# Multi-label Abnormality Classification using Frontal and Lateral Chest X-ray Images

Project presentation

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# Outline

- Introduction
- Motivation
- Related Work
- Proposed Approach
- Evaluation
- Conclusion and Future Work

# Introduction

- Chest X-ray (CXR) is the most common radiology examination used for diagnosis of thoracic diseases.
- Several research done in recent years have shown that deep learning techniques can be used for analyzing chest x-rays.
- Most Computer Aided Diagnosis (CAD) approaches make use of the frontal x-ray images.
- The inclusion of lateral x-rays means inclusion of additional information,
  - which potentially can improve performance of models.

# Introduction

- This project aims to study:
    1. the advantages of using <u>both *frontal* and *lateral*</u> CXR images to train deep learning models.
    2. Explore methods and techniques to modify a deep neural model to effectively learn from two input images.
- Primary goal:
    - Design a deep learning model which utilizes <u>*frontal and lateral* x-ray images together</u> make predictions about possible manifestations.

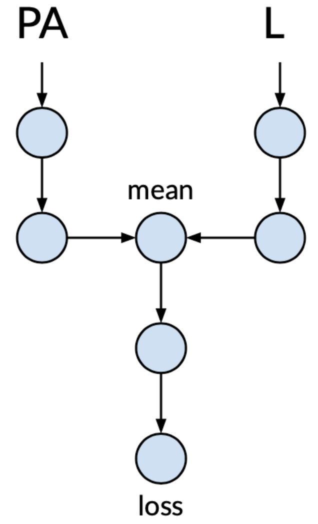
# Motivation

- Physicians and radiologists order additional lateral x-rays when there is diagnostic uncertainty with frontal x-rays.
- CNN based deep learning models for image classification and object recognition have been designed to use a single image as input.
  - Resnet, DenseNet, EfficientNet, etc.
- These models have been used in other domains such as thoracic disease detection in x-rays.
  - But most of these approaches only use *frontal* x-ray images.
  - Very few data and result is available for (*frontal* + *lateral*) image analysis.

- We believe that using both frontal and later images together for training will improve overall performance of the model.

# Related Work

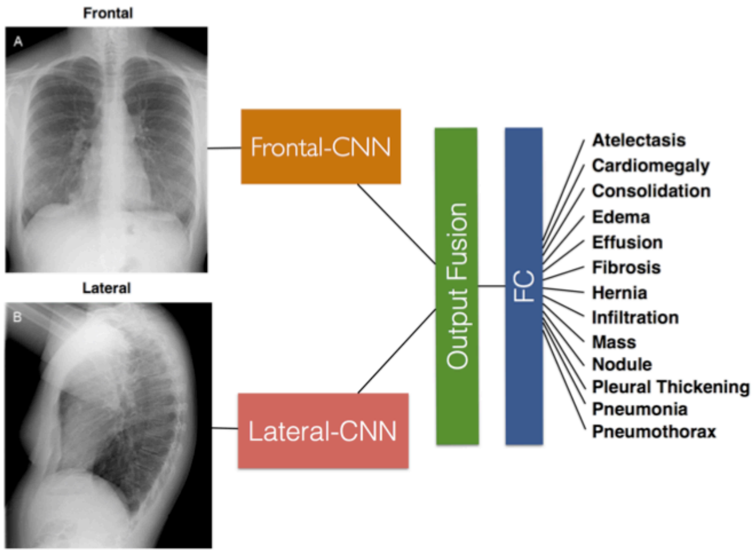
- Setio et al., 2016 uses a techniques such as *committee-fusion* and *late-fusion* to design a multi-view CNN to reduce false positives in Pulmonary Nodule detection in *CT images*.
- Havaei, et al., 2016 proposes the *Hetero-Modal Image segmentation model* where inputs of different modalities are processed different sequences of layers, point-wise mean/moments are computed and concatenated, and passed on to a single series of convolution layers.
  - Bertrand et al., 2019 proposes a HeMIS like model.
  - They use dense blocks to construct the models.
  - Point-wise mean taken to combine result of arms.




HeMIS-like model for 2-view x-ray input.

# Related Work

- Kitamura et al, 2019 uses multiple X-rays of different views to detect fractures. An ensemble approach is taken here.
- Rubin et al, 2018 reports an increase of 3% AUC ROC when both views of MIMIC-CXR is used. This is one of the first works to be done with a recent chest x-rays dataset.
  - Two DenseNets to process the frontal and lateral images separately. This results are concatenated and fed to a fully connected layer.




Visual illustration of DualNet.
Image source, Rubin et al.

- Li et al., 2019 models a multi-view FPN for elision detection.
- Hashir, 2020 compares some of the models with multi-view chest x-rays. They also propose AuxLoss model by modifying the model proposed by Ruben et al.

# Proposed Approach

- Dataset manipulation and data transformation
  - We use the CheXpert dataset as the source of our training data.
  - We make pairs of frontal and later images from studies which have both images.
  - Total 33,151 pairs of images.

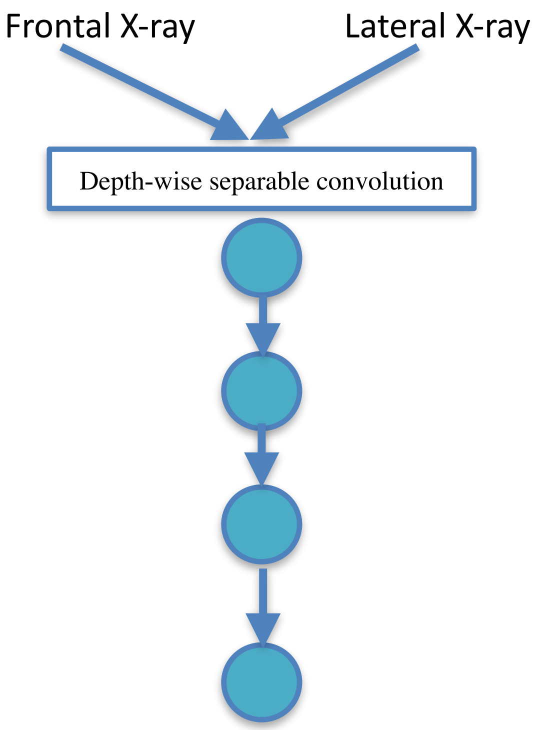
| Pathology | Positive | Uncertain | Negative |
|---|---|---|---|
| Atelectasis | 3743 | 3952 | 25456 |
| Cardiomegaly | 3690 | 1412 | 28049 |
| Consolidation | 1848 | 3433 | 27870 |
| Edema | 2617 | 1193 | 29341 |
| Pleural_Effusion | 9536 | 2095 | 21520 |

# Proposed Approach

- Dataset manipulation and data transformation
  - For training, we augment the dataset by repeating images.
    - Three times for Consolidation and Edema.
    - Two times for other classes.
  - Duplicate instances flipped horizontally with probability 0.5.
  - All images are
    - Resized to 512x512
    - normalized
    - randomly rotated by ±10 degrees.
  - 350 pairs are set aside for testing the trained models.

# Proposed Approach

- We design and implement two models and compare them with other models.
    1. **<u>DenseNet-S</u>**: The idea is to use frontal (PA) image and the corresponding lateral (L) image as 2 separate input channels. This will allow us to work with traditional models without much modification.

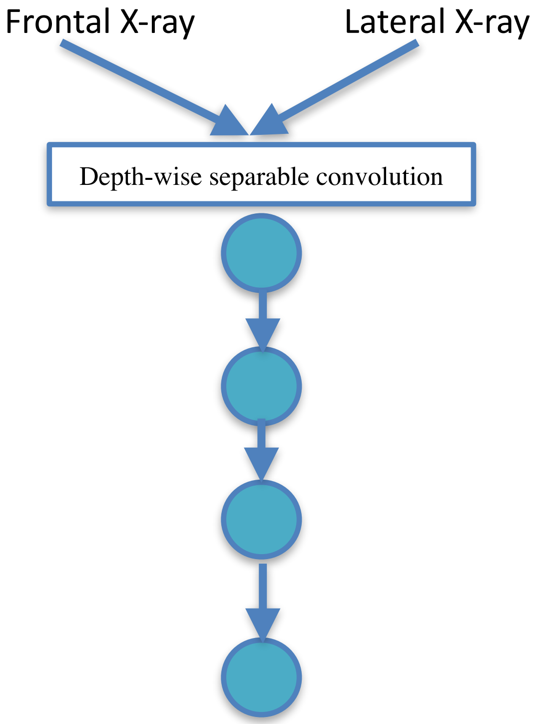



DenseNet-S

# Proposed Approach

- We design and implement two models and compare them with other models.
  1. **<u>DenseNet-S</u>**: The idea is to use frontal (PA) image and the corresponding lateral (L) image as 2 separate input channels. This will allow us to work with traditional models without much modification.

- Both the frontal and lateral views are "stacked" to form the input.
- The first layer of a DenseNet-121 is changed to a "depth-wise separable convolution" layer.
- This is the only change made.

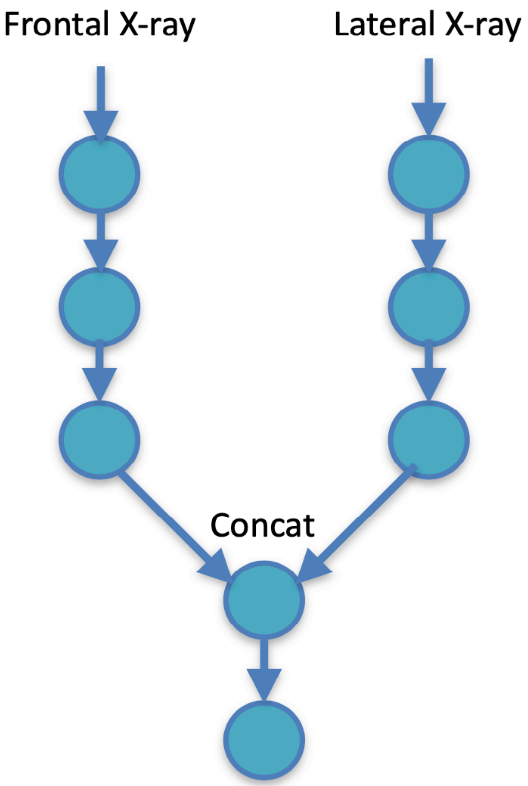



DenseNet-S

# Proposed Approach

- The plan is to have two implementations and compare them with other models:
  2. **DenseNet-D**: This approach is inspired from Rubin et al. and Hashir et al. The model will have two separate DenseBlock arms to process the inputs, the result would be concatenated and processed further by a fourth DenseBlock.

- For this approach we also implement Hierarchical multi-label classification using conditional probability of the labels.
  - CheXpert label ontology was used for this.



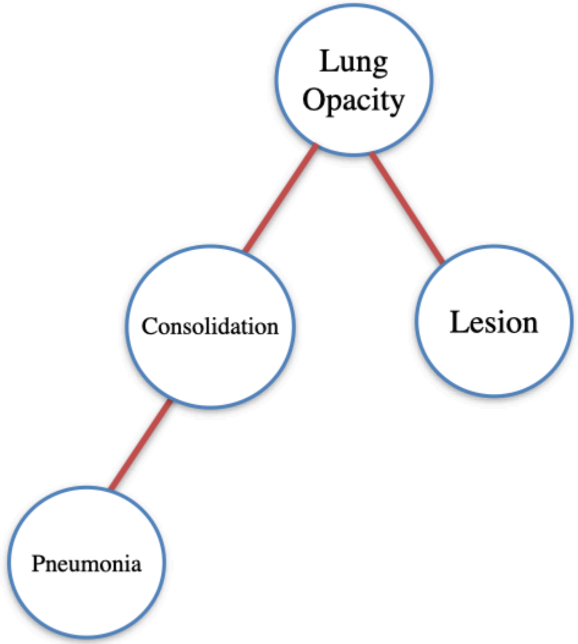

DenseNet-D

# Proposed Approach

- ***Hierarchical structure of the diseases*** is exploited for conditional training.

- Due to time constraints, this technique was only applied to DenseNet-D.

- **Language and Libraries:**
    - Python v3.7 and PyTorch.




$$
\begin{aligned}
P(Pneumonia) = {} & P(LungOpacity) \\
& \cdot P(Consolidation|LungOpacity) \\
& \cdot P(Pneumonia|Consolidation)
\end{aligned}
$$

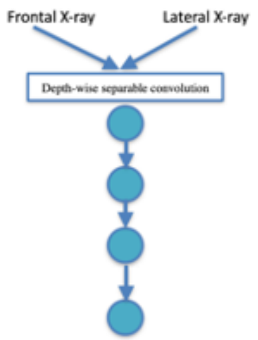
An example of how probability of Pneumonia is calculated for the given label hierarchy.

# Experiments and Results

- Receiver operating characteristic (RoC) curve shows how a binary classifier performs how its discrimination threshold is changed.
  - So for 5 classes we will have 5 curves.

- Mean-AUC is used to measure performance of the models.
  - It is calculated by computing the mean of AUC-ROC of all the 5 classes.
  - Higher is the AUC, better is the performance.
  - Training is done for 30 epochs.
  - The predictions of DenseNet-S, DenseNet-D are averaged over 3 runs.

# Experiments and Results

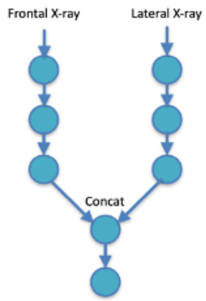



- Mean AUC of DenseNet-S and other models.

| | ***DenseNet-121*** | ***DenseNet-121 (Stacked input)*** | ***DenseNet-S*** |
|---|---|---|---|
| without preprocessing | 0.653 | 0.698 | **0.768** |
| with preprocessing | 0.721 | 0.733 | **0.795** |

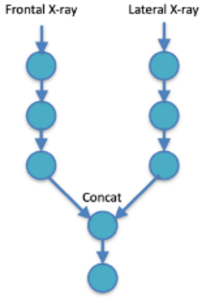
# Experiments and Results

- Mean AUC of DenseNet-D and other models.

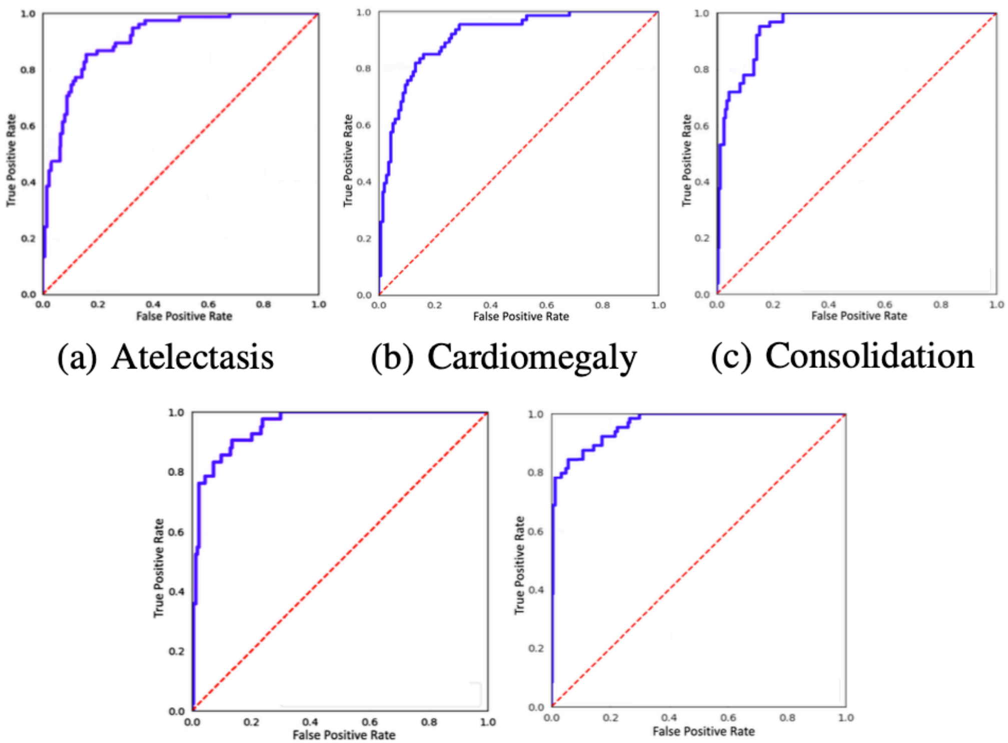



| | *DenseNet-121 (frontal only)* | *DenseNet-D (pair-wise)* | *DualNet [Ruben et al, 2016]* | *DenseNet-D (Hierarchical Classification)* |
|---|---|---|---|---|
| without pre-processing | 0.653 | **0.720** | N.A. | N.A. |
| with pre-processing | 0.721 | 0.802 | 0.721 | **0.814** |

# Experiments and Results




- ROC AUC of DenseNet-S with Hierarchical Classification.




(a) Atelectasis (b) Cardiomegaly (c) Consolidation

(d) Edema (e) Pleural Effusion

# Conclusion and Future work

- In this project we designed and implemented two models which can analyze frontal and lateral x-ray images.
- Results indicate that inclusion of lateral x-rays can improve performance of CNN models.
- The performance of the models should increase with more training examples.
- In our future work,
  - we plan to include more instances from other datasets.
  - Implement noisy-student learning policy.
  - Make improvements by fine-tuning training parameters.

Thank you.