Models Genesis: Generic Autodidactic Models for 3D Medical Image Analysis

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Project page: github.com/MrGiovanni/ModelsGenesis

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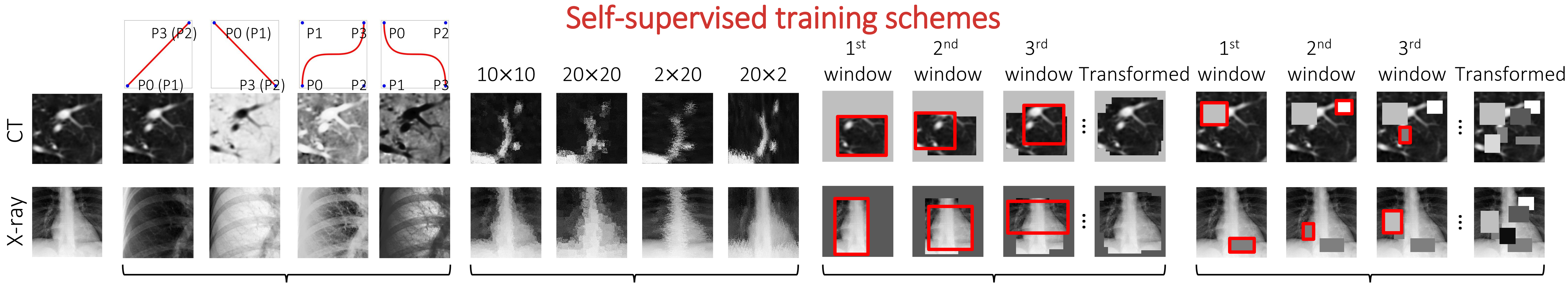
We provide pre-trained 3D models for 3D medical image analysis

Background: **Transfer learning** from *natural* images to *medical* images has established as **one of the most practical paradigms** in deep learning for medical image analysis. However, to fit this paradigm, 3D imaging tasks in the most prominent imaging modalities (*e.g.*, CT and MRI) have to be reformulated and solved in 2D, losing rich 3D anatomical information and inevitably compromising the performance. **Pre-trained 3D models have yet to emerge for 3D medical imaging.**

Contribution: A collection of pre-trained 3D generic source models, called **Models Genesis,** built directly from unlabeled 3D images with our novel self-supervised learning method to learn common visual representation of anatomy for generating powerful application-specific target models via transfer learning.

Vision: Through **open science**, we envision that Models Genesis may serve as a primary resource in transfer learning for 3D medical imaging, in particular, with limited annotation, and hope that such collaborative efforts will lead to the **Holy Grail of Models Genesis**, **effective across diseases, organs, and modalities**.

Self-supervised training schemes



Transformations: I. Non-linear | II. Local-shuffling | III. Out-painting | IV. In-painting

Learning perspectives: Organ appearance | Organ texture and local boundaries | Organ spatial layout and global geometry | Local continuities of organs

V. Combination

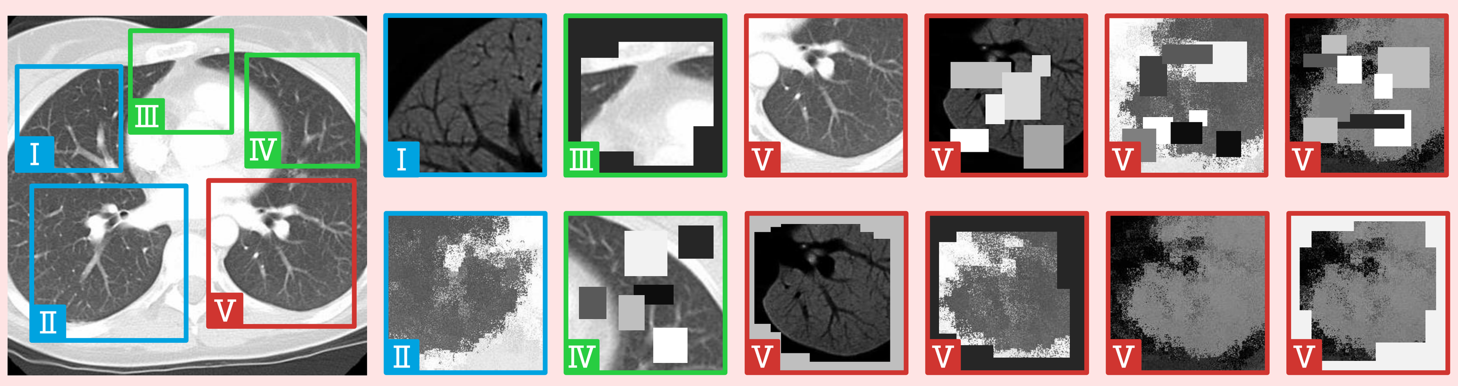


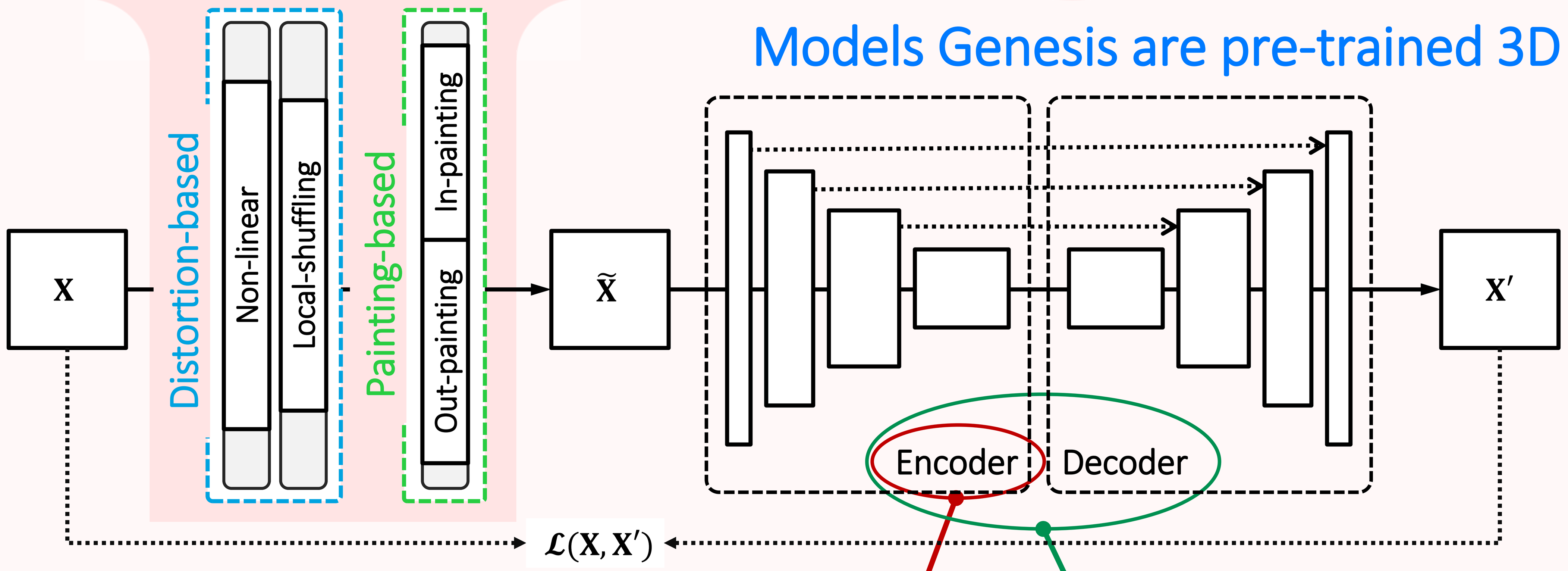
Image transformation

Ablation study: Learning from multiple perspectives leads to robust models

Task	Scratch (%)	I & II (%)	III & IV (%)	V (%)	*p*-value
Lung nodule false positive reduction	94.25±5.07	96.46±1.03	**98.20±0.51**	97.90±0.57	0.0848
Lung nodule segmentation	74.05±1.97	77.08±0.68	77.02±0.58	**77.62±0.64**	0.0520
PE false positive reduction	79.99±8.06	**88.04±1.40**	87.18±2.72	87.20±2.87	0.2102
Liver segmentation	74.60±4.57	79.08±4.26	78.62±4.05	**79.52±4.77**	0.4249
Brain tumor segmentation	90.16±0.41	**90.60±0.20**	90.46±0.21	90.59±0.21	0.4276

The statistical analyses are conducted between the top-2 models in each row highlighted in red.

Models Genesis are pre-trained 3D models for 3D medical image analysis



Properties of Models Genesis:

- Autodidactic—requiring no manual labeling
- Robust—learning from multiple perspectives
- Scalable—accommodating many training schemes
- Generic—yielding diverse applications

Take the pre-trained encoder for target classification tasks

Take the pre-trained encoder-decoder for target segmentation tasks

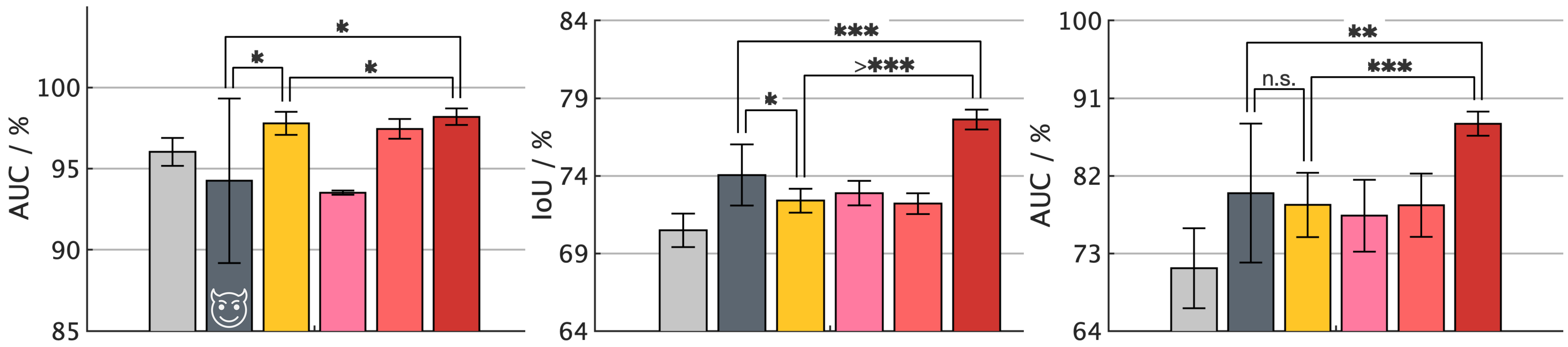
Result 1: Models Genesis outperform 3D models trained from scratch

Task	Modality	Metric	Scratch (%)	Genesis (%)	*p*-value
Lung nodule false positive reduction	CT	AUC	94.25±5.07	**98.20±0.51**	0.0180
Lung nodule segmentation	CT	IoU	74.05±1.97	**77.62±0.64**	1.04e-4
PE false positive reduction	CT	AUC	79.99±8.06	**88.04±1.40**	0.0058
Liver segmentation	CT	IoU	74.60±4.57	**79.52±4.77**	0.0361
Brain tumor segmentation	MRI	IoU	90.16±0.41	**90.60±0.20**	0.0041

The statistical analyses are conducted between Scratch and Genesis.

Scratch 2D
Scratch 3D
ImageNet
Genesis X-ray 2D
Genesis CT 2D
Genesis CT 3D
n.s. no significance
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$
>*** $p < 0.0001$

Result 2: Models Genesis consistently top any 2D approaches



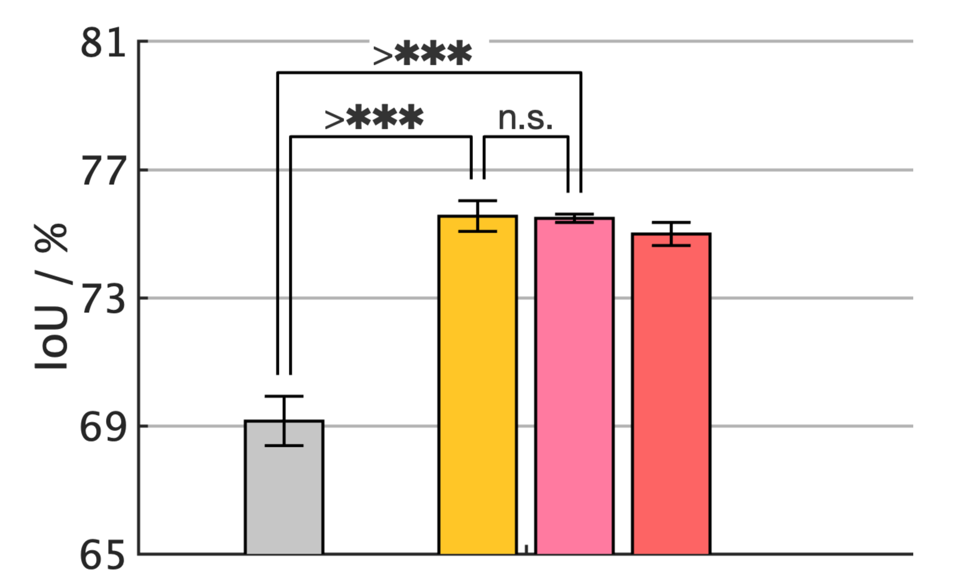
Lung nodule false positive reduction 3D CT [LUNA-2016]

Lung nodule segmentation 3D CT [LIDC-IDRI]

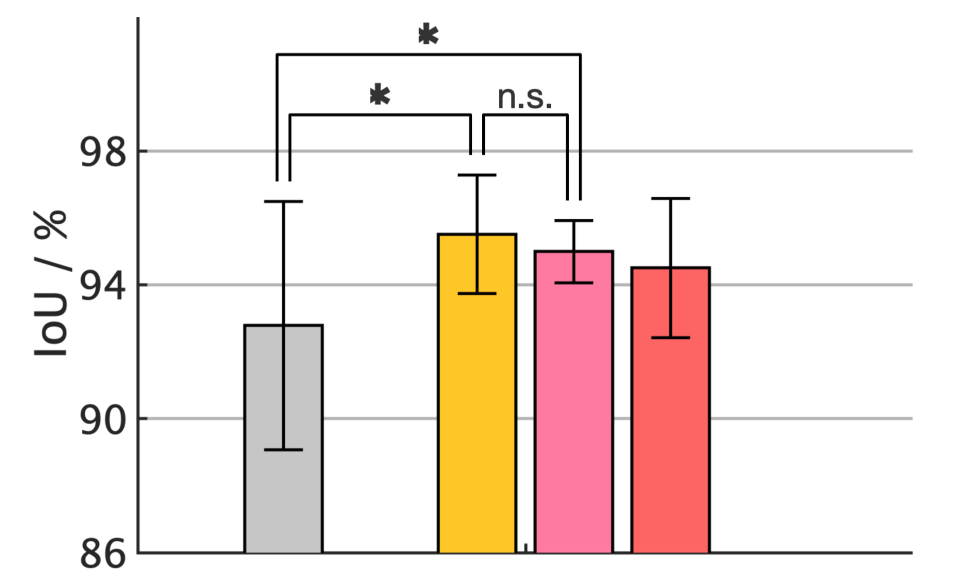
PE false positive reduction 3D CT [PE-CAD]

😈: Learning from scratch *simply* in 3D may not necessarily yield performance better than ImageNet-based transfer learning in 2D

Result 3: Models Genesis (downgraded 2D) offer performances equivalent to supervised pre-trained models (unprecedentedly)



Eight pulmonary diseases classification 2D X-ray [ChestX-ray8]



RoI/bulb/background classification 2D Ultrasound [UFL MCAEL]

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