using CNNs to alert clinicians of potential findings immediately after image acquisition before a final radiologist report this technology may aid in triaging work lists and providing a “second look” for radiologists, helping to reduce human error
Pre-training on tangentially related datasets such as ImageNet has been shown to help in circumstances where training data is limited, but may introduce unintended biases which are undesirable in a clinical setting.
verifies that without pre-training, a carefully designed baseline model that ignores the label dependencies is able to outperform the pre-trained state-of-the-art by a large margin.

explicitly exploit the conditional dependencies among abnormality labels for better diagnostic results. Existing RNNs are purposely modified to accomplish such a goal. The results on the proposed metrics consistently indicate their superiority over models that do not consider interdependencies.

Given a finite set of possible labels, the multi-label classification problem is to associate each instance with a subset of those labels.

Another approach for multi label classification includes Pairwise Error (PWE) loss that inherently models label dependencies in the sense that it tries to maximize the margin between positive and negative labels within an example

We design a boosted cascade architecture that is specifically tailored for multi label classification task of type of ChestX-ray14 dataset. The proposed approach models complex dependencies between class labels and benefits from the training strategy of boosting methods to provide improved performance as compared to single classifiers trained using cross-entropy and PWE loss.

attention guided convolutional neural network (AG-CNN) which diagnoses thorax diseases by combining the global and local information. AG-CNN improves the recognition performance by correcting image alignment and reducing the impact of noise.

shows that Deep learning with ImageNet training may be sufficient for general medical image recognition tasks.