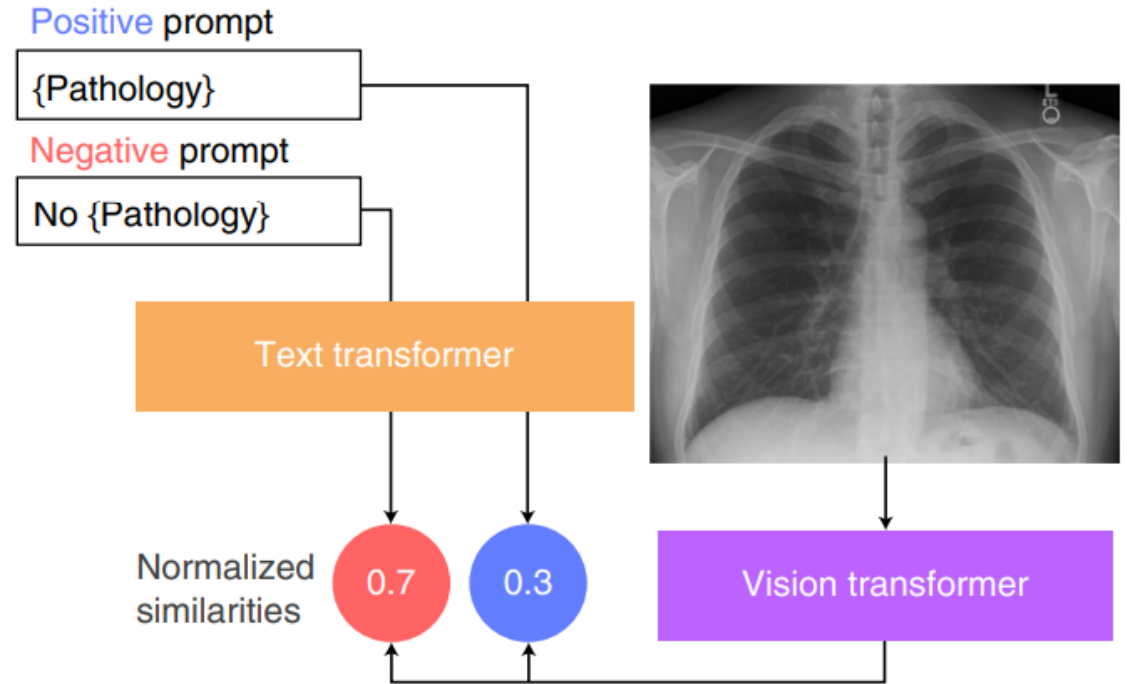


Contrastive Language-Image Pre-training

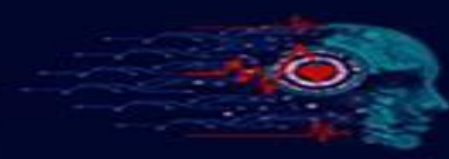
a CheXzero training with chest X-ray image report



b CheXzero zero-shot pathology classification



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.

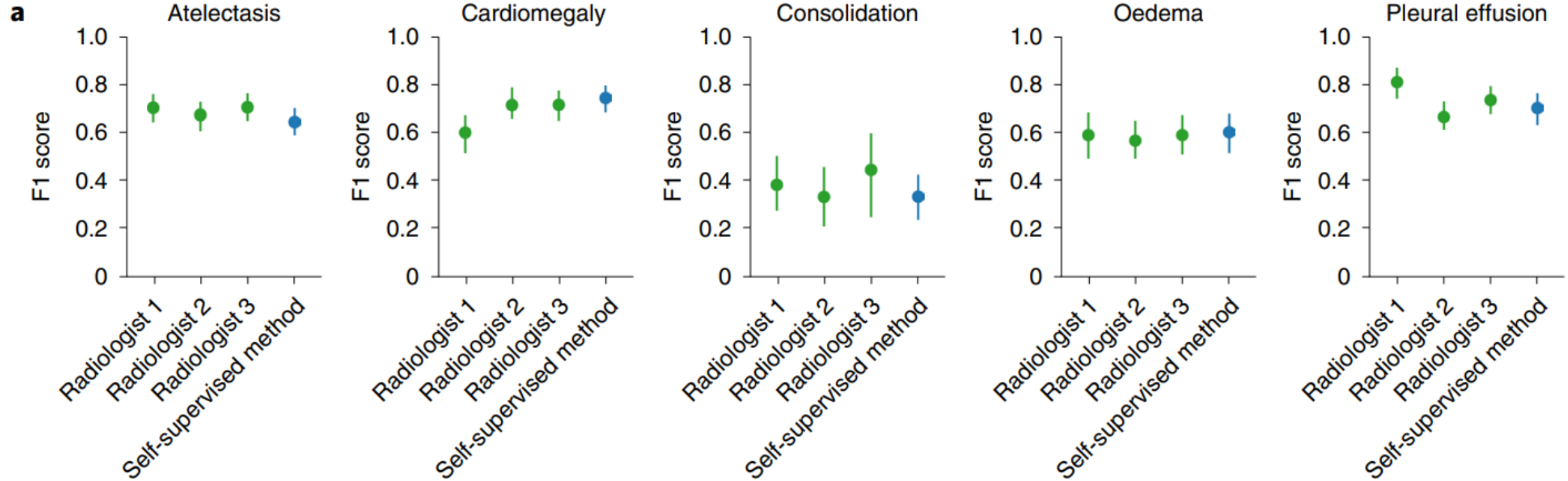
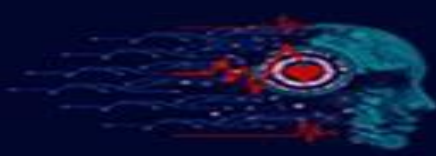


	Model	Mean AUC
Supervised	DAM	0.931
	DenseNet-121	0.902
Self-supervised	GLoRIA ^a	0.534
	ConVIRT- ResNet-50—1%	0.870
	ConVIRT- ResNet-50—10%	0.881
	ConVIRT-ResNet-50—100%	0.881
	ConVIRT-ViT—1% ^b	0.725
	ConVIRT-ViT—10% ^b	0.809
	ConVIRT-ViT—100% ^b	0.856
	MedAug—1%	0.810
	MoCo-CXR—1%	0.802
	MoCo-CXR—10%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

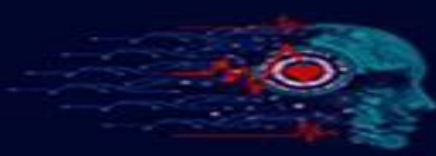
Tiu, Ekin, et al.
self-supervised learning.

Pattern Recognition Engineering (2024), 1000–1006.

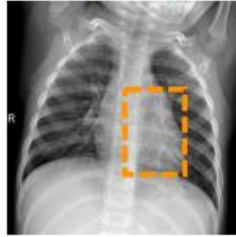
X-ray images via
106.



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.

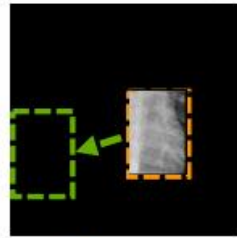


Normal chest radiograph



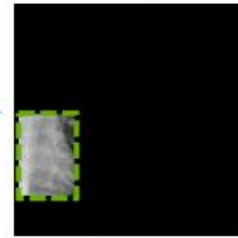
X_{normal}

Random crop



X_{crop}

Random paste



X_{paste}

Anatomical mask



X_{mask}

$$X_{\text{normal}} * (1 - X_{\text{mask}}) + X_{\text{paste}} * X_{\text{mask}}$$

Augmented anomaly



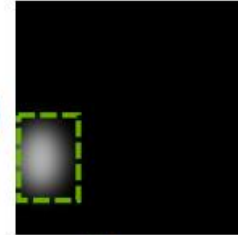
X_{anomaly}

Segmented lung region



X_{seg}

Blurred region

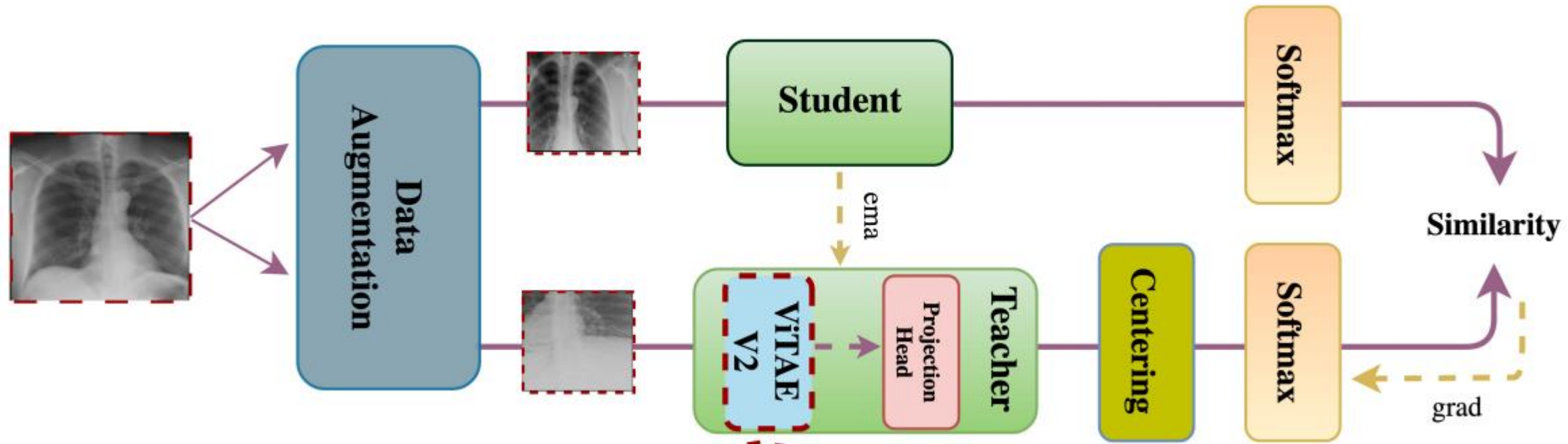
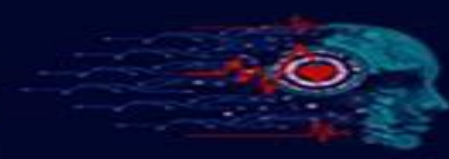


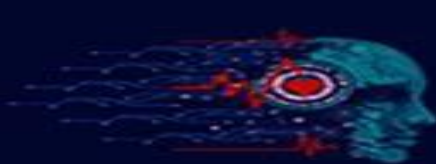
X_{blur}



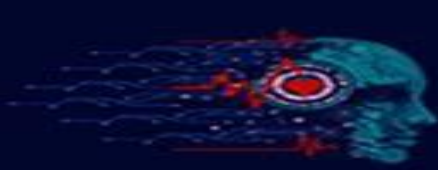
- Cropping region
- Pasting region
- Element-wise multiplication

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



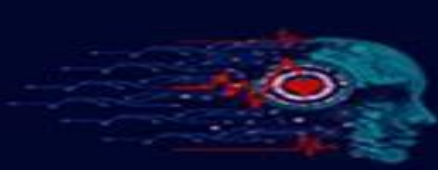


		Non-COVID-19		COVID-19		
Method	ACC	F1-Score	Precision	F1-Score	Precision	Recall
COVIDNet-CXR [29]	67.82±6.11	73.31±3.79	3.36±6.15	56.94±5.05	81.65±6.02	46.82±17.59
COVID-CAPS [1]	65.34±3.26	65.15±5.02	65.62±3.98	64.87±4.42	66.07±4.49	64.93±9.71
COVID-SDNet [26]	76.18±2.70	76.94±2.82	74.74±3.89	75.71±3.35	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



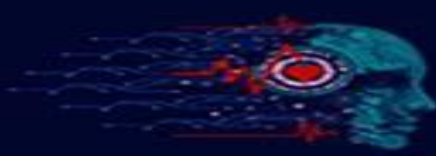
Discussion: The Future of SSL in Medicine

- 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



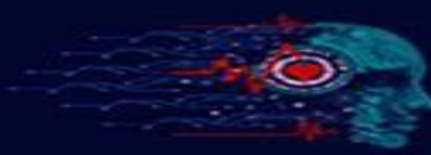
Future Research Directions

- 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
- Explainability
- Hardware Limitations



Open Challenges and Opportunities

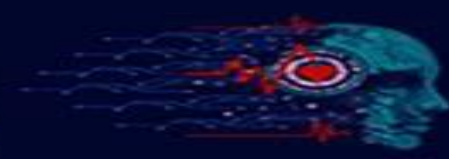
- Overcoming computational demands of SSL
- Lack of large, diverse datasets in medicine
- Ensuring robustness across diverse populations
- Scaling up from research to clinical practice



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

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 (۰۹:۰۰ صبح - ۱۲:۰۰)
اولین کنگره بین المللی مجازی
کاربرد هوش مصنوعی
در علوم پزشکی



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