

Abstract

- Analysing the effectiveness of pretraining on ImageNet in contrast to pretraining on a different in-domain dataset in the setting of pathology detection in chest x-rays.
- In-domain pretraining slightly improves performance for bigger models but slightly hurts performance for smaller ones..

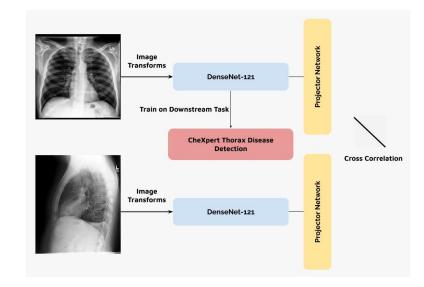
Dataset

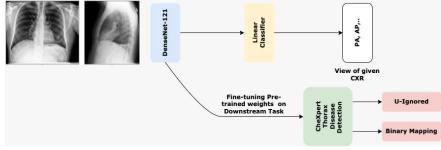
- CheXpert 224,316 chest radiographs of 65,240 patients, each report labeled for the presence of 14 observations as positive, negative, or uncertain.
- ChestX-ray8 108,948 of CXR images of 32,717 unique patients, comprising classified images of 8 popular diseases.

Replication of Related Work

- Implemented the experiments by Irvin et al[1] on CheXpert dataset, ResNet50, ResNet152, and DenseNet121 (DenseNet121 - reported best performance).
- Used the "ignoring" uncertainty handling technique, treating different viewing angles as separate examples instead of taking the max prediction across both angles when available.
- Implemented the binary mapping technique of uncertainty handling as described in the paper by replacing all uncertain [-1] labels by [1] and then calculating the pathology loss.

Our Approach on the problem statement







Experiments and Results

	Atelectasis	Cardiomegaly	Consolidation	Edema	Pleural Effusion
ImageNet Pre-trained ResNet-50	0.7931	0.7883	0.8299	0.8295	0.7695
ImageNet Pre-trained DenseNet-121	0.7477	0.7853	0.8173	0.8279	0.7647
Random Initialised ResNet-50	0.7915	0.8078	0.8529	0.8221	0.7895
Random Initialised DenseNet-121	0.7778	0.7809	0.8737	0.8248	0.807
NIH Pre-trained ResNet-50	0.764	0.7873	0.8389	0.8103	0.7669
NIH Pre-trained DenseNet-121	0.7302	0.7752	0.8238	0.7997	0.7611
Redundancy Reduction DenseNet-12	0.7472	0.7877	0.8404	0.8238	0.7649
Redundancy Reduction DenseNet-12 with AUC Maximization	0.8482	0.8665	0.8971	0.9402	0.9224

