Medical Image Classification with Self-Supervised Learning

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Problem Statement:

- Medical image classification (e.g., pneumonia detection) requires large labeled datasets.
- Manual labeling in medical imaging is costly and time-consuming.
- Goal: Use Self-Supervised Learning (SSL) to leverage large unlabeled chest X-ray datasets to learn representations that improve classification with limited labeled data.
- Compare multiple SSL models to identify the best for pneumonia detection.

Objective

- Pretrain SSL models on NIH ChestX-ray14 (unlabeled, ~60k images).
- Fine-tune on RSNA Pneumonia Detection dataset (labeled).
- Evaluate and compare SSL methods: SimCLR, MAE, BYOL, DINO, MoCo.
- Identify the best SSL model for medical image classification in terms of accuracy and efficiency.

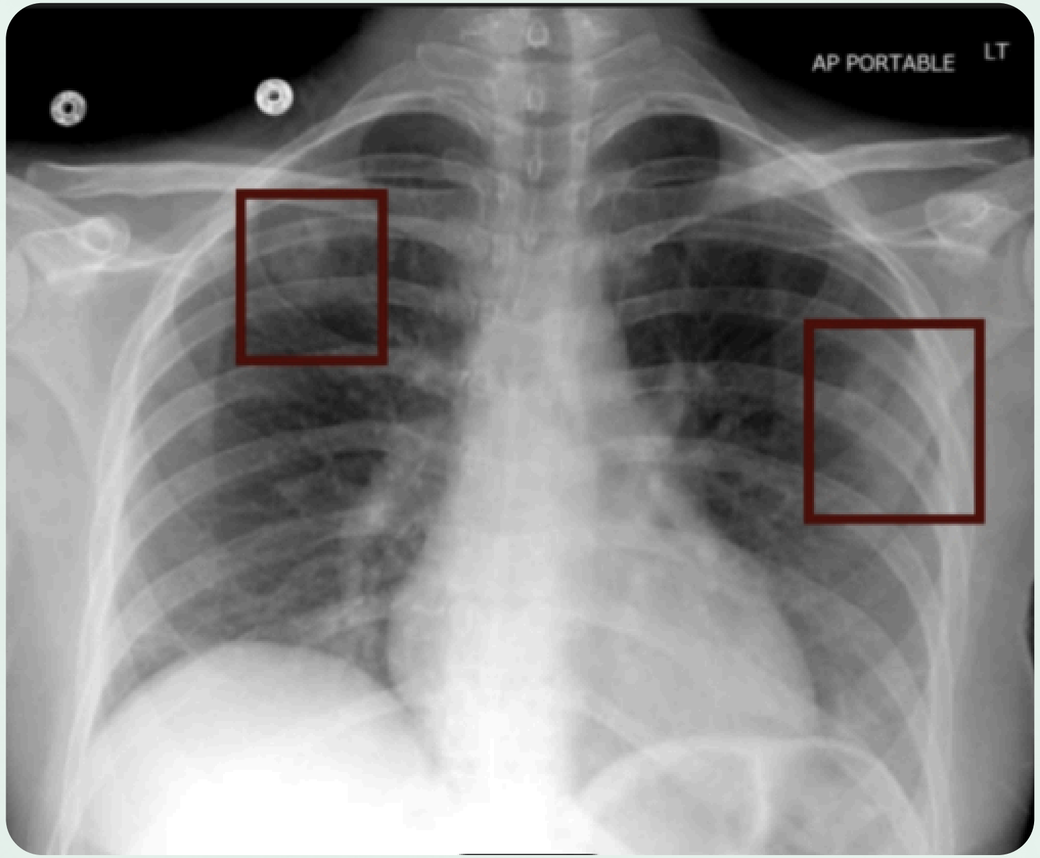
Objective

MAE	BYOL	DINO	SimCLR	MoCo
Generative ViT-B	Predictive ResNet-18	Self-distillation ViT-Tiny / ViT-S	Contrastive ResNet-18	Contrastive ResNet
Mask 75% patches, reconstruct, MSE loss	Minimize cosine similarity between augmented views	Student-teacher learning, cross-entropy loss	NT-Xent loss, temperature=0.2, cosine annealing	Momentum contrast, diverse augmentations

Results

MAE	BYOL	DINO	SimCLR	MoCo
78.49%	76.96%	78.8%	80.22% (final model)	74.2%
Strong feature learning	Good transfer learning	Limited by compute, promising	Best performance overall	Robust pipeline, good feature learning

Contributions



- Demonstrated that SSL can reduce reliance on labeled data for medical image classification.
- Systematic comparison of five prominent SSL methods applied to chest X-ray pneumonia detection.
- Found SimCLR with ResNet-18 encoder provided the best trade-off between accuracy (80.22%) and computational efficiency.
- Validated SSL models on two large datasets: NIH ChestX-ray14 (unlabeled) and RSNA Pneumonia Detection (labeled).
- Provided practical insights into SSL applicability in medical imaging for pneumonia diagnosis.

Conclusion

- SSL methods can effectively learn rich medical image representations from unlabeled data.
- SimCLR emerges as the top performer for pneumonia classification in this study.
- Future directions:
- Explore larger-scale pretraining (e.g., DINO with more compute).
- Experiment with hyperparameter tuning (e.g., SimCLR temperature).
- Extend to other medical imaging tasks and datasets

THANKS!