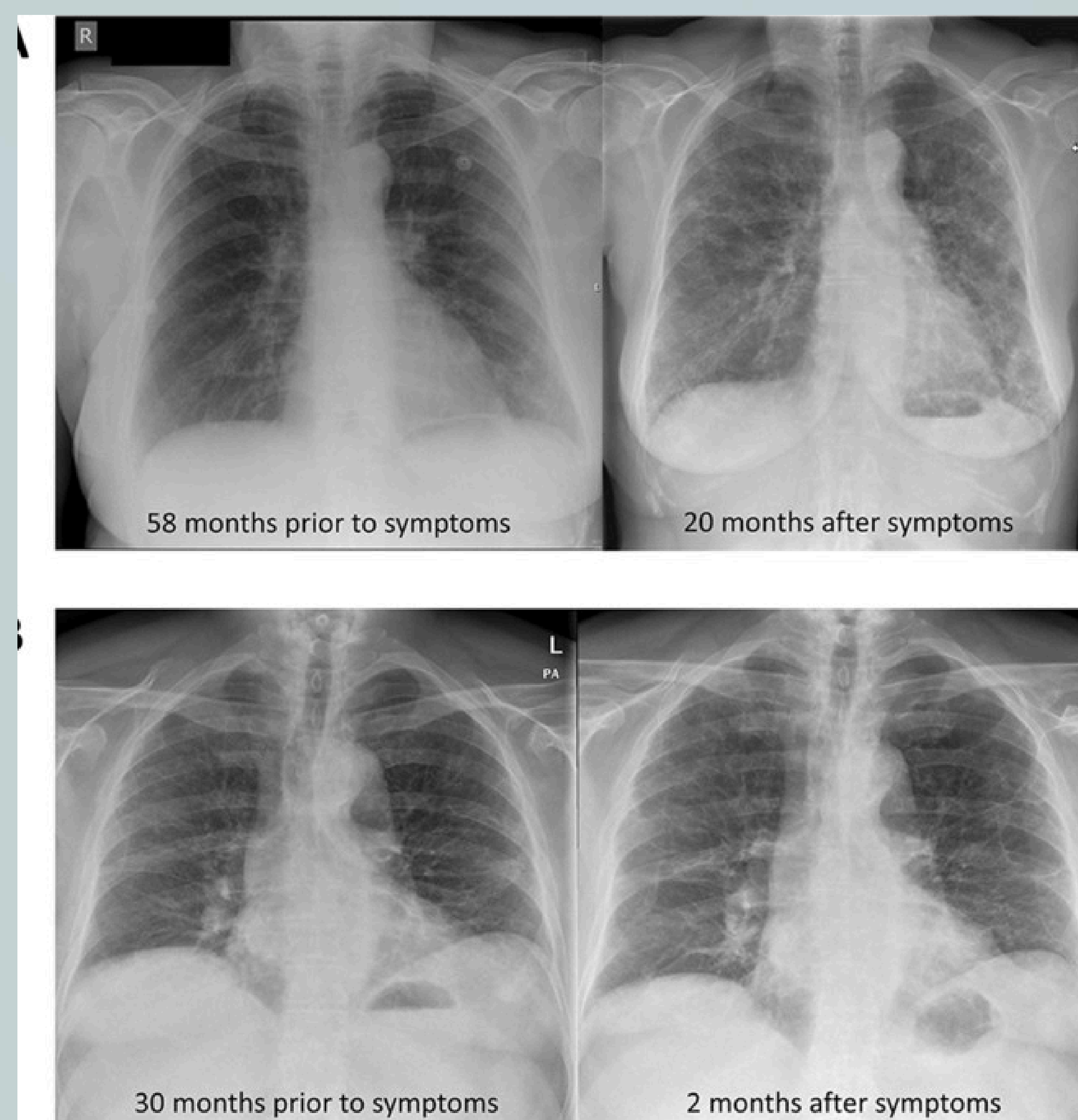


Abstract

Lung diseases are a significant global health concern, causing high morbidity and mortality (death). Early and accurate detection is crucial for effective treatment and improved patient outcomes. Chest X-rays are a non-invasive, readily available, and cost-effective imaging modality used for initial evaluation of lung abnormalities. However, interpreting chest X-rays can be challenging, requiring trained radiologists. This work explores the potential of Convolutional Neural Networks (CNNs) to automate the detection of lung morbidities from chest X-ray images.

The results are expected to demonstrate the feasibility of using CNNs for automated lung morbidity detection from chest X-rays. This could potentially improve diagnostic accuracy, reduce inter-reader variability among radiologists, and expedite patient care. Additionally, the project will explore the limitations of CNNs and address considerations for real-world clinical implementation, such as interpretability and explainability of the models' predictions. By advancing automated lung morbidity detection using CNNs, this work has the potential to contribute significantly to the fight against lung diseases, leading to earlier diagnosis and improved patient outcomes. It also contributes to the body of knowledge in healthcare AI and provides a foundation for future innovations.



Introduction

My work involved collecting a large dataset of chest X-ray images with annotations for various lung morbidities (e.g., Cardiomegaly, Atelectasis, Pneumonia, Pneumothorax & Fibrosis). Then, I employed data preprocessing techniques to standardize the images and improve model performance. I investigated the effectiveness of different CNN architectures, including a custom-designed CNN, pre-trained ResNet-18, ResNet-50 models and also implemented YOLOv5 and Detectron2 of Facebook AI Research (FAIR) on VinDr-CXR and NIH Chest X-Ray dataset containing more than 1 Lakh images for better bounding box detection. The models were trained and evaluated on the prepared dataset using standard metrics like accuracy, classification loss, Mean Average Precision (mAP) to assess their ability to detect lung abnormalities.

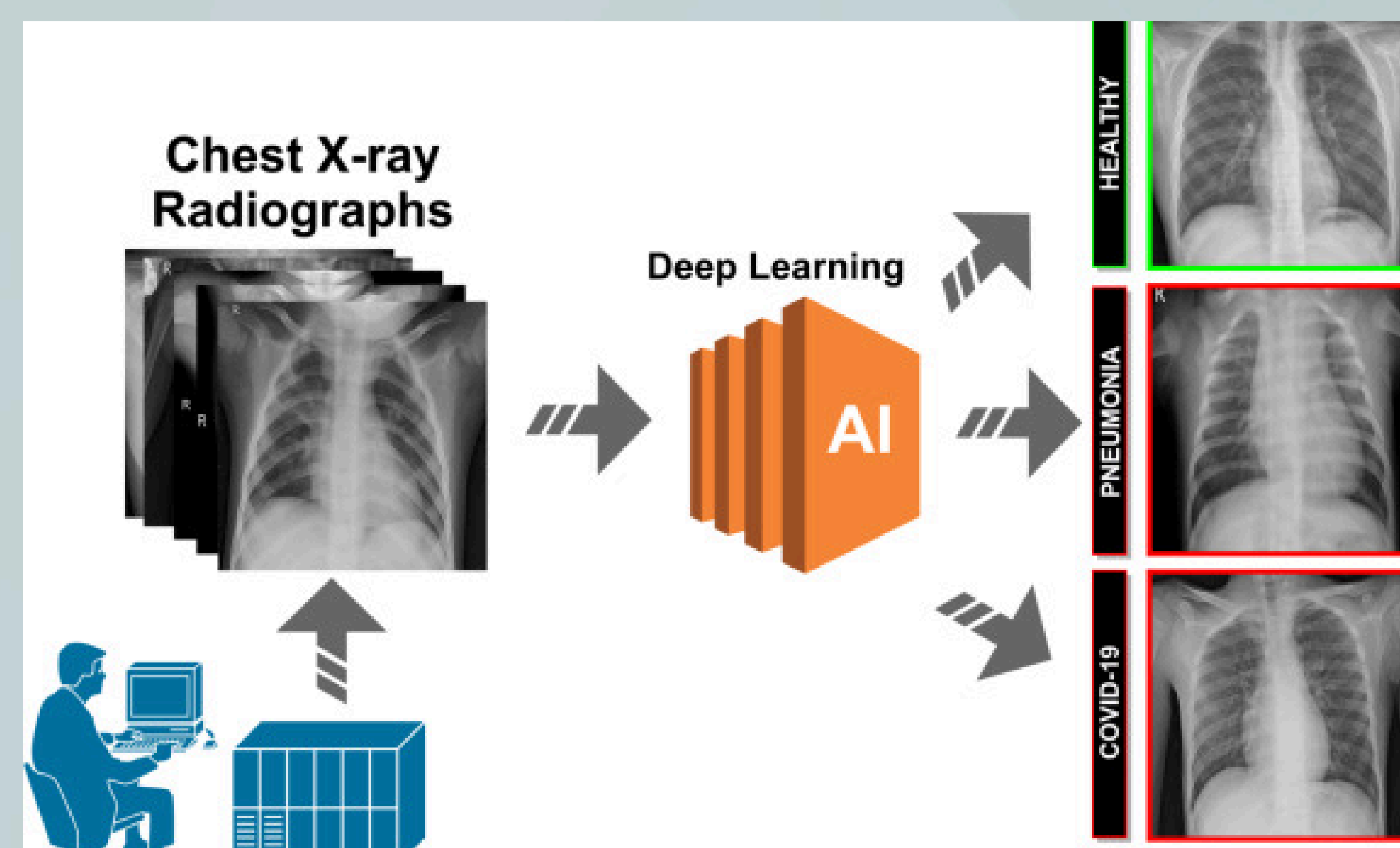
Research Objectives

Investigate techniques to improve the interpretability of the CNN model's predictions. This could involve methods like saliency maps or class activation maps to understand which image regions contribute most to the model's decisions.

- Gain practical experience in designing, training, and evaluating different CNN models for medical image analysis.
- Understand the potential and limitations of different models like ResNet18, ResNet50, YOLOv5 and Detectron2 for object detection in chest X-ray images.
- Develop skills in performance evaluation metrics for image classification and object detection tasks.

Study Methodology

- Collecting and Compiling Dataset:
 - Chest X-ray datasets were collected from various publicly available sources (NIH ChestX-ray8, VinDr-CXR & Kaggle datasets).
 - Data Preprocessing: Images were resized to a standard format (224x224 pixels).
 - Data augmentation techniques (random cropping, flipping) have been used to artificially increase the size and diversity of the training dataset.
- Model Development and Evaluation:
 - A custom CNN architecture was designed and implemented from scratch (using convolutional layers, pooling layers, fully connected layers).
 - A pre-trained ResNet-18 model, was fine-tuned by adjusting the weights of the final layers on the lung X-ray dataset to learn task-specific features for lung morbidity classification.
 - Following the same principles as ResNet-18, a pre-trained ResNet-50 model with deeper architecture was employed.
 - A pre-trained YOLOv5 model was chosen for its object detection capabilities, and used to detect the bounding boxes of the annotations of the lung anomalies, made on the images dataset.
 - Similarly, Detectron2 model of Facebook AI Research (FAIR) was implemented for even better BBox detection.



- Comparison and Analysis:
 - The performance of all the models (traditional CNN, ResNet-18, ResNet-50, and YOLOv5, Detectron2) was compared based on the evaluation metrics.
 - This comparison helped identify the model with the better accuracy, precision, recall, and F1-score (for classification) or mAP (for object detection) for lung anomaly detection.

Results and Impact

- Obtained prediction accuracy of 78.33% and 89.42% with ResNet-18 and ResNet-50 models respectively.
- The YOLOv5 model was able to accurately determine the bounding boxes for the localized anomaly with an AP of 0.78.
- The Detectron2 model had a learning rate of 0.00025 and gave the following evaluation results in terms of Average Precision (AP) & Average Recall (AR):
 - AP (@ IoU=0.50:0.95) = 0.928
 - AP (@ IoU=0.50) = 0.785
 - AP (IoU=0.75) = 0.682
 - AR (@ IoU=0.50:0.95 | area=all | maxDets=1) = 0.642
 - AR (@ IoU=0.50:0.95 | area=all | maxDets=10) = 0.712
 - AR (@ IoU=0.50:0.95 | area=all | maxDets=100) = 0.688

References

- Recent Study of Lung Disease Detection Using Deep Learning Techniques | https://www.researchgate.net/publication/370425258_Recent_Study_of_Lung_Disease_Detection_Using_Deep_Learning_Techniques
- Lung Cancer Classification and Prediction Using Machine Learning and Image Processing | <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9424001/>
- Automated abnormality classification of chest radiographs using deep convolutional neural networks | <https://www.nature.com/articles/s41746-020-0273-z>