Are Natural Domain Foundation Models Useful For Medical Image Classification?

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Deep learning is converging towards the use of foundation models. We attempt to investigate the transferability of these to medical image classification tasks. We explore different training settings to fully harness their potential and gain insights on their applicability in this domain.

1 MODELS

Foundation models:

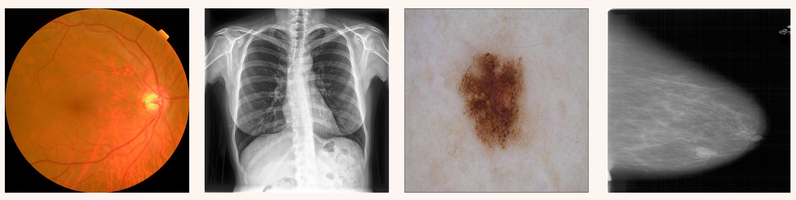
- SAM (88.8M parameters) [1]
- SEEM (29.9M parameters) [2]
- DINOv2 (86.5M parameters) [3]
- OpenCLIP (86.2M parameters) [4]
- BLIP (85.7M parameters) [5]

Baselines:

- ImNet-1k-Sup (DeiT) [6]
- DINOv1 [7]
- ResNet152 [8]

2 METHODS

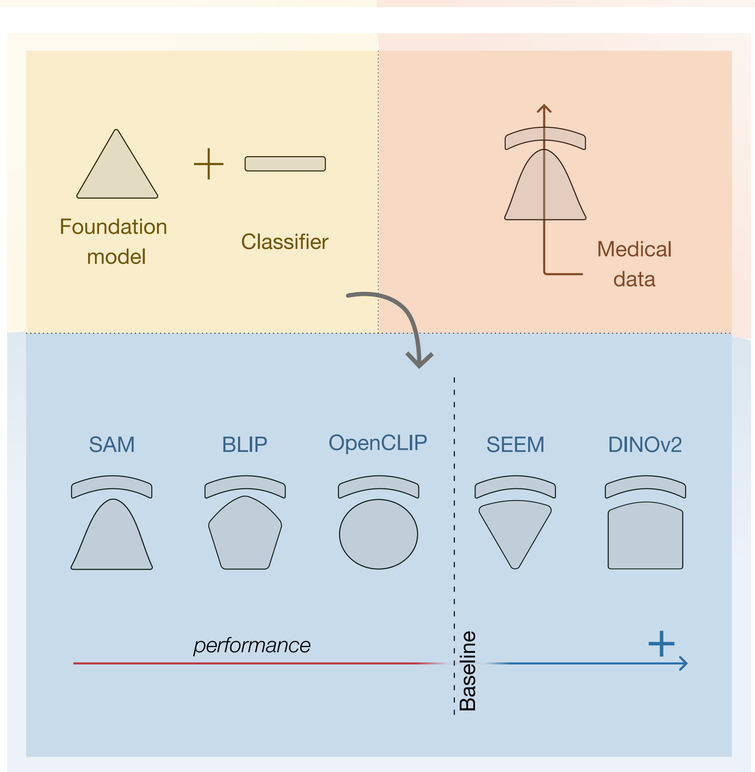
Medical datasets:



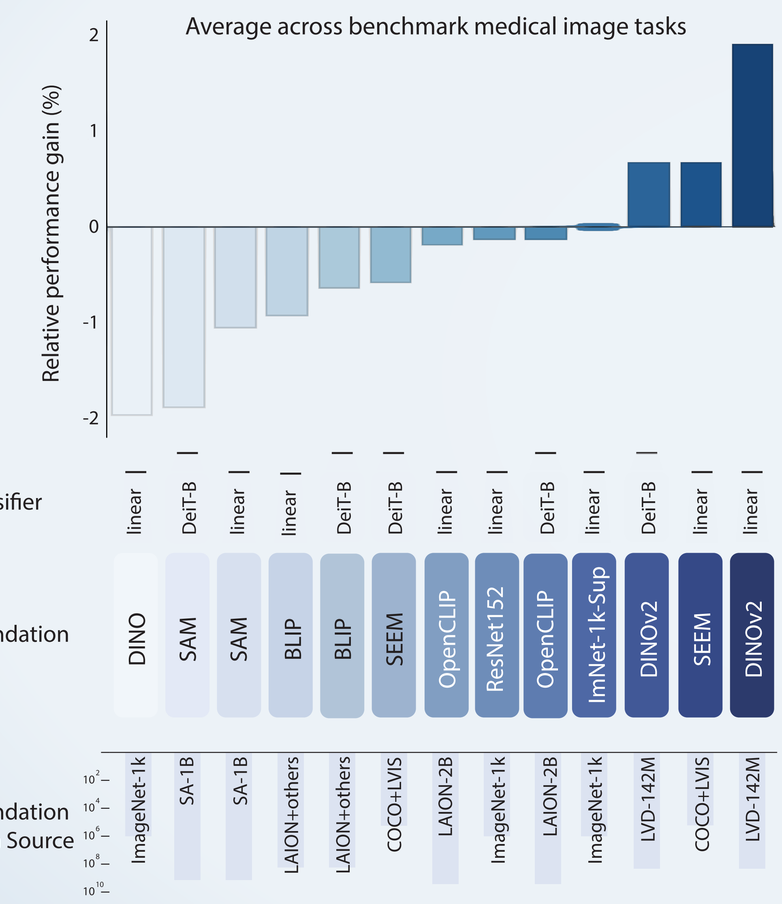
APTOS2019 CheXpert ISIC2019 DDSM

Evaluation scenarios:

- Frozen foundation with linear head
- Unfrozen foundation with linear head
- Frozen foundation with appended DeiT classifier
- Unfrozen foundation with appended DeiT classifier



3 RESULTS



KEY FINDINGS:

- DINOv2 serves as a solid base for transfer learning and SEEM competes effectively while being a smaller model. Other foundations fail to outperform baselines effectively.
- DINOv2 converges faster compared to the other models.
- Adapting the foundation models to downstream tasks, especially their deeper layers, is key.
- Appending a DeiT classifier to the foundation models results in marginal performance gains.
- Both architectural differences and pre-training objectives significantly influence transfer learning success.

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