Unsupervised Pretraining of Foundation Models for Medical Imaging

Scott Chase Waggener

September 24, 2023

Overview

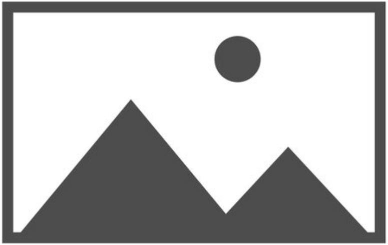
- Motivation
    - Convolutional networks and their limitations
    - Transformers, strengths and weaknesses
    - Desired properties of a medical imaging foundation model
- Unsupervised Pretraining Methods
    - Masked Autoencoder
    - Contrastive Embedding
    - Query Box Localization
- Results

Motivation

- Deep learning models can analyze medical images (such as mammograms) to assist in diagnosis [7]
- Many such models use convolutional architectures [2], which incorporate a locality prior
- Such a prior can accelerate learning, but can also be restrictive

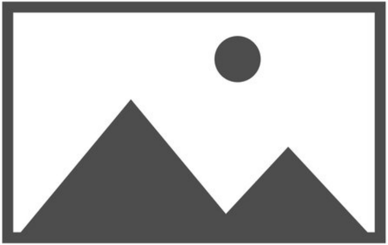
Motivation

- Mammographic screenings capture four standard views of the breasts
  - Medio-lateral oblique (MLO)
  - Cranio-caudal (CC)
  - MLO and CC views are approximately orthogonal



Motivation

- The standard views are typically examined together to leverage bilateral symmetry
- Reference images are used (when available) to compare to the standard views
- Sometimes lesions will appear in multiple views



Motivation

A strong mammography model should incorporate all available information:

- Orthogonal nature of MLO and CC views is incompatible with a locality prior
- Additional imaging may be available with similar incompatible relationships
- Textual information may also be available (medical reports)

Similar considerations apply to other medical imaging modalities

Motivation

Objectives to improve mammographic performance:

- Relax the locality prior
- Support a variable number of additional context images
- Support textual information

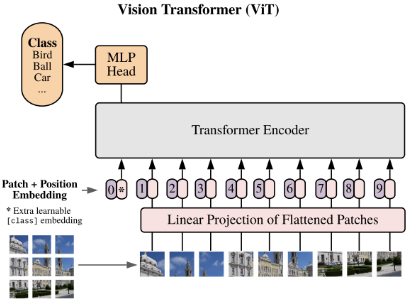
These objectives will also improve performance on other medical imaging modalities like:

- X-ray
- CT
- MRI
- Ultrasound

Motivation

Vision Transformers (ViTs) can address these objectives:

- Vision Transformers (ViTs) can achieve state-of-the-art results on image classification tasks [5]
- Attention is not restricted by a locality prior
- Transformers are cardinality invariant
- Transformers can support multiple modalities (Med-PaLM2) [8]



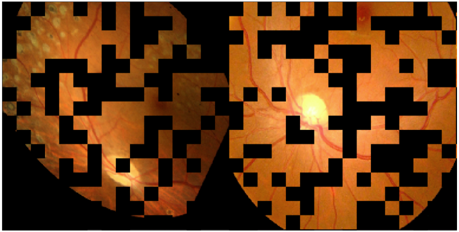
Motivation

ViTs are not without drawbacks:

- They require a large amount of labeled data (JFT-300M) [5]
  - Medical imaging datasets are often small and expensive to label
  - Thousands of images instead of millions or billions
- Or they require clever training methods (DeiT) [9]
- Self attention is expensive to compute (quadratic)
- Relatively difficult to train from scratch
  - Numerical instability
  - Sensitivity to batch size
  - Resource intensive

Masked Autoencoder

- Follows from masked language modeling (BERT) [4]
- Mask a subset of the input patches, regress to the original input



Contrastive Embedding

- Follows from popular contrastive learning methods (DINO) [1]
- Model creates an embedding vector for each image
- Embeddings should be similar for augmented versions of the same image
- Embeddings should be dissimilar for different images

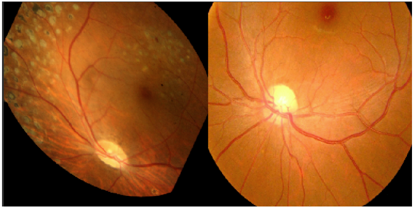


Figure: Global augmentation

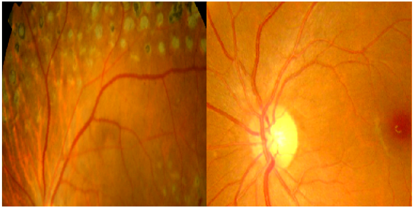


Figure: Local augmentation

Query Box Localization

- Inspired by UP-DETR, a pretraining method for detection models [3]
- Regions of interest are randomly selected and augmented
- Given the original image and the augmented image, the model should predict the bounding box of the region of interest

Figure: Original image

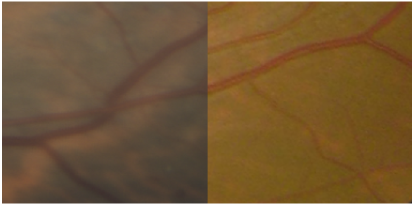


Figure: Augmented ROIs

Methods

Architecture:

- Inspired by ViTDet [6]
- Standard patch embedding with log-spaced sinusoidal position embeddings
- Window attention without shifting
- Global attention at periodic intervals

Training:

- One or more of the pretraining methods are incorporated into the training process
- Tasks are cyclically sampled at each minibatch

References

[1] Mathilde Caron et al. *Emerging Properties in Self-Supervised Vision Transformers*. 2021. arXiv: 2104.14294 [cs.CV].

[2] Timothy Cogan, Maribeth Cogan, and Lakshman Tamil. "RAMS: Remote and automatic mammogram screening". In: *Computers in Biology and Medicine* 107 (2019), pp. 18–29. ISSN: 0010-4825. DOI: https://doi.org/10.1016/j.compbiomed.2019.01.024. URL: https://www.sciencedirect.com/science/article/pii/S0010482519300307.

[3] Zhigang Dai et al. "Unsupervised Pre-Training for Detection Transformers". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2022), pp. 1–11. DOI: 10.1109/tpami.2022.3216514. URL: https://doi.org/10.1109%2Ftpami.2022.3216514.

[4] Jacob Devlin et al. *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. 2019. arXiv: 1810.04805 [cs.CL].

[5] Alexey Dosovitskiy et al. *An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale*. 2021. arXiv: 2010.11929 [cs.CV].

[6] Yanghao Li et al. *Exploring Plain Vision Transformer Backbones for Object Detection*. 2022. arXiv: 2203.16527 [cs.CV].

[7] Scott Mayer McKinney et al. "International evaluation of an AI system for breast cancer screening". In: *Nature* 577.7788 (2020), pp. 89–94. ISSN: 1476-4687. DOI: 10.1038/s41586-019-1799-6. URL: https://doi.org/10.1038/s41586-019-1799-6.

[8] Karan Singhal et al. *Towards Expert-Level Medical Question Answering with Large Language Models*. 2023. arXiv: 2305.09617 [cs.CL].

[9] Hugo Touvron et al. "Training data-efficient image transformers & distillation through attention". In: *International Conference on Machine Learning*. Vol. 139. July 2021, pp. 10347–10357.