Indian Institute of Technology Kanpur

Perception & Intelligence Lab

MID-TERM EVALUATION REPORT

Automated Lung Morbidity Detection from Non-Invasive Images using CNNs

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Guide:

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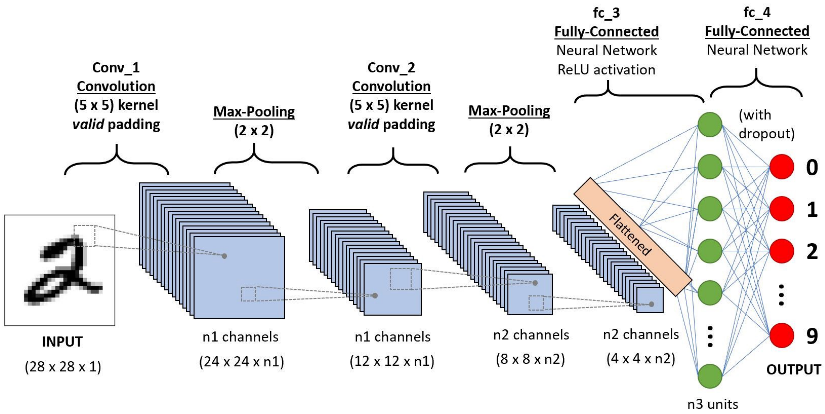
1 Abstract

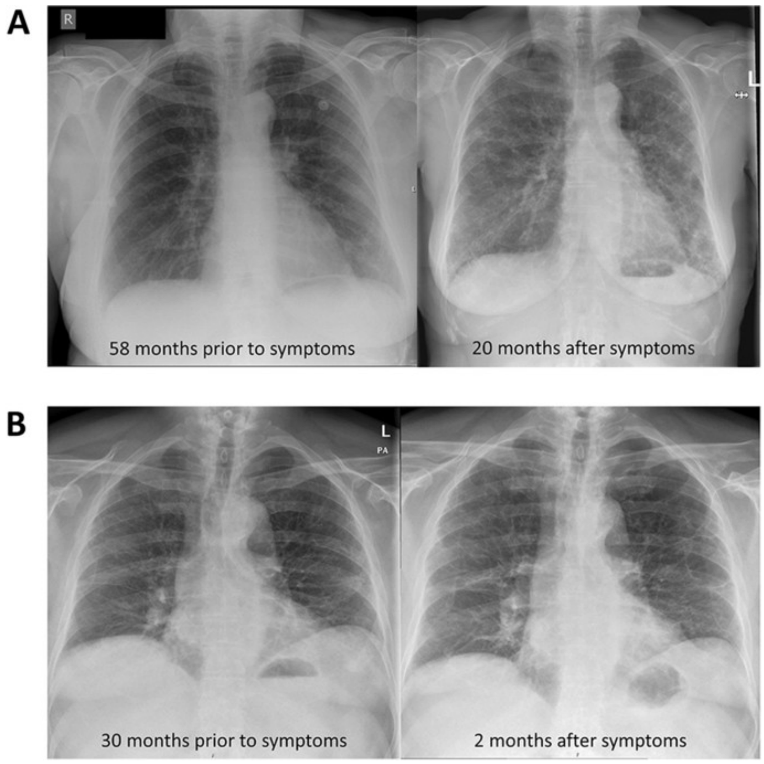
Lung diseases are a significant global health concern, causing high morbidity and mortality (death). Early and accurate detection is crucial for effective treatment and improved patient outcomes. **Chest X-rays** are a **non-invasive**, readily available, and cost-effective imaging modality used for 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** for better **object 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.



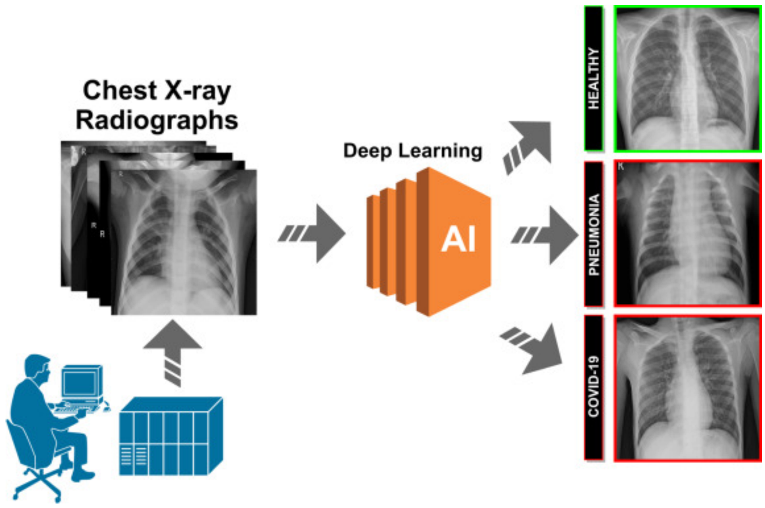


1.1 Challenges faced with Chest X-ray Diagnosis:

- **Subtle Abnormalities**: Early-stage lung diseases may present with subtle findings on chest X-ray, requiring expertise for accurate diagnosis.
- **Inter-reader Variability**: Interpretations can vary among radiologists due to experience, fatigue, and subjective judgment.
- **Workload Burden**: Radiologists face increasing workloads, potentially impacting interpretation time and accuracy.

1.2 Convolutional Neural Networks (CNNs):

CNNs are a type of deep learning algorithm which is particularly well-suited for **image analysis**. They can automatically learn features from large datasets of chest X-rays, enabling them to **identify patterns** associated with various lung abnormalities.

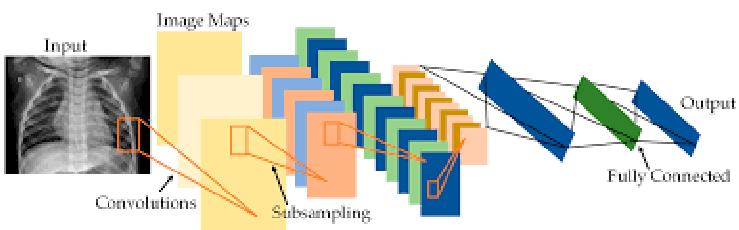


Benefits of CNNs for Lung Morbidity Detection:

- **Improved Accuracy:** CNNs can achieve high accuracy in detecting lung diseases, potentially surpassing human performance in some cases.
- **Reduced Inter-reader Variability:** CNNs provide consistent and objective analysis, minimizing variability between radiologists.
- **Faster Detection:** CNNs can analyze chest X-rays rapidly, facilitating faster diagnosis and treatment initiation.
- **Workload Reduction for Radiologists:** CNNs can act as a decision support tool, assisting radiologists in prioritizing cases and reducing workload burden.

Challenges of CNNs:

- **Data Dependence:** CNN performance relies heavily on the quality and quantity of training data. Biases can be introduced if the training data is not representative of the target population.
- **Explainability:** Understanding the rationale behind CNN predictions can be challenging, limiting interpretability for clinical decision-making.
- **Overfitting:** CNNs can overfit to the training data, leading to poor performance on unseen data. Careful regularization techniques are needed to prevent this.



2 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 **ResNet18**, **ResNet50** and **YOLOv5** for object detection in chest X-ray images.
- Develop skills in performance evaluation metrics for image classification and object detection tasks
- Explore approaches to enhance the interpretability and explainability of CNN models in a medical context.
- Evaluate the feasibility and potential benefits of using CNNs for automated lung morbidity detection in clinical settings.

3 Methodology

3.1 Collecting and Compiling Dataset

- Chest X-ray datasets were collected from various publicly available sources (**NIH ChestX-ray8, 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.

3.2 Model Development and Evaluation

3.2.1 Traditional CNN Model

- **Architecture:** A custom CNN architecture was designed and implemented from scratch (using convolutional layers, pooling layers, 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.
- The accuracy obtained with this model was **67.89%**.

3.2.2 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.
- The accuracy obtained with this model was just**36.33%**.

3.2.3 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.
- The accuracy obtained with this model was **86.68%**.

3.2.4 YOLOv5 for Object Detection

- **Pre-trained Model:** A pre-trained YOLOv5 model was chosen for its object detection capabilities.
- **Transfer Learning:** The pre-trained **YOLOv5 model** was adapted to the lung abnormality detection task. This involved modifying the model's head architecture to output class probabilities for the target **lung morbidities**.
- **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.

3.3 Comparison and Analysis

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