Automated Detection and Localization of Abnormalities in Chest X-rays using Weakly-Supervised Learning

Presentation order: 15

Members:
Lu Jinzhou A0329981M
Song Yiran A0294421H
Wu Yuhang A0294425Y

01 Introduction

- ***Chest X-rays*** *are essential for diagnosing conditions like pneumonia, pleural effusion, and cardiomegaly.*
- *Traditional interpretation is* ***time-consuming*** *and relies heavily on* ***physician experience****.*

Cord Challenge:

- ***High Cost of Data Annotation:*** *Pixel-level annotation for medical images is expensive and time-consuming, a major bottleneck for AI applications.*
- ***"Black Box" Model Problem:*** *The opaque decision-making process of deep learning models leads to a lack of trust from clinicians.*

Goal:

- *To develop an AI-assisted diagnostic framework with both* ***high accuracy*** *and* ***high interpretability*** *to address the core challenges of data cost and model trust.*

02

Problem Statement

Task

- ***Multi-Label Classification & Explainable AI (XAI)***
  Develop a model that not only ***predicts multiple chest abnormalities*** *but also* ***explains its decisions.***

Input & Process

- ***Input:*** *A single frontal chest X-ray image from the MIMIC-CXR dataset.*
- ***Process:*** *Train a deep convolutional neural network using only image-level "weak labels" (e.g., "Pneumonia").*

Output

- ***Classification:*** *Predict the presence of multiple common thoracic abnormalities.*
- ***Localization & Explanation:*** *Generate a* ***heatmap*** *to visually highlight regions the model focuses on for diagnosis.*

03

Methodology

Data Processing

- ***Dataset:*** *Subset of the public MIMIC-CXR dataset (1000 samples),which contains chest X-rays and their corresponding radiology reports. Split into training, validation and test sets with a 8:1:1 ratio.*
- ***Automated Weak Labeling:*** *Use the CheXpert NLP tool to automatically extract image-level labels from free-text radiology reports.*
- ***Advantage:*** *Bypasses the need for manual pixel-level annotation, significantly improving data preparation efficiency.*
- ***Preprocessing:*** *Normalize all images to a fixed size (e.g., 224x224 pixels), transformed into tensors and normalized using ImageNet's mean and standard deviation values*

Model Selection

- ***Backbone Model:*** *primarily use DenseNet-121 with ResNet-50 as comparison, pre-trained on ImageNet.*
- ***Reasoning:*** *Achieves high performance with greater parameter efficiency, which helps reduce the risk of overfitting.*

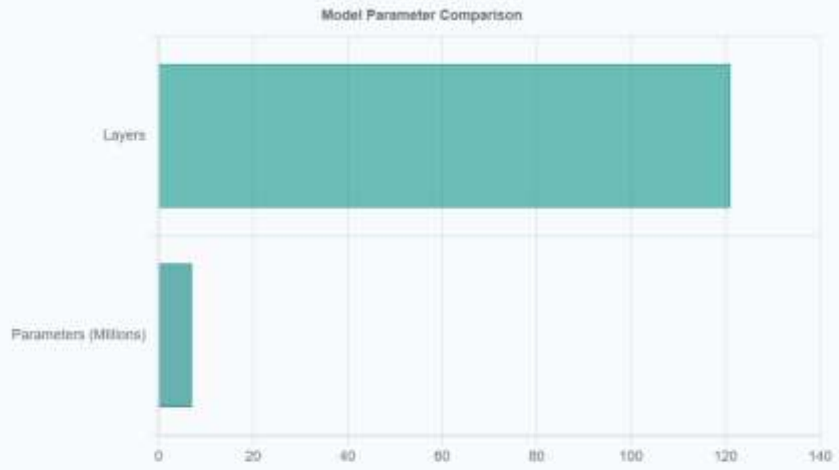
03 Methodology-Comparison

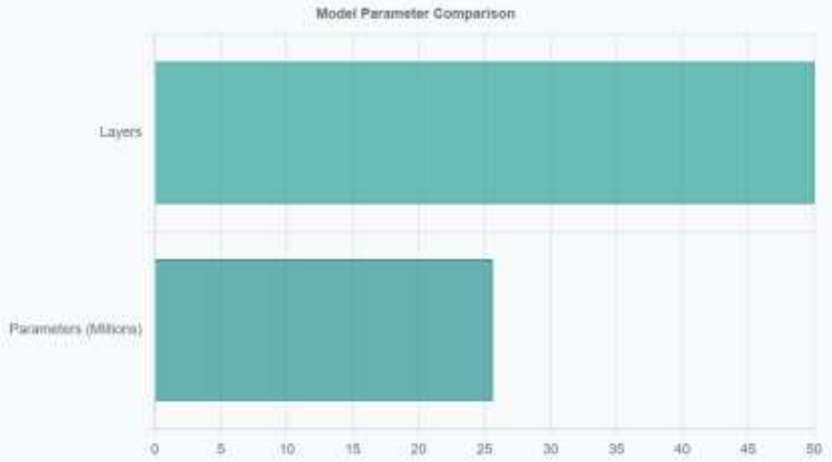
DenseNet-121 Architecture Features

- **Dense Connectivity:** Each layer is connected to every other layer in a feed-forward fashion, which strengthens feature propagation and encourages feature reuse.
- **Parameter Efficiency:** Achieves high performance with fewer parameters than traditional CNNs, reducing the risk of overfitting.
- **Mitigates Vanishing Gradients:** The dense connection path improves the flow of information and gradients throughout the network.

ResNet-50 Architecture Features

- **Residual Learning:** Introduces "shortcut connections" that allow the network to learn residual functions, making it easier to train much deeper networks.
- **Solves Degradation Problem:** Effectively addresses the performance degradation issue in deep networks, allowing for a significant increase in the number of layers.
- **Modular Structure:** Composed of stacked residual blocks, making the architecture clean and easy to extend.





04

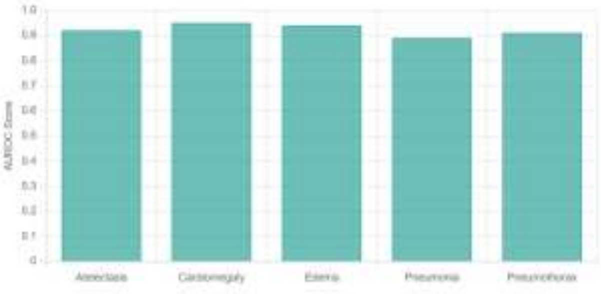
Methodology

Training Methodology

- ***Loss function:*** *BCEWithLogitsLoss (Suitable for multi-label classification).*
- ***Optimizer:*** *Adam Optimizer.*
- ***Output Layer:*** *A Sigmoid activation function is used to support multi-label classification (i.e., one image can have multiple findings).*
- ***XAI(Explainable AI):*** *Apply* ***Grad-CAM*** *(Gradient-weighted Class Activation Mapping) post-training to generate explanation* ***heatmaps****.*
- ***Auxiliary Methods:*** *Explore methods like* ***LIME, DeepLift, and Integrated Gradients*** *to understand the model's behavior from different perspectives and* ***enhance trust*** *in the results.*

Evaluation Metrics

- ***Quantitative Evaluation:*** *We use standard metrics such as* ***AUROC, Accuracy, F1-Score, and confusion matrices*** *on an independent test set to evaluate classification performance.*



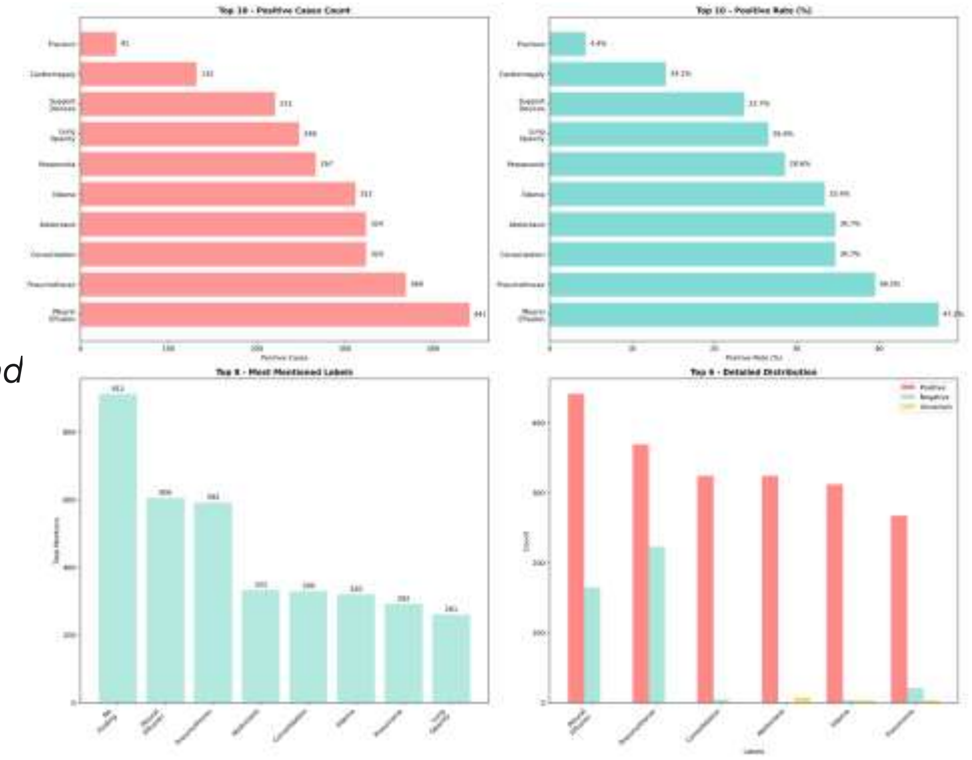
Expected AUROC scores for different conditions

05

Initial Progress

Preliminary Data Analysis

- ***Data pre-processing:*** *extract DICOM metadata, organize anonymized reports, and export CSV files;*
- ***NLP report labeling:*** *applied the CheXpert pipeline to classify 14 chest findings;*
- ***Statistical analysis:*** *generate descriptive statistics and label distributions;*
- ***Visualization & reporting***



934
Total Reports Processed

242
Total Unique Patients

2732
Total Positive Findings

05 Summary & Novelty

Summary:

- *Our project provides a* ***practical solution for developing efficient, trustworthy, and implementable clinical AI tools.***

Novelty:

- ***Automated Weak Labeling****: Uses CheXpert NLP to generate multi-label image annotations directly from radiology reports, bypassing manual labeling.*
- ***Efficient Multi-label Classification****: DenseNet-121 backbone with Sigmoid outputs enables accurate prediction of multiple findings per X-ray.*
- ***Explainable AI Integration****: Grad-CAM and auxiliary XAI methods provide visual explanations, improving model interpretability and trust.*

Reference:

[1]Tanno, R., Barrett, D. G. T., 2025. Collaboration between clinicians and vision-language models in radiology report generation. Nature medicine, 31(2), 599–608. https://doi.org/10.1038/s41591-024-03302-1
[2]L. N. Rohmah and A. Bustamam, "Improved Classification of Coronavirus Disease (COVID-19) based on Combination of Texture Features using CT Scan and X-ray Images," 2020 3rd International Conference on Information and Communications Technology (ICOIACT), Yogyakarta, Indonesia, 2020, pp. 105-109, doi: 10.1109/ICOIACT50329.2020.9332123.
[3]Thapa, M., & Kaur, R. (2025). An explainable deep-learning based multi-label image classification for chest X-rays. Procedia Computer Science, 239, 281–288.https://doi.org/10.1016/j.procs.2025.04.505

Code Lab(Up to date):

https://github.com/Yuhang20/BN5212.git
https://github.com/stanfordmlgroup/chexpert-labeler.git

THANK YOU