**1. Automated Identification of Thoracic Pathology from Chest Radiographs with Enhanced Training Pipeline — DSouza, Abidin, Wismüller (2020)**

**Abstract**

Chest x-rays are the most common radiology studies for diagnosing lung and heart disease. Hence, a system for automated pre-reporting of pathologic findings on chest x-rays would greatly enhance radiologists’ productivity. To this end, we investigate a deep-learning framework with novel training schemes for classification of different thoracic pathology labels from chest x-rays. We use the currently largest publicly available annotated dataset ChestX-ray14 of 112,120 chest radiographs of 30,805 patients. Each image was annotated with either a ‘NoFinding’ class, or one or more of 14 thoracic pathology labels. Subjects can have multiple pathologies, resulting in a multi-class, multi-label problem. We encoded labels as binary vectors using k-hot encoding. We study the ResNet34 architecture, pre-trained on ImageNet, where two key modifications were incorporated into the training framework: (1) Stochastic gradient descent with momentum and with restarts using cosine annealing, (2) Variable image sizes for fine-tuning to prevent overfitting. Additionally, we use a heuristic algorithm to select a good learning rate. Learning with restarts was used to avoid local minima. Area Under receiver operating characteristics Curve (AUC) was used to quantitatively evaluate diagnostic quality. Our results are comparable to, or outperform the best results of current state-of-the-art methods with AUCs as follows: Atelectasis:0.81, Cardiomegaly:0.91, Consolidation:0.81, Edema:0.92, Effusion:0.89, Emphysema: 0.92, Fibrosis:0.81, Hernia:0.84, Infiltration:0.73, Mass:0.85, Nodule:0.76, Pleural Thickening:0.81, Pneumonia:0.77, Pneumothorax:0.89 and NoFinding:0.79.

**2. Multi-Label Classification of Chest X-ray Abnormalities Using Transfer Learning Techniques — J. Kufel et al. (2023)**

**Abstract**

In recent years, deep neural networks have enabled countless innovations in the field of image classification. Encouraged by success in this field, researchers worldwide have demonstrated how to use Convolutional Neural Network techniques in medical imaging problems. In this article, the results were obtained through the use of the EfficientNet in the task of classifying 14 different diseases based on chest X-ray images coming from the NIH (National Institutes of Health) ChestX-ray14 dataset. The results were compared with the achievements of other teams available in the literature and it was shown that it is possible to obtain state-of-the-art results for complicated medical diagnosis problems by applying existing deep learning architecture such as the EfficientNet architecture, transfer learning technique, data augmentation or extended callback functions. Defining the network features leading to such results and refining general models based on this information remains a pertinent issue. The presented results were obtained by using a consumer-class GPU (Nvidia GTX 1080 Ti). It is very promising that just by applying such methods, the model was able to outperform all previous works and achieve state-of-the-art performance in the task of X-ray chest disease recognition.

**3. Anatomy-XNet: Anatomy Aware Convolutional Neural Network for Thoracic Disease Classification in Chest X-rays — Kamal, Zunaed, Nizam, Hasan (2021)**

**Abstract**

Thoracic disease detection from chest radiographs using deep learning methods has been an active area of research in the last decade. Most previous methods attempt to focus on the diseased organs of the image by identifying spatial regions responsible for significant contributions to the model's prediction. In contrast, expert radiologists first locate the prominent anatomical structures before determining if those regions are anomalous. Therefore, integrating anatomical knowledge within deep learning models could bring substantial improvement in automatic disease classification. Motivated by this, we propose Anatomy-XNet, an anatomy-aware attention-based thoracic disease classification network that prioritizes the spatial features guided by the pre-identified anatomy regions. We adopt a semi-supervised learning method by utilizing available small-scale organ-level annotations to locate the anatomy regions in large-scale datasets where the organ-level annotations are absent. The proposed Anatomy-XNet uses the pre-trained DenseNet-121 as the backbone network with two corresponding structured modules, the Anatomy Aware Attention (A³) and Probabilistic Weighted Average Pooling (PWAP), in a cohesive framework for anatomical attention learning. We experimentally show that our proposed method sets a new state-of-the-art benchmark by achieving an AUC score of 85.78%, 92.07%, and, 84.04% on three publicly available large-scale CXR datasets — NIH, Stanford CheXpert, and MIMIC-CXR, respectively.

**4. ChestNet: A Deep Neural Network for Classification of Thoracic Diseases on Chest Radiography — Hongyu Wang & Yong Xia (2018)**

**Abstract**

Computer-aided techniques may lead to more accurate and more accessible diagnosis of thorax diseases on chest radiography. Despite the success of deep learning-based solutions, this task remains a major challenge in smart healthcare, since it is intrinsically a weakly supervised learning problem. In this paper, we incorporate the attention mechanism into a deep convolutional neural network, and thus propose the ChestNet model to address effective diagnosis of thorax diseases on chest radiography. This model consists of two branches: a classification branch serves as a uniform feature extraction-classification network to free users from troublesome handcrafted feature extraction, and an attention branch exploits the correlation between class labels and the locations of pathological abnormalities and allows the model to concentrate adaptively on the pathologically abnormal regions. We evaluated our model against three state-of-the-art deep learning models on the ChestX-ray14 dataset using the official patient-wise split. The results indicate that our model outperforms other methods, which use no extra training data, in diagnosing 14 thorax diseases on chest radiography.

**5. Automated Identification of Thoracic Pathology from Chest Radiographs with Enhanced Training Pipeline — Adora M. DSouza, Anas Z. Abidin, Axel Wismüller (2020)**

**Abstract**

Chest x-rays are the most common radiology studies for diagnosing lung and heart disease. Hence, a system for automated pre-reporting of pathologic findings on chest x-rays would greatly enhance radiologists’ productivity. To this end, we investigate a deep-learning framework with novel training schemes for classification of different thoracic pathology labels from chest x-rays. We use the currently largest publicly available annotated dataset ChestX-ray14 of 112,120 chest radiographs of 30,805 patients. Each image was annotated with either a ‘NoFinding’ class, or one or more of 14 thoracic pathology labels. Subjects can have multiple pathologies, resulting in a multi-class, multi-label problem. We encoded labels as binary vectors using k-hot encoding. We study the ResNet34 architecture, pre-trained on ImageNet, where two key modifications were incorporated into the training framework: (1) Stochastic gradient descent with momentum and with restarts using cosine annealing, (2) Variable image sizes for fine-tuning to prevent overfitting. Additionally, we use a heuristic algorithm to select a good learning rate. Learning with restarts was used to avoid local minima. Area Under receiver operating characteristics Curve (AUC) was used to quantitatively evaluate diagnostic quality. Our results are comparable to, or outperform the best results of current state-of-the-art methods with AUCs as follows: Atelectasis:0.81, Cardiomegaly:0.91, Consolidation:0.81, Edema:0.92, Effusion:0.89, Emphysema: 0.92, Fibrosis:0.81, Hernia:0.84, Infiltration:0.73, Mass:0.85, Nodule:0.76, Pleural Thickening:0.81, Pneumonia:0.77, Pneumothorax:0.89 and NoFinding:0.79.