Indian Institute of Technology Kanpur

Perception & Intelligence Lab

SURGE INTERNSHIP REPORT

Automated Lung Morbidity Detection from Non-Invasive Images using CNNs

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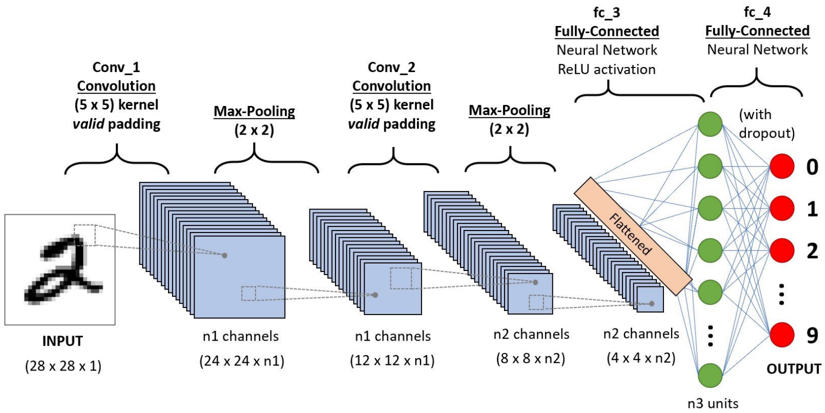
1 Abstract

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 work involved collecting a large dataset of **chest X-ray images** with annotations for various lung morbidities (e.g., pneumonia, COVID-19, Tuberculosis). **Data preprocessing** techniques were employed to standardize the images and potentially 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 **1,12,120** images for better bounding box detection. The models were trained and evaluated on the prepared dataset using standard metrics like **accuracy**, precision, recall, and **F1-score** (for classification) to assess their ability to detect lung abnormalities.

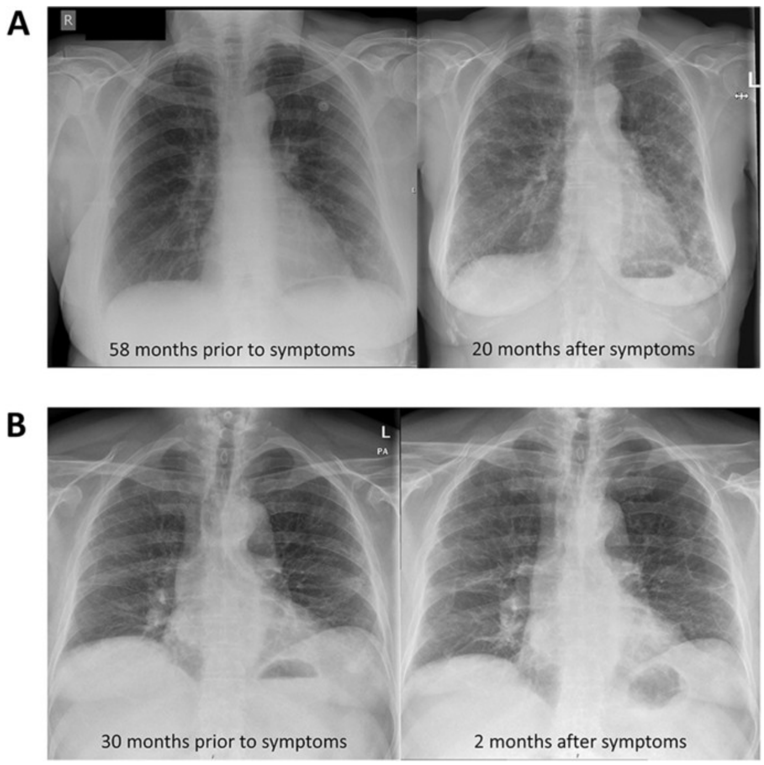
The results are expected to demonstrate the feasibility of using CNNs for **automated lung morbidity detection** from chest X-rays. This could potentially improve diagnostic accuracy, reduce inter-reader variability among radiologists, and expedite patient care. Additionally, the project will explore 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.



2 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.



3 Objectives and Learning Outcomes

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.
Learning Outcomes:

- Gain practical experience in designing, training, and evaluating different CNN models for medical image analysis.
- Understand the potential and limitations of different models like **ResNet-18**, **ResNet-50** for image classification and **YOLOv5** and **Detectron2** for object detection in chest X-ray images.

4 Methodology

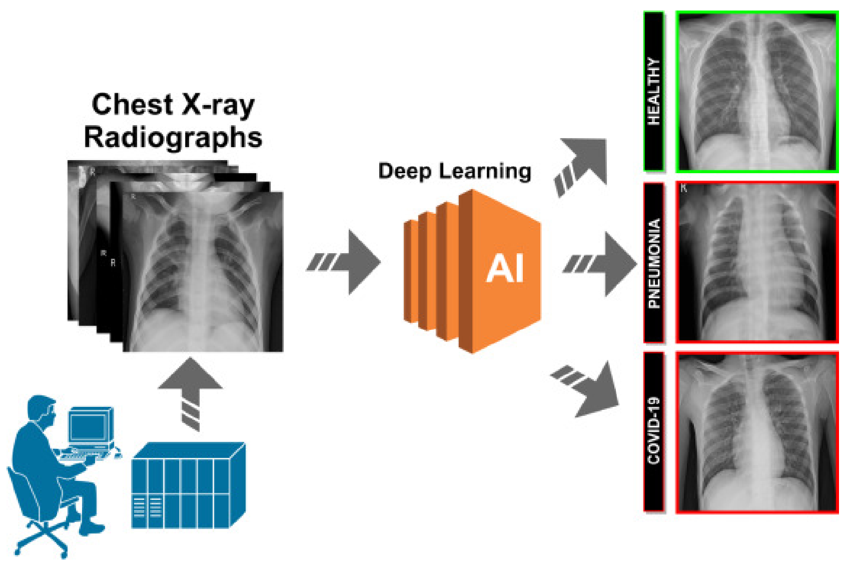
4.1 Collecting and Compiling Dataset

- Chest X-ray datasets were collected from various publicly available sources (**NIH ChestX-ray, VinDr-CXR dataset, Kaggle datasets**)
- **Data Preprocessing:** Images were resized to a standard format (224x224 pixels).
- **Normalization techniques** (mean-variance normalization) have been applied to standardize pixel intensities.
- **Data augmentation** techniques (random cropping, flipping) have been used to artificially increase the size and diversity of the training dataset.

4.2 Model Development and Evaluation

4.2.1 Traditional CNN Model

- **Architecture:** A custom CNN architecture was designed and implemented from scratch (using convolutional layers, pooling layers, and fully connected layers).
- **Training:** The model was trained on a portion of the preprocessed dataset using an appropriate optimizer (e.g., Adam) and loss function (e.g., categorical cross-entropy).
- Techniques like learning **rate scheduling** and **dropout regularization** could be used to prevent overfitting.
- **Evaluation:** The trained model's performance was evaluated on a held-out test set using standard metrics like accuracy, precision, recall, and **F1-score** for each lung morbidity class.



4.2.2 ResNet-18:

- **Pre-trained Model:** A pre-trained ResNet-18 model, known for its performance on image classification tasks, was utilized.
- **Fine-tuning:** The pre-trained 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.
- **Evaluation:** Similar to the traditional CNN, the fine-tuned ResNet-18 model was evaluated on the test set using the aforementioned metrics.

4.2.3 ResNet-50

- Following the same principles as ResNet-18, a pre-trained **ResNet-50** model with deeper architecture was employed.
- Fine-tuning was performed on the lung X-ray dataset, and the model's performance was evaluated on the test set.

4.2.4 YOLOv5 for Object Detection

- **Pre-trained Model:** A pre-trained YOLOv5 model was chosen for its object detection capabilities.
- **Training:** The adapted **YOLOv5 model** was trained on the **lung X-ray dataset**, aiming to detect and classify bounding boxes around regions containing lung abnormalities.
- Metrics like **mean average precision** (mAP) at different **Intersection over Union** (IoU) thresholds were used for evaluation.

4.2.5 Detectron2 for Annotation Bounding-Box detection

- The images were first converted into the **COCO format** and the dataset was registered on the model.
- A **JSON file** was created with the custom annotations and then the model was described accordingly.
- **Training:** The adapted **Detectron2 model** was trained on the **VinDr-CXR** and **NIH Chest X-Ray** dataset, comprising of **3,31,000** and **1,12,120** images of chest X-Rays respectively, with the annotations of them in bounding boxes, aiming to detect the given bounding boxes of localized **lung anomaly**.
- Each of the image was classified into **14** different classes of anomalies, some of them being - **Cardiomegaly**, **Atelectasis**, **Pneumonia**, **Pneumothorax** & **Fibrosis** - among others.

5 Results and Impact

5.1 Results

- The accuracy obtained with the **traditional CNN model** was **67.89%**.
- The accuracy obtained with the **ResNet-18** model was **78.33%**.
- The accuracy obtained with **ResNet-50** model was **89.42%**.
- The **mAP** for the **YOLOv5** model was obtained as **0.584**.
- The **mAP** for the **Detectron2** model was obtained as **0.928**.

5.2 Impact

- Demonstrates potential for **reducing diagnostic times** and support **remote** and **underserved** areas.
- Contributes to the body of knowledge in **healthcare AI** and provides a foundation for **future innovations**.

6 References

- Recent Study of Lung Disease Detection Using Deep Learning Techniques
  www.researchgate.net
- Lung Cancer Classification and Prediction Using Machine Learning and Image Processing
  www.ncbi.nlm.nih.gov
- Automated abnormality classification of chest radiographs using deep convolutional neural networks
  www.nature.com