Chest X-Ray Classifier

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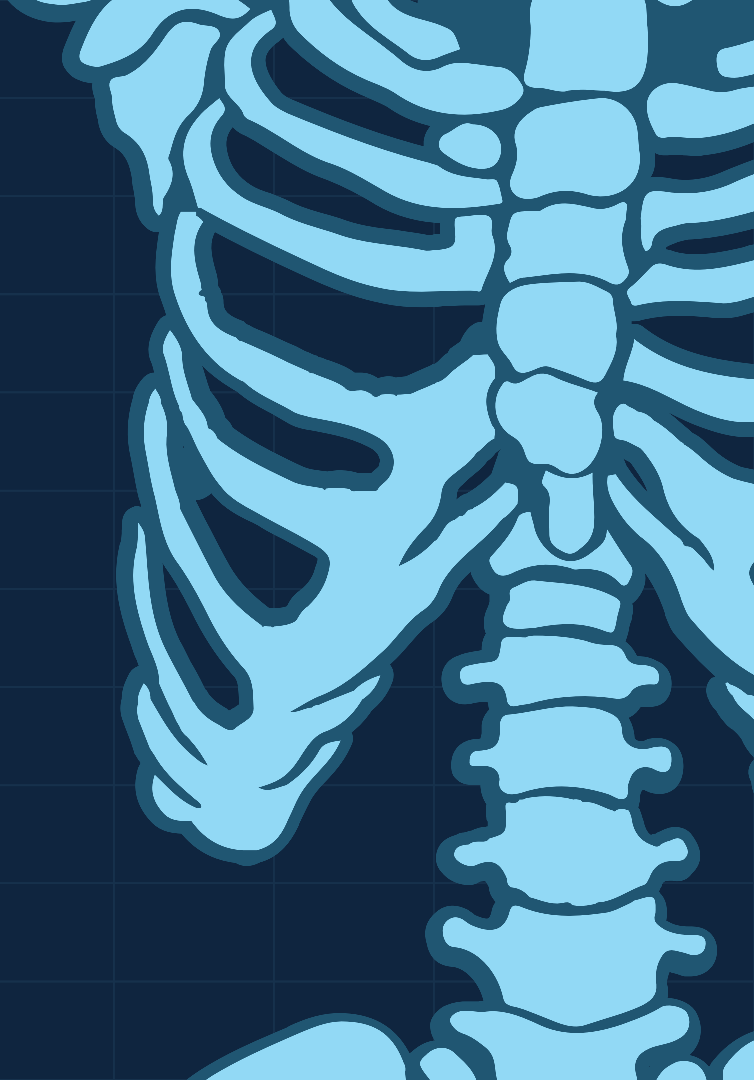

PROBLEM STATEMENT

- Train a model to classify images of Chest X-Ray(Input) for finding underlying disease (Output)
- Improve accuracy and reliability of machine learning models in disease classification of chest X-Rays
- Compare different models and set up a Federated learning prototype
- Employing Wavelets in classification techniques

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MOTIVATION

In the ever-evolving landscape of data-driven technologies, we're poised to embark on a transformative journey within the healthcare sector. The health industry already accounts for around 30% of the world's data, a number that's projected to surge to 35-40% by 2025.

So, Why not harness this vast reservoir of data by leveraging the power of AI?

Our project is driven by the need to improve medical diagnostics and patient care through the power of AI in analyzing Chest X-rays, reducing the burden on healthcare professionals while improving patient care.

And, perhaps, earn some top-notch grades along the way xD

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Reference for data statistics: class notes

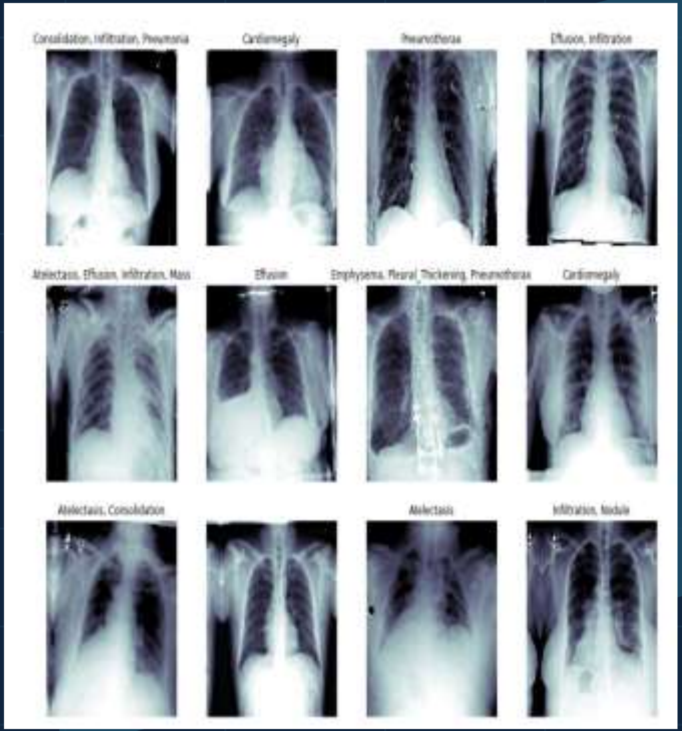
CHEST X-RAY 8 DATASET

108,948 frontal x-ray images

32,717 unique patients

Images labelled with 14 different medical conditions

- Hernia
- Cardiomegaly
- Emphysema
- Effusion
- Infiltration
- Mass
- Nodule
- Atelectasis
- Pneumothorax
- Pleural_Thickening
- Pneumonia
- Fibrosis
- Fibrosis
- Edema
- Consolidation



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IS IT A CLASSIFICATION OR REGRESSION PROBLEM?

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DATA PROCESSING

1) DATA LEAKAGE MITIGATION:

Ensured that split is done on the patient level so that there is no “leakage” between the train, validation and testing datasets

2) IMAGE PREPARATION:

- Used data augmentation and standardized the input distribution to mean 0 and std deviation 1
- Converted single channel X-ray images(grayscale) to three-channels for using pretrained model
- Shuffle the input after every epoch and set the image size to be 320px by 320px

3) HANDLING DATA IMBALANCE:

- Prevalence of positive cases varied significantly across the different pathologies
- Multiplied each sample from each class by a class-specific weight factor, w_pos & w_neg
- This will ensure that overall contribution of each class is same

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TECHNIQUES
/MODELS
/ARCHITECTURES

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General Remarks for All Models

Loss Function

Weighted Mean Squared Error Loss

(1/N) * ∑[weights * (y_true- y_pred)^2]

Optimizer

Adam

The most commonly used and currently the best optimizer for ML Models

Learning Rate

Built a custom learning rate scheduler which changes values according to the training loss

Metrics

ROC Curve

Number of Epochs - 5

Base Classification Model with a Classifier built upon it

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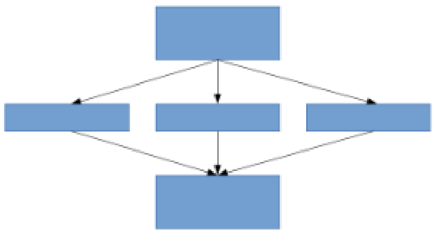
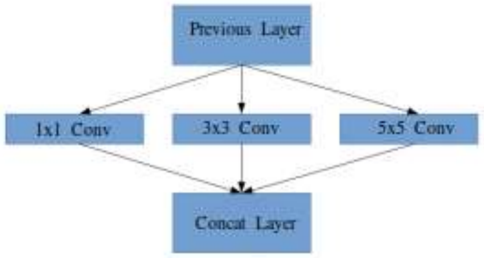
BASE MODEL 1
INCEPTION

- Handles deep neural networks with reduced computational cost
- Uses sparsely connected architecture

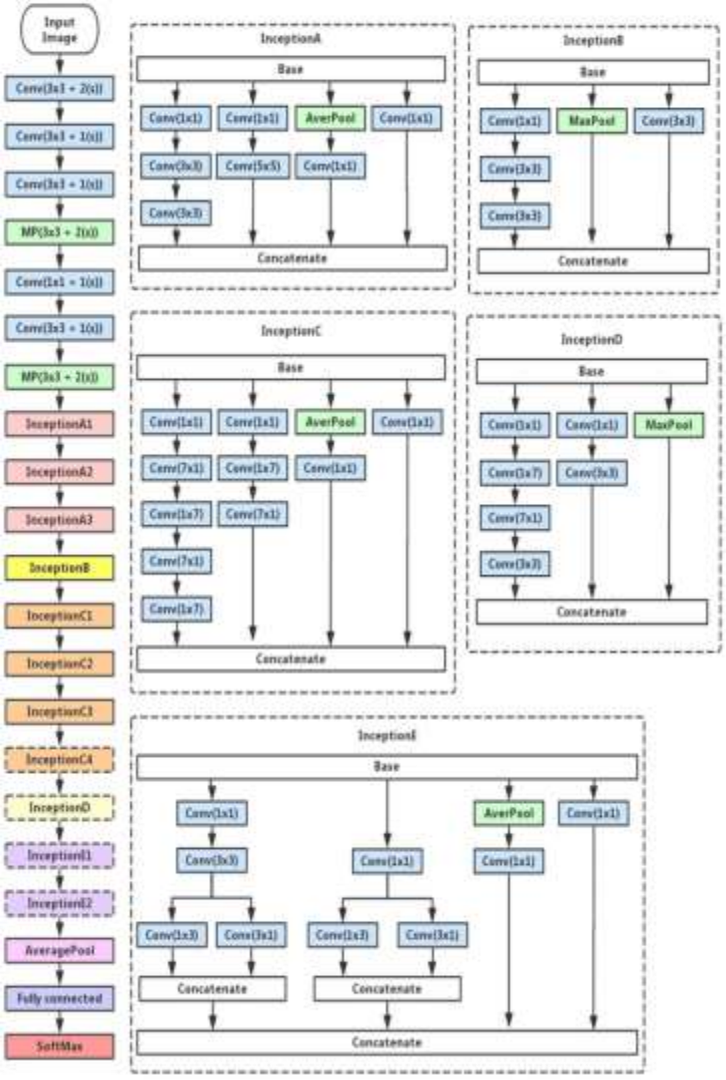


Sparsely connected architecture



Idea of an Inception module

Source: https://arxiv.org/abs/1409.4842



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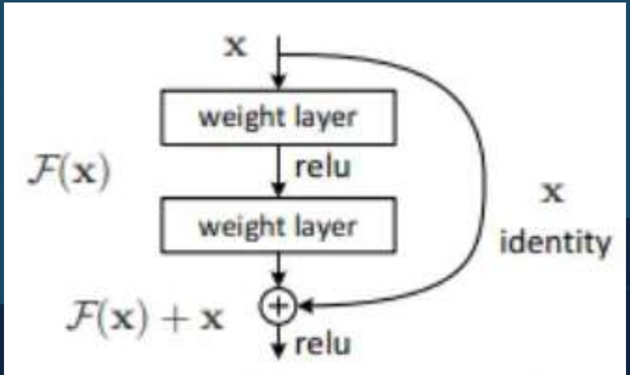
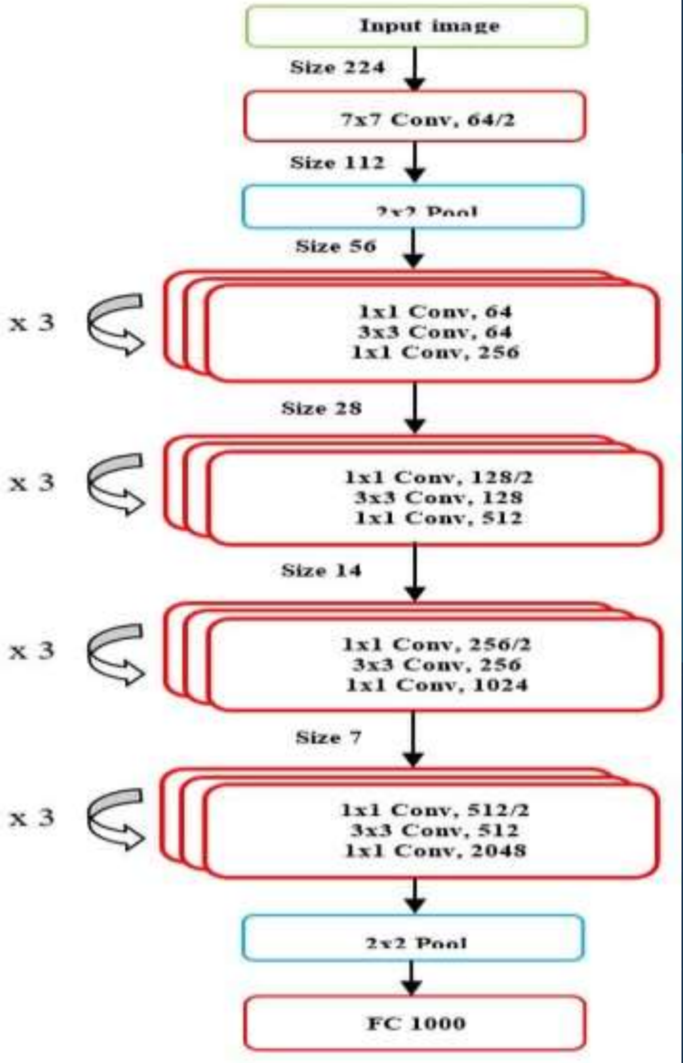
BASE MODEL 2
ResNet

- Introduced residual connections to address vanishing gradient problems
- Fit a residual mapping instead of directly trying to fit a desired underlying mapping





Source: https://arxiv.org/abs/1512.03385

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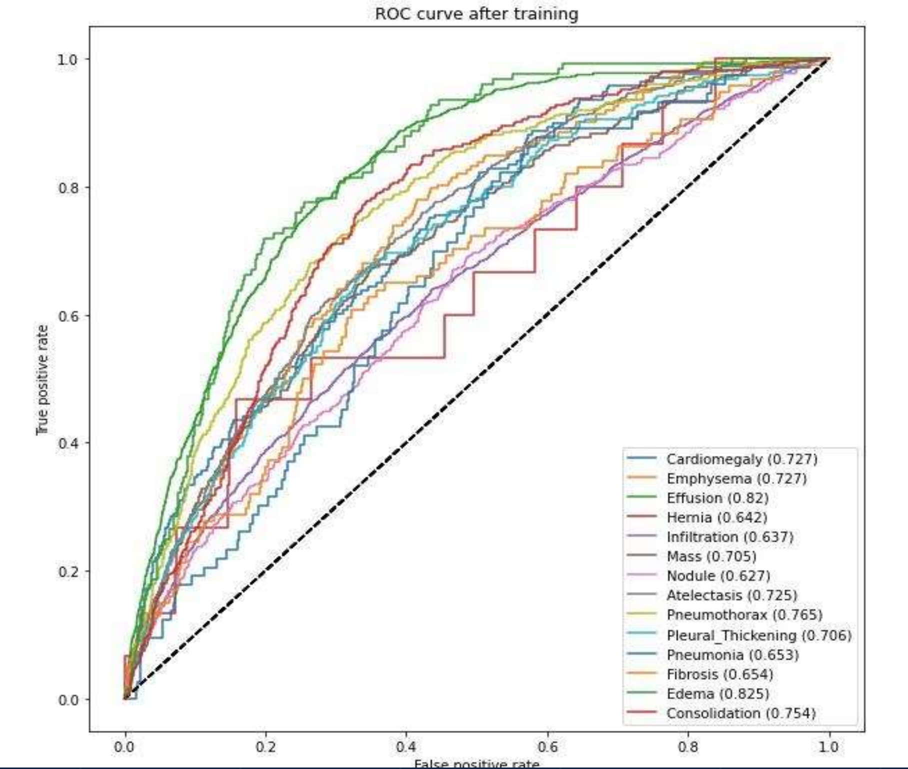
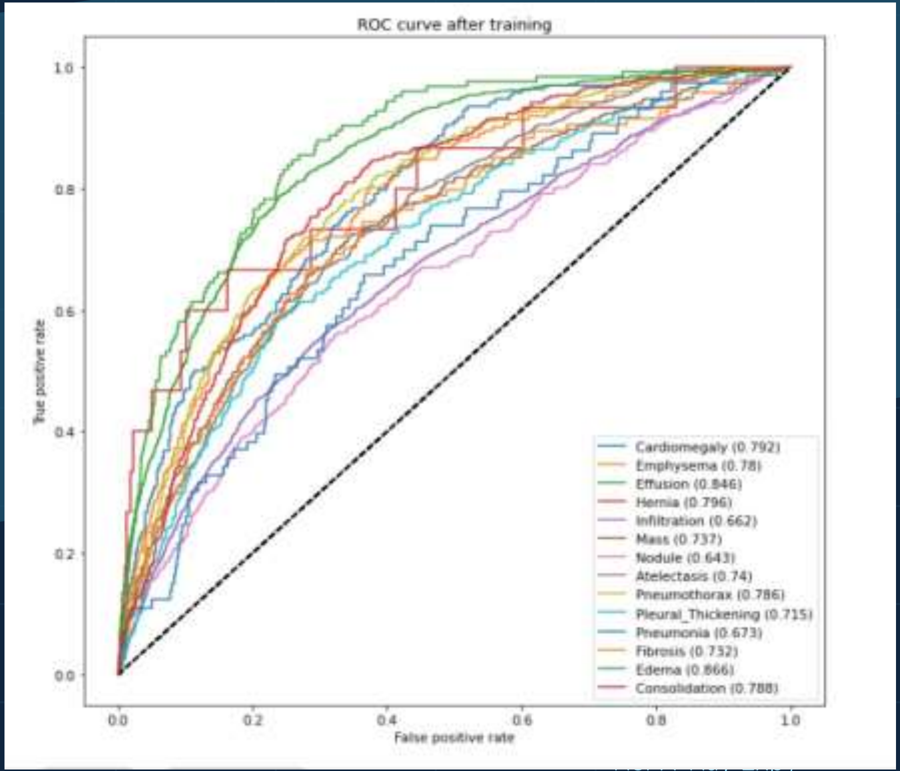
RESULTS

ROC for training with **INCEPTION** as the base model

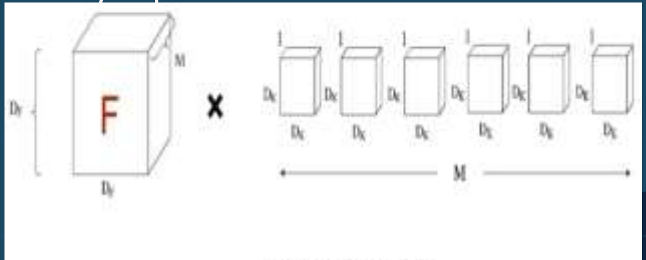


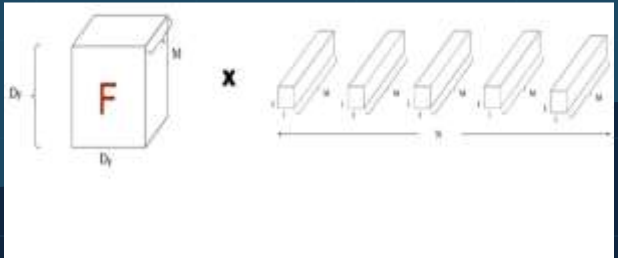
ROC for training with **RESNET** as the base model

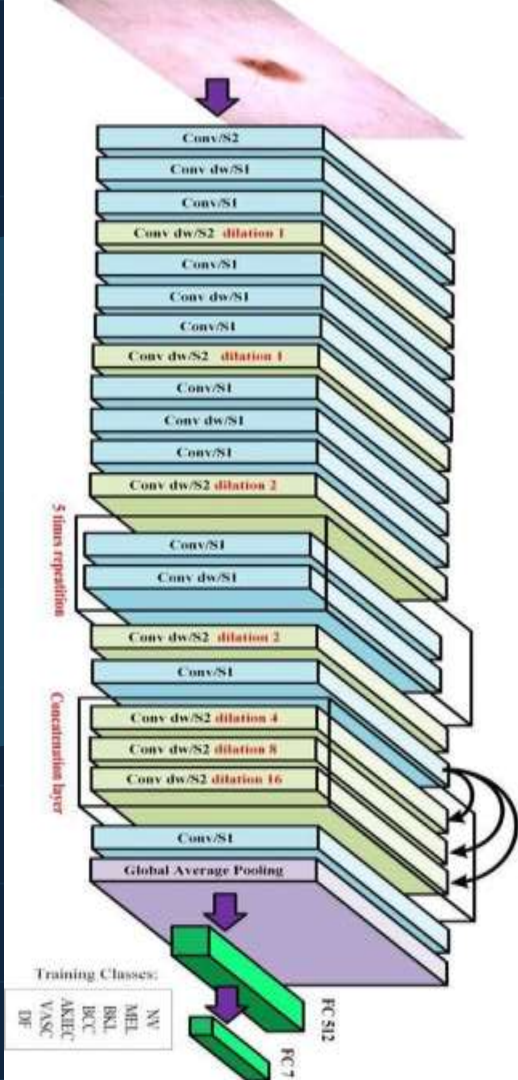


BASE MODEL 3 MOBILENET

- Uses Depth-wise separable convolutions
- Consists of 2 layers -> Depth-wise convolution and Point-wise convolution
- Depth-wise convolution - Filter the input channels
- Point-wise convolution - Combine them to create a new


Depth-wise Convolution


Point-wise Convolution



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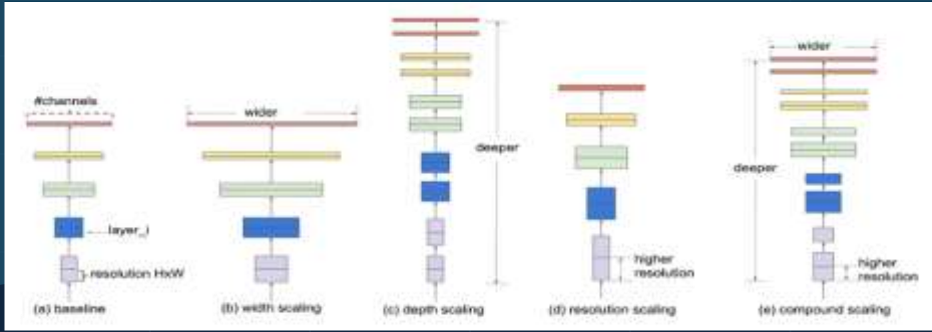
Source: https://arxiv.org/abs/1704.04861

BASE MODEL 4
EfficientNet

- Uses Compound Scaling, including depth, width and resolution scaling
- Based on the idea of balancing dimensions of width, depth, and resolution by scaling with a constant ratio
- One of the most power CNN architecture



Source: https://arxiv.org/abs/1905.11946

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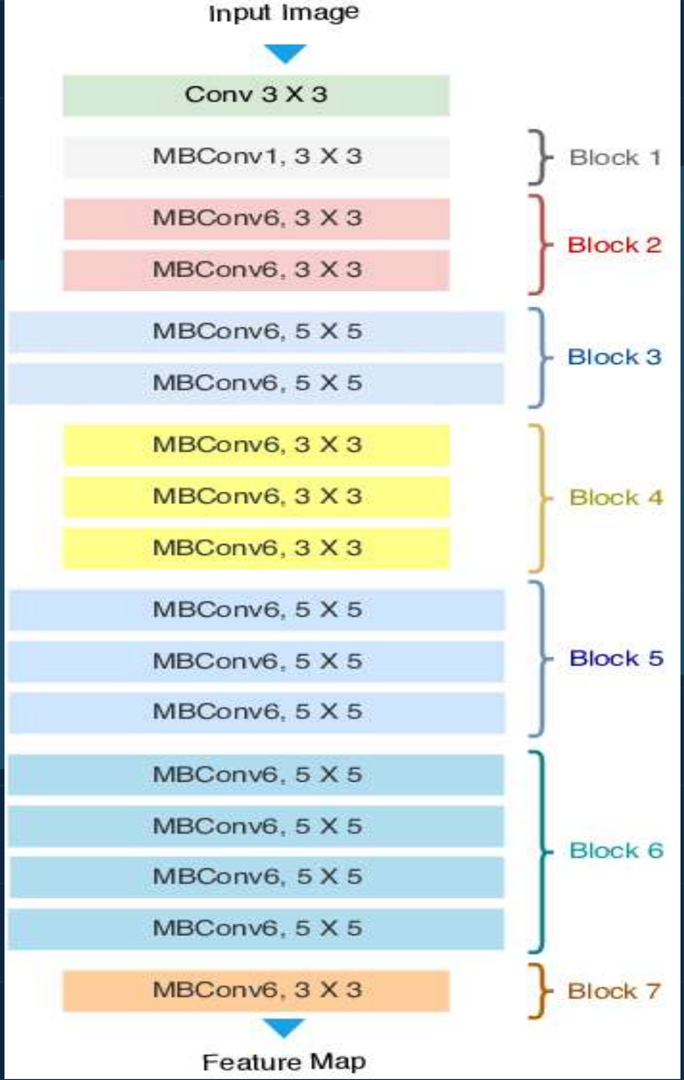
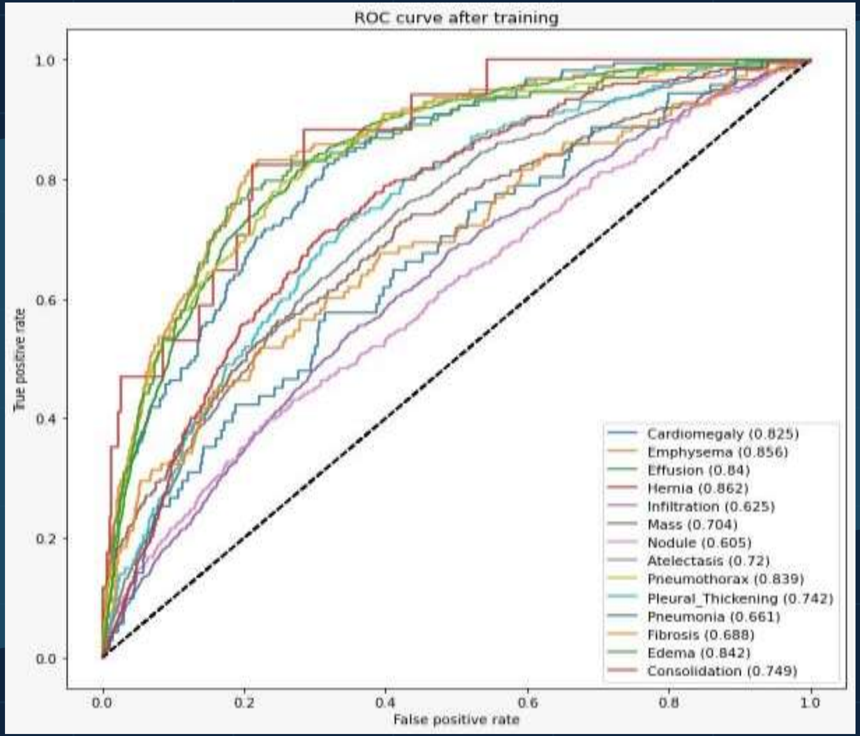
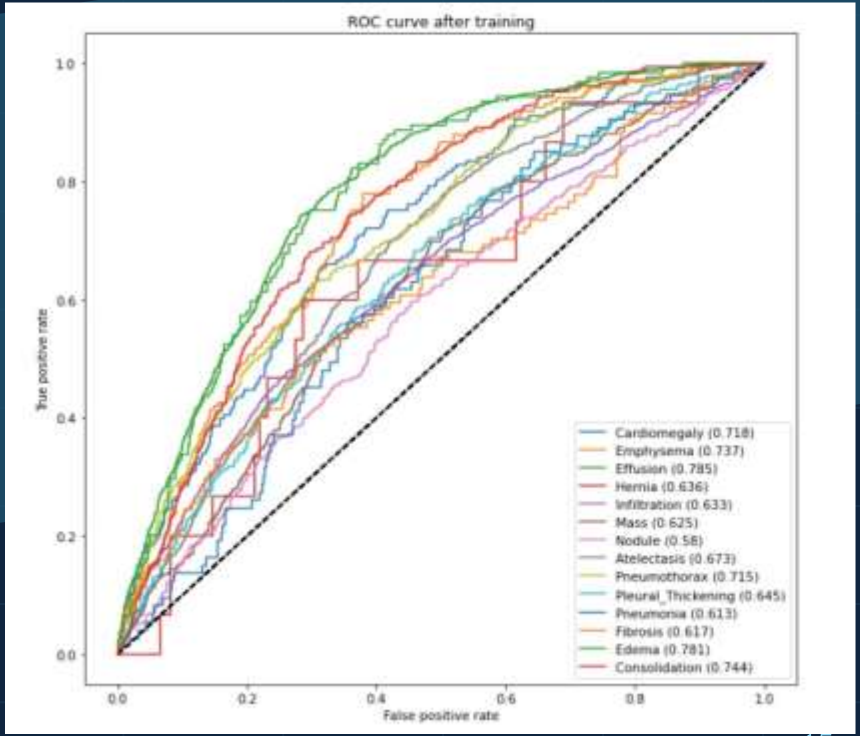


RESULTS

ROC for training with **EFFICIENTNET** as the base model



ROC for training with **MOBILENET** as the base model



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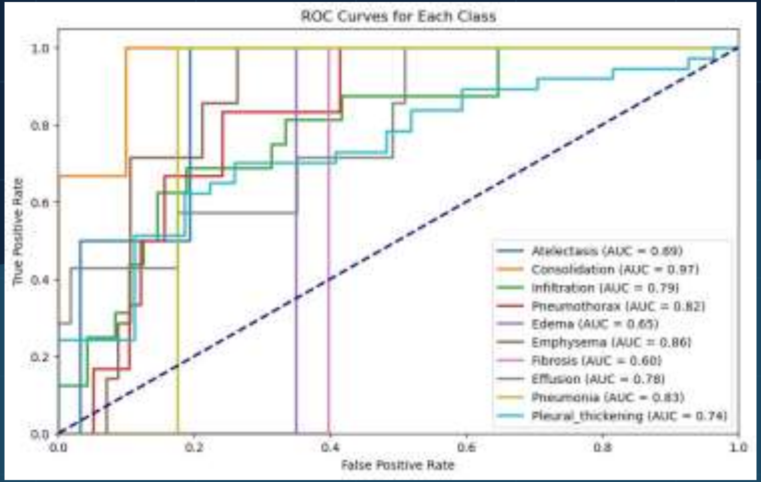
CONCLUSIONS

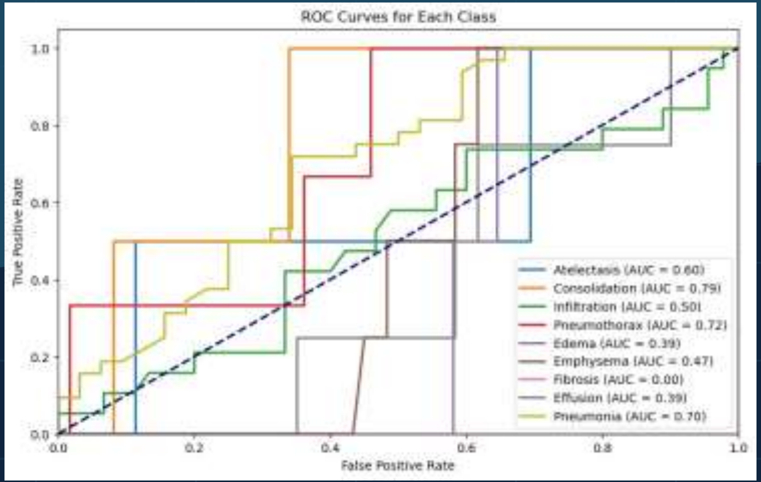
- Accuracy order observed from above ROC curves is as follows:
  EfficientNet(2019) > ResNet(2015) > Inception(2014) > MobileNet(2017)
- In practise, EfficientNet is often considered state-of-the-art for a wide range of tasks due to its efficiency- accuracy trade off but it requires abundant computational resources.
- For a robust and easy to train model which doesn’t require many computational resources, ResNet is most preferred.
- MobileNet is specialized for mobile vision applications and resource-constrained environments. While it excels in these contexts, it may not be a good choice for general image classification tasks on high performance hardware which is evident from its accuracy
- Inception is known for its computational efficiency and competitive performance but it is a quite old model and many new models have replaced this

MODEL 5

Federated learning

Next, we tried using federated learning that we learnt in the course. We used ResNet for each client while making sure that no data leakage occurs within test-train split and splitting of the data amongst the clients. These clients essentially function as distinct models, and their collective insights are amalgamated at the conclusion of our process.





ROC for a model trained on 1/10th and ½ of the actual dataset respectively. We used 10%/50% of the original data to fine-tune a pretrained ResNet-34 model

https://arxiv.org/ftp/arxiv/papers/2205/2205.09513.pdf

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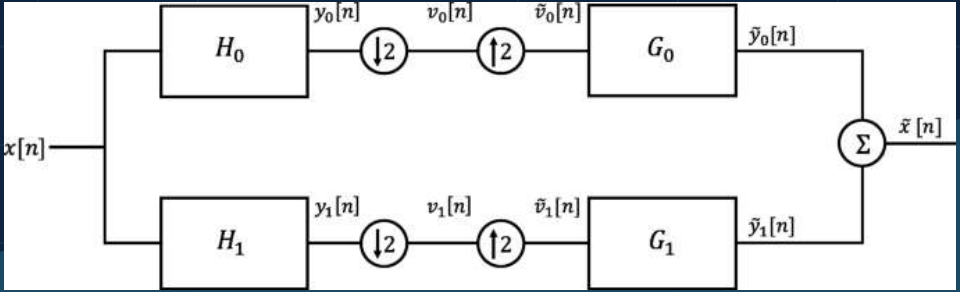
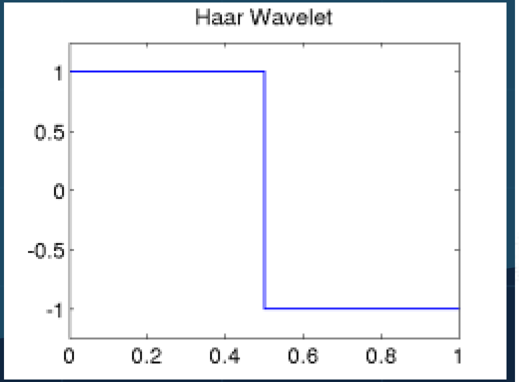
MODEL 6

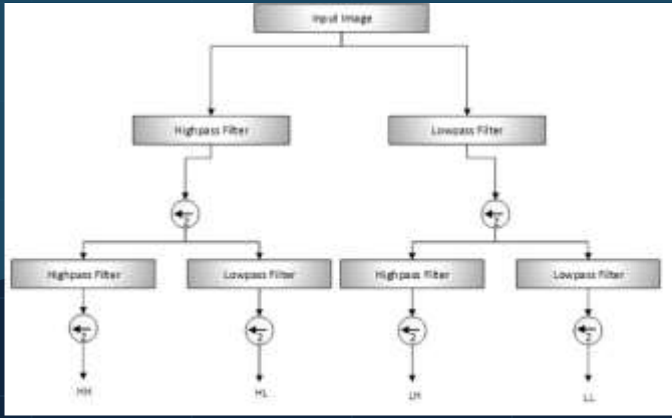
Federated Learning with Wavelet Transform



1D Multi-resolution analysis

We preprocessed the gray-scaled images using Haar DWT. We took the low frequency components which was relatively noise free. We then trained the model using the LL filtered images.
The LL filtered image is the approximate representation of the whole image and HL, LH and HH represent the fine details along the horizontal, vertical and diagonal respectively.





2D Multi-resolution analysis

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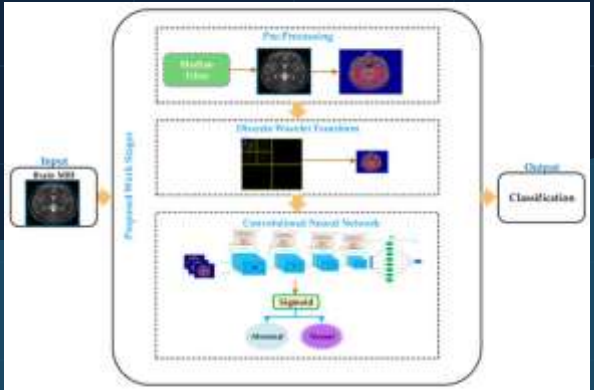
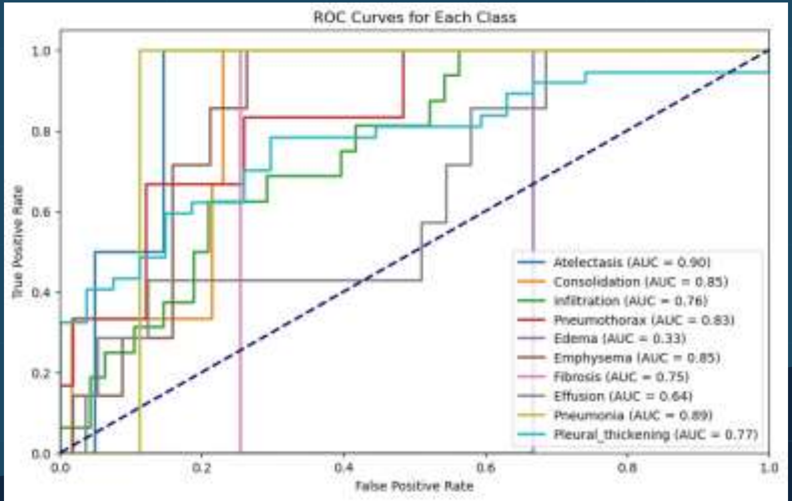
Links: link1 , link2, link3

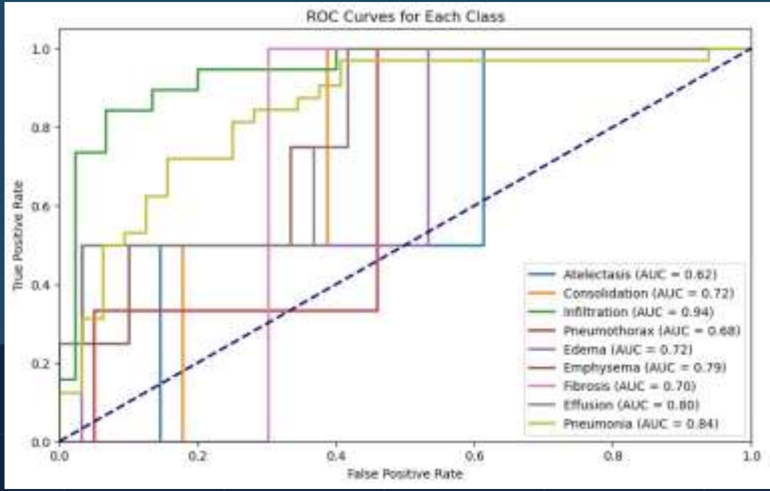
MODEL 6

Federated Learning with Wavelet Transform Results





ROC for a model trained on 1/10th of the actual dataset.



ROC for a model trained on 1/2 of the actual dataset. We used the same ResNet-34 pretrained model to be fine-tuned.

Links: link1

PROPOSED/ FUTURE WORK

1) **HARNESSING THE CONCEPT OF WAVELETS TO THE FULLEST**

- We have not used wavelets to the fullest extent. Using HL, LH, and HH is very useful in fine feature extraction.
- It has been found that using wavelets transform for feature extraction reduces the model parameters to a huge extent and also give similar results after less training then CNNs
- Fourier transform gives us information about the magnitude of a frequency component (presence), wavelet transform tells us the location along with the magnitude, but Shearlets allow us to perceive direction also.

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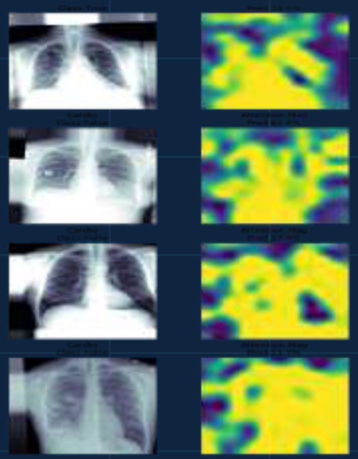
2) **USING ATTENTION MODEL**

- Global Average Pooling(GAP) is too simplistic since some of the regions are more relevant than others
- Use an attention mechanism to mask out the most useful values for the classification (helps the model learn to avoid shoulder, bones and so forth)
- Example - Classification of Cardiomegaly (All attention should be focused on heart region)



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THANKYOU!

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