Benchmarking and Boosting Transformers for Medical Image Classification

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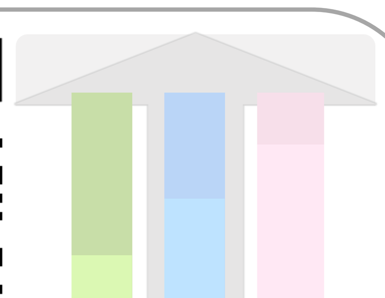
MAYO CLINIC

MOTIVATION: Transformers have good properties for medical images

- Pay attention to whole image to model global context of a body region
- Capture intra-image relations to detect co-occurrence of pathologies
- Build hierarchical feature maps to identify lesions at different scales



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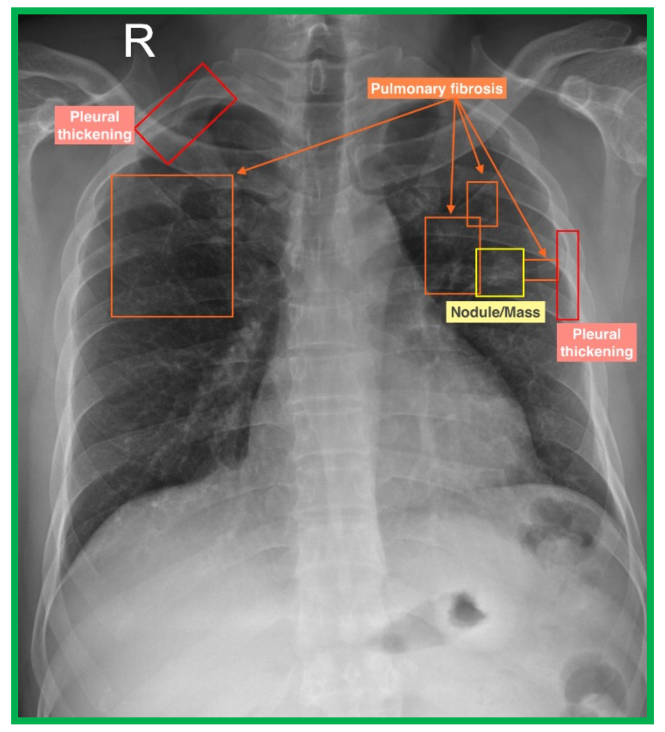


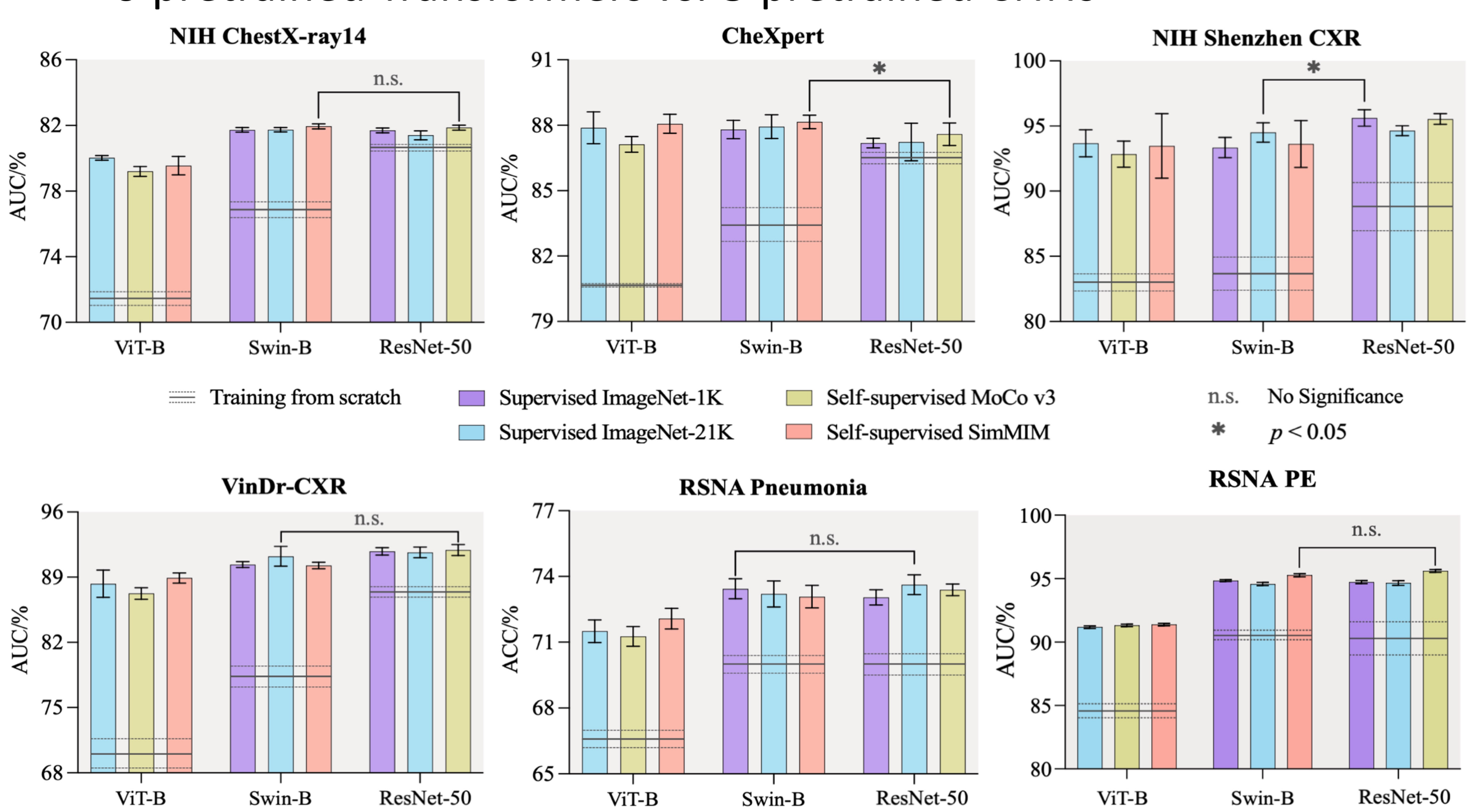
Q1
How do visual transformers perform on medical images?

Transformers need pretraining to achieve competitive performance on medical images

Benchmarking:

2 Transformer architectures *vs.* **1** CNN architecture

6 pretrained Transformers *vs.* **3** pretrained CNNs



Result I : Transformers significantly underperform CNNs when training from scratch

Result II: Transformers can offer similar results as CNNs with ImageNet pretraining

Q2
What pretraining method for transformers performs the best?

Self-supervised learning based on masked image modeling can learn preferable features for medical tasks

Comparing:

Supervised pretraining using both ImageNet images and labels *vs.* Self-supervised pretraining using only ImageNet images

Method		ChestX-ray14	CheXpert	Shenzhen	VinDr-CXR	RSNA Pneumonia	RSNA PE
Supervised	ViT-B	80.05±0.17	87.88±0.50	93.67±1.03	88.30±1.45	71.50±0.52	91.19±0.11
	Swin-B	81.73±0.14	87.80±0.42	93.35±0.77	**90.35±0.31**	73.44±0.46	94.85±0.07
SimMIM	ViT-B	79.55±0.56	88.07±0.43	93.47±2.48	88.91±0.55	72.08±0.47	91.39±0.10
	Swin-B	**81.95±0.15**	**88.16±0.31**	**94.12±0.96**	90.24±0.35	**73.66±0.34**	**95.27±0.12**
Swin-B vs. Swin-B		*	n.s.	*	n.s.	n.s.	*

*The best methods are bolded while the others are highlighted in green if they achieve equivalent performance compared with the best one (i.e., p > 0.05).

Result III: Self-supervised SimMIM model with the Swin-B backbone outperforms fully-supervised baselines

Q3
Can we further boost transformers' performance for medical images?

Domain-adaptive pretraining using a large-scale in-domain dataset can further boost transformers' performance

Boosting:

Create a large-scale in-domain dataset by assembling 13 datasets to satisfy transformer's data hunger → X-rays(926K)

Adopt self-supervised learning to overcome heterogeneity of expert labels

Model (SimMIM+Swin-B)	ChestX-ray14	CheXpert	Shenzhen	VinDr-CXR	RSNA Pneumonia
Scratch	77.04±0.34	83.39±0.84	92.52±4.98	78.49±1.00	70.02±0.42
ImageNet	81.95±0.15	88.16±0.31	94.12±0.96	90.24±0.35	73.66±0.34
ChestX-ray14	78.87±0.69	86.75±0.96	93.03±0.48	79.86±1.82	71.99±0.55
X-rays(926K)	82.72±0.17	87.83±0.23	95.21±1.44	90.60±1.95	73.57±0.27
ImageNet→ChestX-ray14	82.45±0.15	87.74±0.31	94.83±0.90	90.33±0.88	73.85±0.72
ImageNet→X-rays(926K)	**83.04±0.15**	**88.37±0.40**	**95.76±1.79**	**91.71±1.04**	**74.09±0.39**
ImageNet vs. ImageNet→X-rays(926K)	>***	n.s.	*	>***	*

*The best methods are bolded while the others are highlighted in green if they achieve equivalent performance compared with the best one (i.e., p > 0.05).

Result IV: The domain-adapted model with learning experience on both ImageNet and a large-scale in-domain data (X-rays(926K)) achieves the highest performance