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

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Project page: github.com/MrGiovanni/ModelsGenesis

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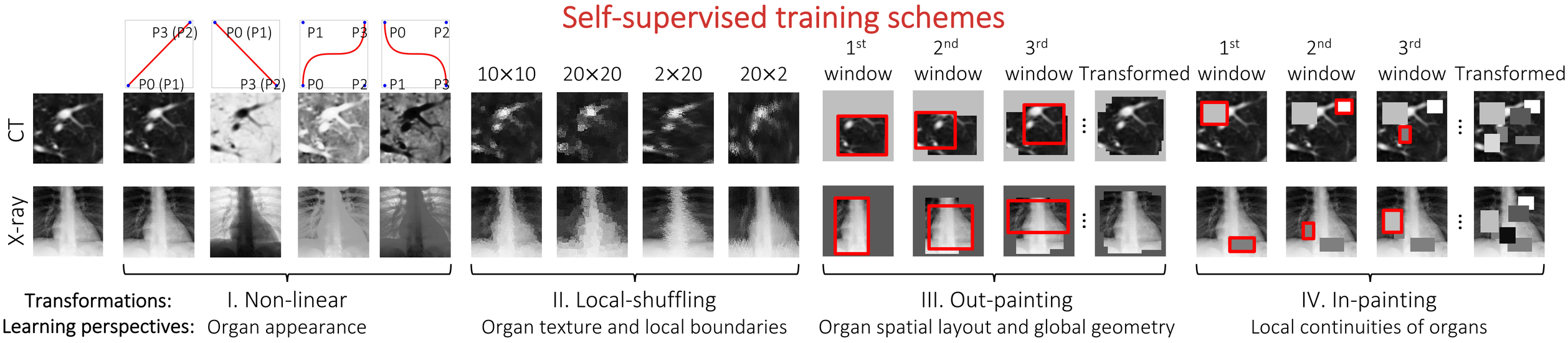
## We provide pre-trained 3D models for 3D medical image analysis

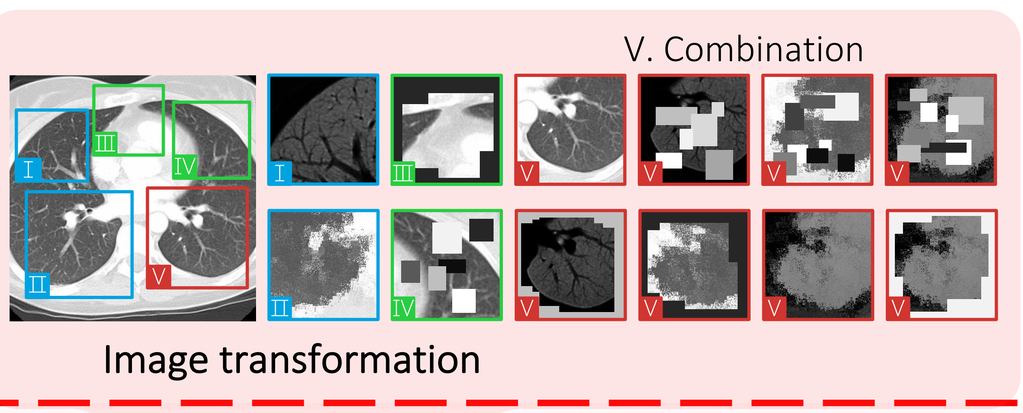
Background: **Transfer learning** from *natural* images to *medical* images has established as **one of the most practical paradigms** in deep learning for medical image analysis. However, to fit this paradigm, 3D imaging tasks in the most prominent imaging modalities (*e.g.*, CT and MRI) have to be 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 Generic Autodidactic Models, nicknamed Models Genesis. They are built directly from unlabeled 3D image data with our novel self-supervised learning method, for **generating powerful application-specific target models through 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



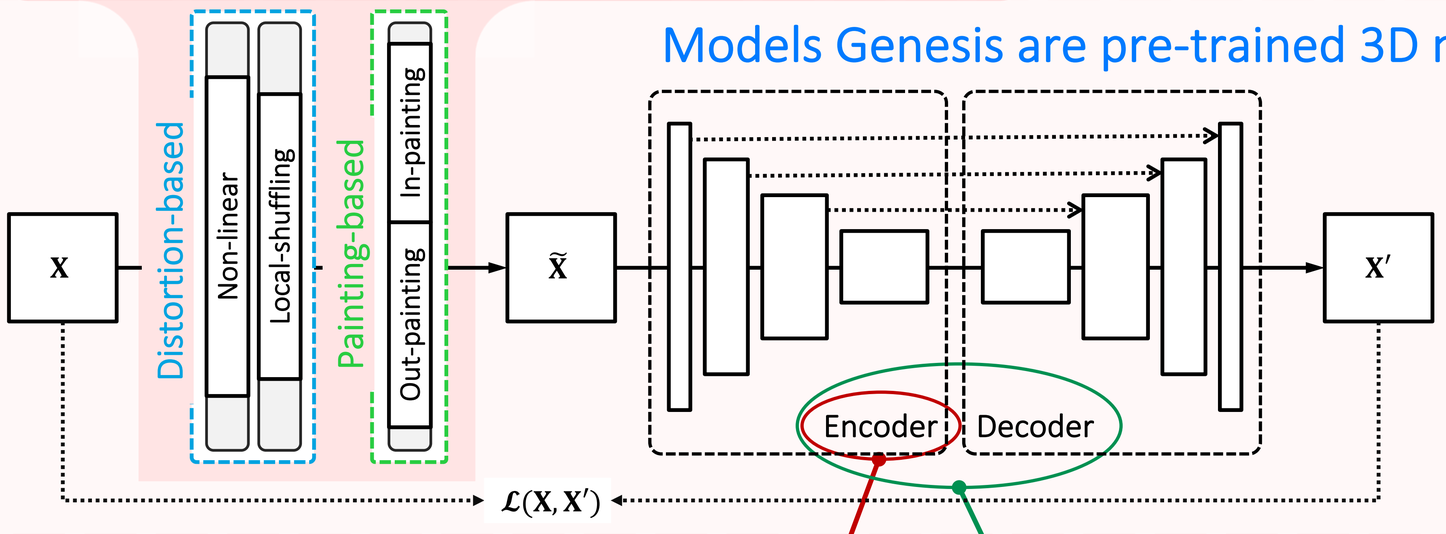




Ablation study: **Learning from multiple perspectives leads to robust models**

| 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




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

### Properties of Models Genesis:

- Autodidactic—requiring no manual labeling
- Robust—learning from multiple perspectives
- Scalable—eliminating proxy-task-specific heads
- Generic—yielding diverse applications

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

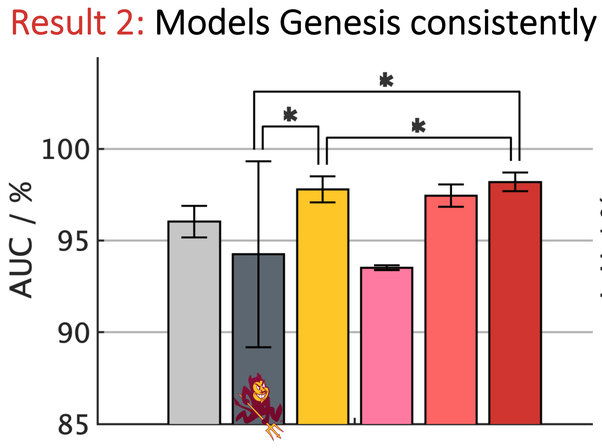
| Task | Modality | Metric | Scratch (%) | Genesis (%) | *p*-value |
|---|---|---|---|---|---|
| Lung nodule false positive reduction | CT | AUC | 94.25±5.07 | **98.20±0.51** | 0.0180 |
| Lung nodule segmentation | CT | IoU | 74.05±1.97 | **77.62±0.64** | 1.04e-4 |
| PE false positive reduction | CT | 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 |

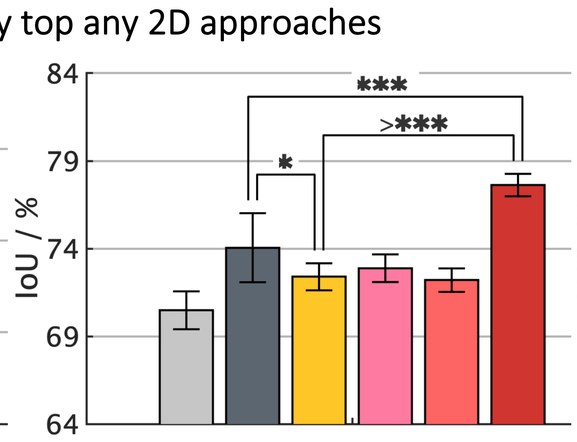
The statistical analyses are conducted between Scratch and Genesis.

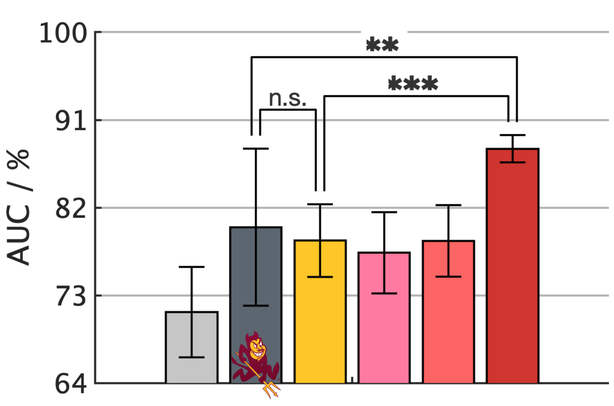
Scratch 2D
Scratch 3D
ImageNet
Genesis X-ray 2D
Genesis CT 2D
Genesis CT 3D

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**

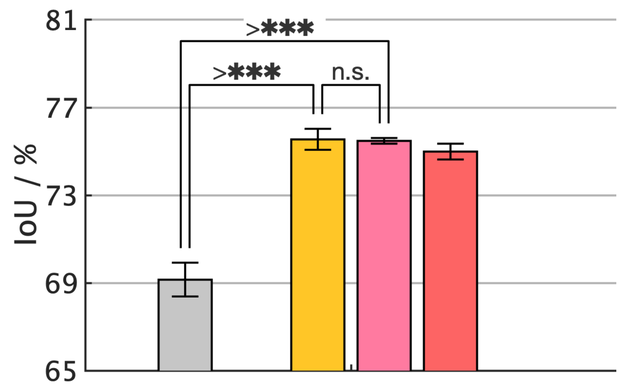


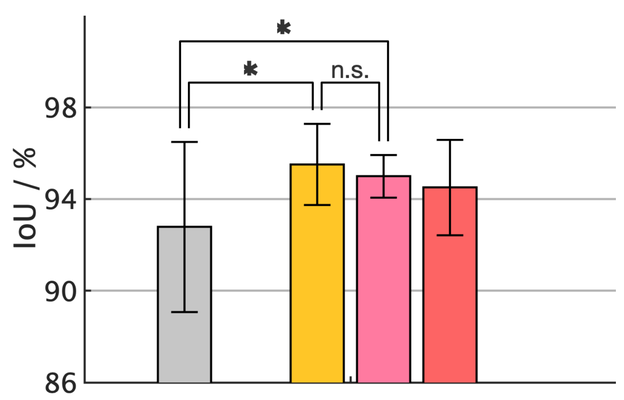




: Learning from scratch *simply* in 3D may not necessarily yield performance better than ImageNet-based transfer learning in 2D

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

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