

# CAPSTONE PROJECT DOCUMENT

# BLOCK-WISE ATTENTION-DRIVEN SOFT SEGMENTATION FOR IMBALANCED MULTI-LABEL CHEST X-RAY CLASSIFICATION

DSP391m - Group 4

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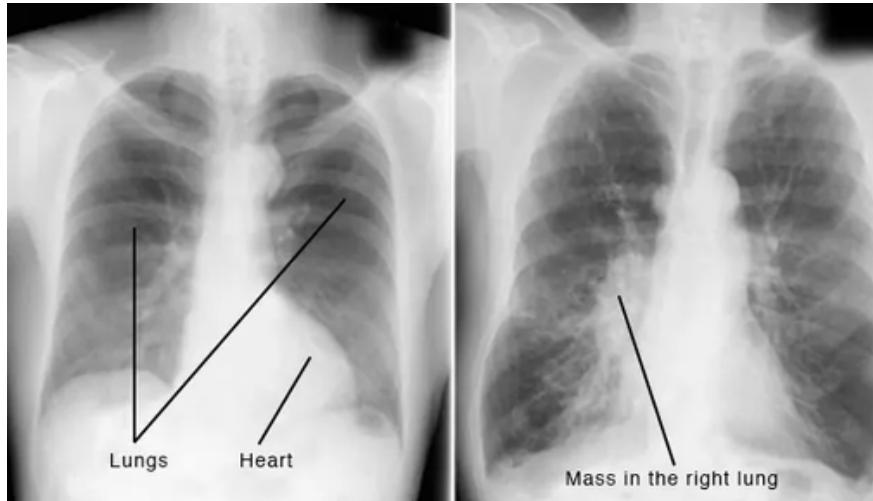
# Outlines

1. Introduction
2. Related Work
3. Main Contribution
4. Experiment
5. Demo
6. Conclusion
7. References

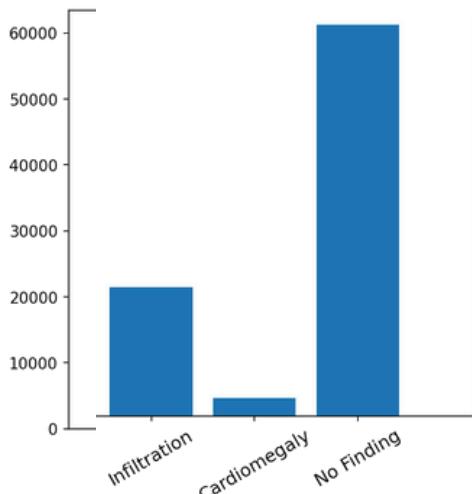
# 1. Introduction

# Background Context

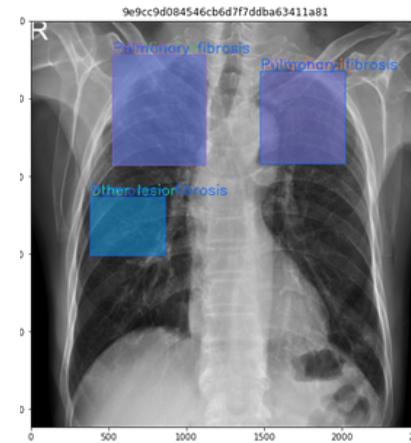
- Chest X-ray can help doctors see clearly the inside of the lungs and heart
- AI models to support more effective diagnosis.



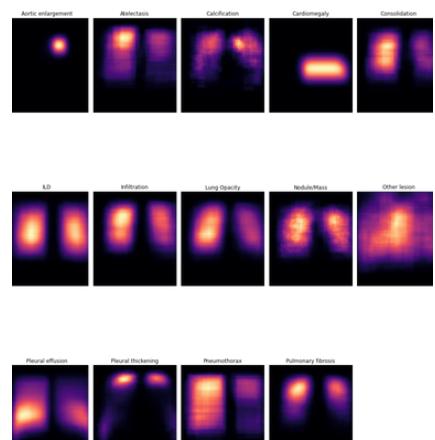
# Common Problems



Class Imbalance



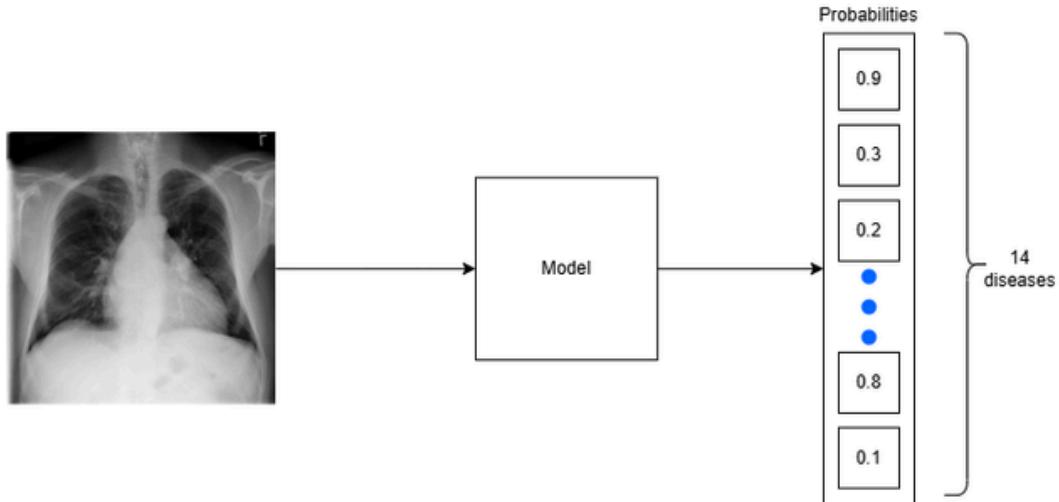
Annotation Limitations



Feature Discrimination

# Research Questions

- How to improve the performance of multi-label thoracic disease classification by **extracting specialized feature** with low resource consumption? → **Lightweight attention modules** integrated into CNN backbones
- Are current traditional evaluation methods suitable for the classification problem for **imbalance dataset?** → **Focal Loss**



# Our contributions

- **Solutions**
  - We proposed an end-to-end model comprising following methods:
    - Apply Attention Modules inspired by **Large Kernel Attention (LKA) as Soft Segmentation**
    - **Block-Wise Attention** within CNNs (DenseNet121, VGG16)
    - Two-Stage Training Strategy (**BCE Loss + Focal Loss**)
- **Achievements**
  - Achieves **0.8818** average AUC, surpassing state-of-the-art methods
  - **Computational efficiency**

## 2. Related Work

# Learning Techniques

- Common Workflow
  - Data Pre-processing
    - Clean and normalize raw data
    - Prepare data format for model input
  - Learning Representation Space
    - Encode data into meaningful embeddings
    - Capture essential patterns or features
  - Learning the Classifier
    - Map embeddings to class labels
    - Minimize prediction errors

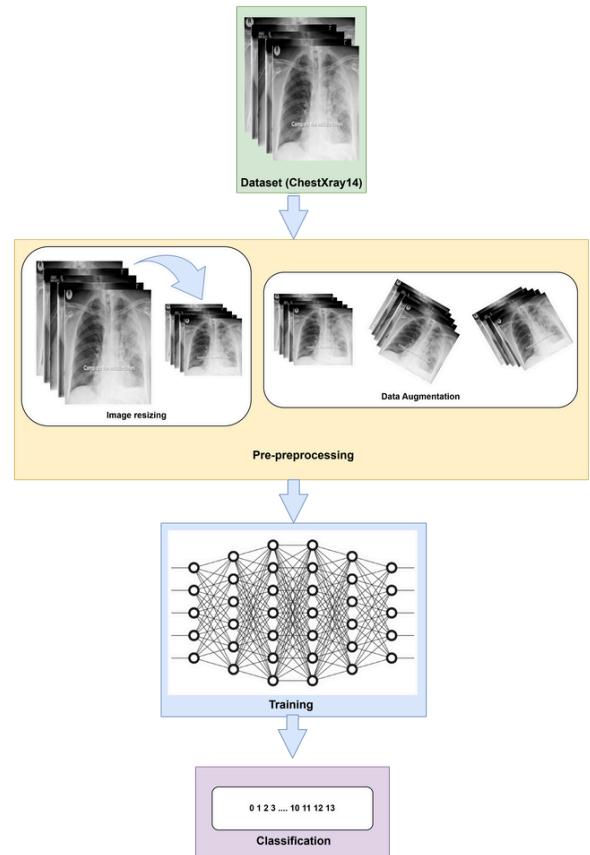
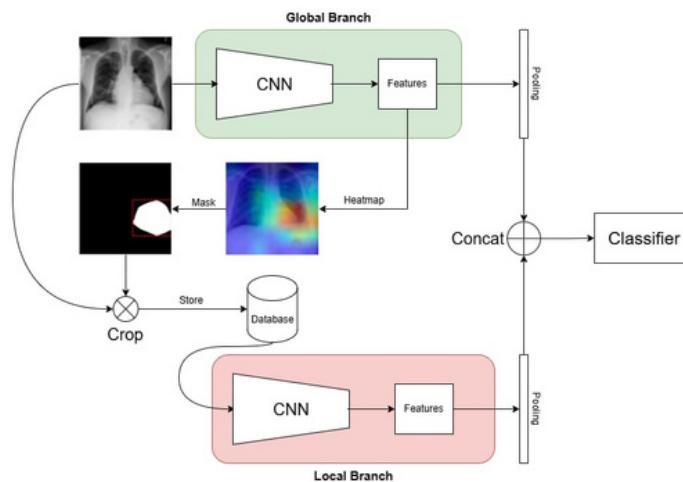


Fig: The workflow of Learning Technique for ChestXray14 multi-label classification.

# AG-CNN Architecture (1/2)

- Their Contributions:

- **Global branch:** Analyzes the entire X-ray image
- **Local branch:** Focuses on pathological regions through attention mechanism
- **Fusion branch:** Combines information



[\*] Guan, Q., Huang, Y., Zhong, Z., Zheng, Z., Zheng, L., Yang, Y.: Diagnose like a radiologist: Attention guided convolutional neural network for thorax disease classification. arXiv preprint arXiv:1801.09927 (2018).

# AG-CNN Architecture (2/2)

- **Advantages:**

- Learns to ignore irrelevant background and emphasizes diagnostic regions.
- Global, local, and fusion branches capture both context and fine-grained lesion details, boosting classification accuracy.

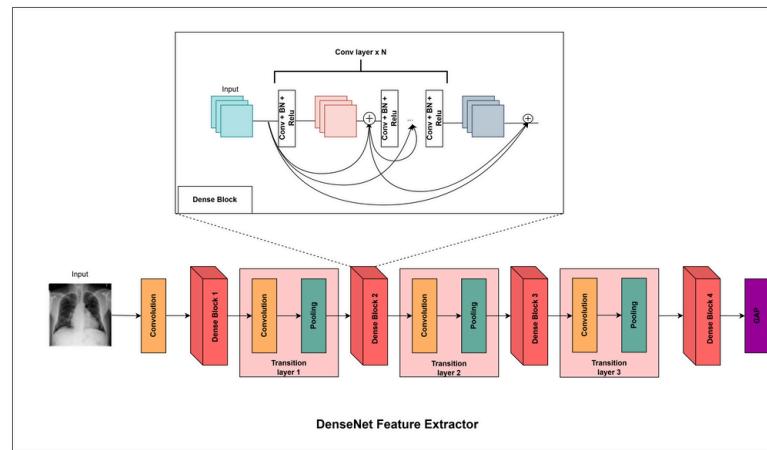
- **Limitations:**

- Three branches increase computational, making real-world deployment challenging

# DenseNet121 Extractor (1/2)

- **Core Components:**

- **Dense block:** Convolution layer, Batch Normalization and ReLU function.
- **Transition layer:** Use to connect dense blocks, has 2 main purpose:
  - Reduce number of feature map
  - Downsampling the dimension of feature map



# DenseNet121 Extractor (2/2)

- **Advantages:**

- Reduce vanishing gradient
- Feature reuse
- Fewer parameters

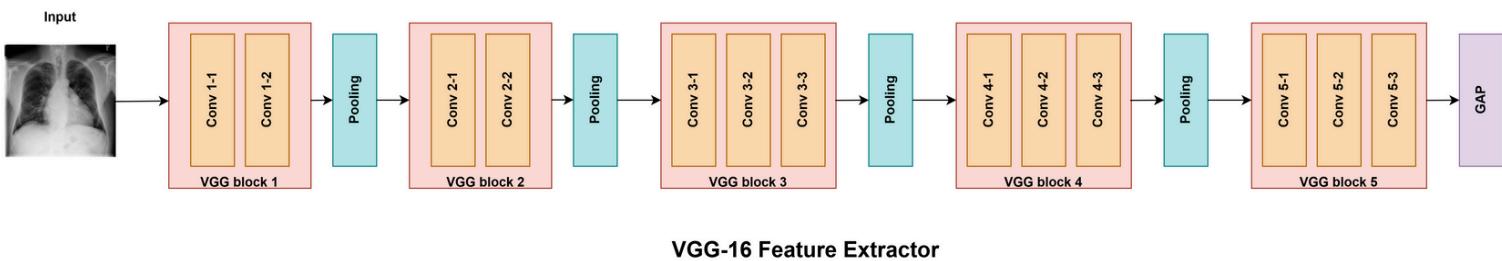
- **Limitations:**

- High Memory Consumption
- Computational Complexity
- Implementation Complexity

# VGG16 Extractor (1/2)

- **Core Components:**

- Contains 16 weight layers: 13 Convolutional layers and 3 Fully Connected layers
- Uses small ( $3 \times 3$ ) convolution filters with stride 1 and padding 1
- Includes 5 Max Pooling layers ( $2 \times 2$ , stride 2) for downsampling
- Uses ReLU activation after each convolution



# VGG16 Extractor (2/2)

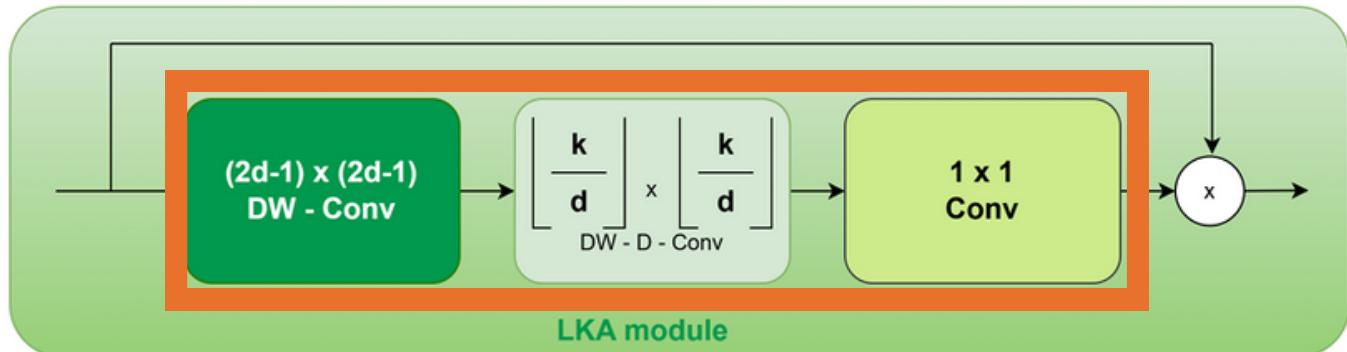
- **Advantages:**
  - Basic architecture
  - Strong in feature extractor
  - Suitable for pretraining
- **Limitations:**
  - Lots of parameter
  - High risk of overfitting because of not having skip connection

# Large Kernel Attention (LKA)

- Based on the attention mechanism of Visual Attention Network\*
- Mathematical Formulation of LKA's Attention Map

$$a = A(u) = W_p * (K_2 * (K_1 * u))$$

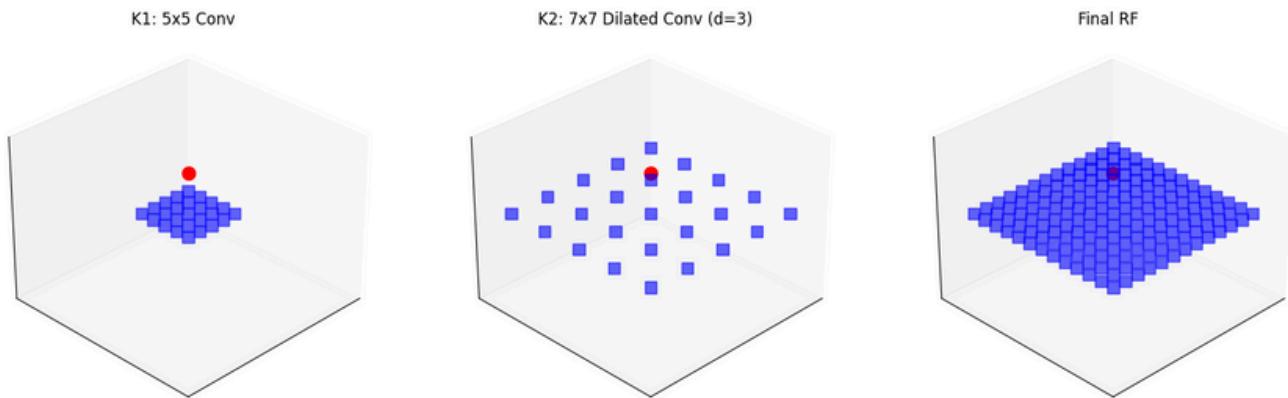
where  $K_1 \in \mathbb{R}^{C \times 1 \times k_1 \times k_1}$ : Depthwise convolution kernel with  $k_1 = 5$ ,  $K_2 \in \mathbb{R}^{C \times 1 \times k_2 \times k_2}$ : Dilated depthwise convolution with  $k_2 = 7$ , dilation  $d = 3$ ,  $W_p \in \mathbb{R}^{C \times C \times 1 \times 1}$ : Pointwise convolution for channel mixing.



# Receptive Field in LKA

- The receptive field of LKA is:

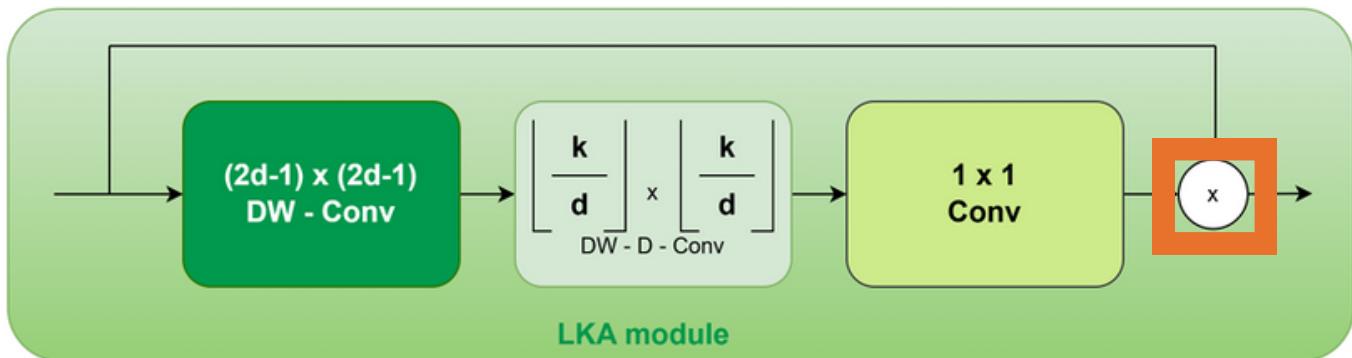
$$R = k_2 + (k_2 - 1)(d - 1) - \text{padding} = 7 + (7 - 1)(3 - 1) - 6 = 7 + 12 - 6 = 13$$



**Fig: Illustration of the receptive field of the LKA modules.**

# LKA as Soft Segmentation

- Using element-wise product, the attention map acts as a soft mask to highlight important regions of the input.



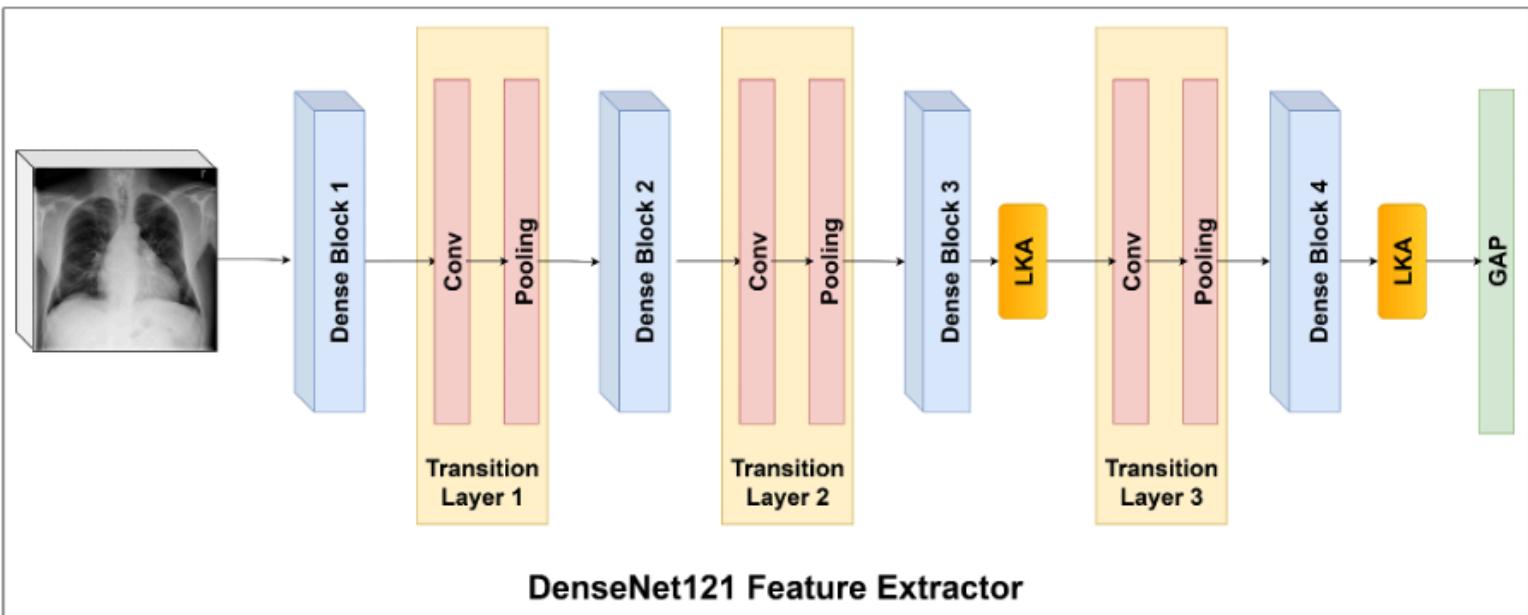
$$y_{i,j,c} = u_{i,j,c} \cdot a_{i,j,c}$$

**Soft Mask**

### 3. Main Contribution

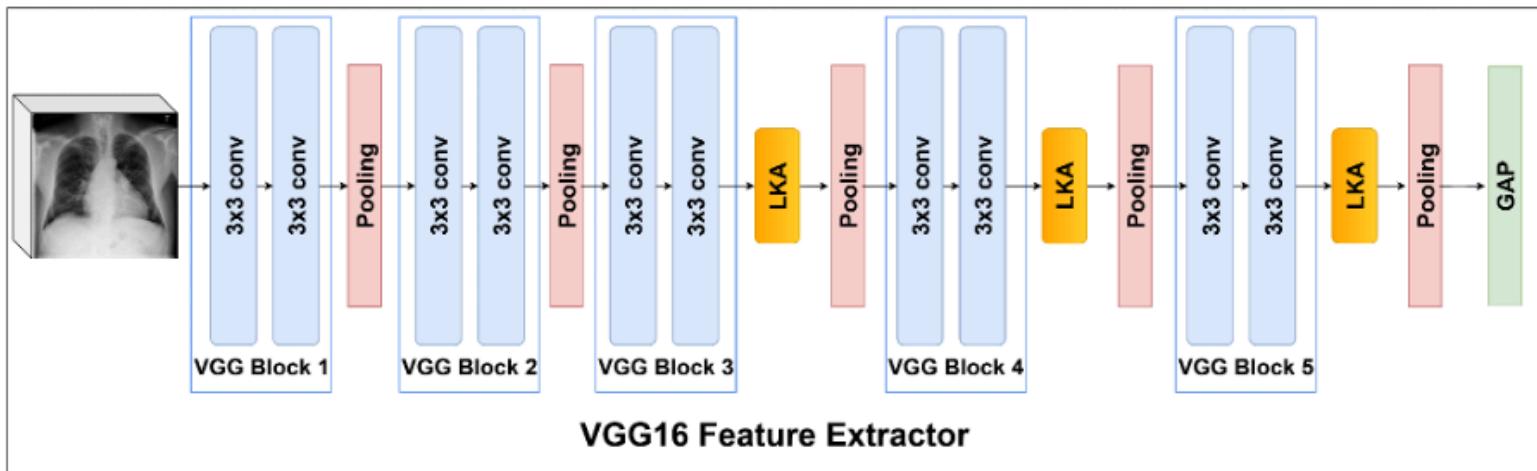
# Block-Wise DenseNet121

- Taking advantage of DenseNet121's strengths, we integrate LKA into the following blocks.



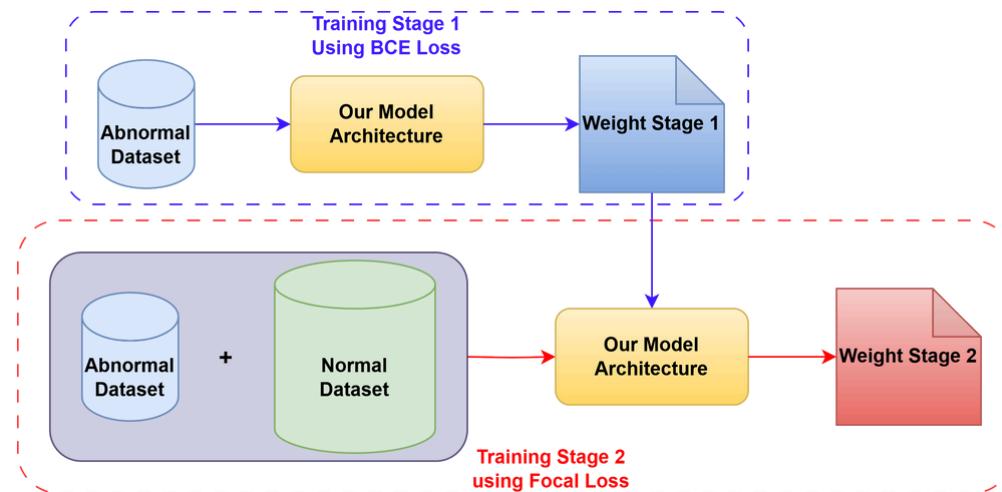
# Block-Wise VGG16

- Taking advantage of VGG16's strengths, we integrate LKA into the following blocks.



# Training Strategy

- Based on the **training strategy of SynthEmsemble\***
- **Change:** Employs **Focal Loss** in the 2nd stage instead of standard loss
- **Insight:** To better handle the severe class imbalance



[\*] Ashraf, S.N., Mamun, M.A., Abdullah, H.M., Alam, M.G.R.: Synthensemble: a fusion of cnn, vision transformer, and hybrid models for multi-label chest x-ray classification. In: 2023 26th International Conference on Computer and Information Technology (ICCIT). pp. 1–6. IEEE (2023)

# Loss Function

- **Stage 1:** Abnormal Data Pretraining using **binary cross-entropy loss**

$$L_{BCE} = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^{N_c} [y_{i,c} \log(\sigma(z_{i,c})) + (1 - y_{i,c}) \log(1 - \sigma(z_{i,c}))]$$

- **Stage 2:** Full Data Training with **Focal Loss\***

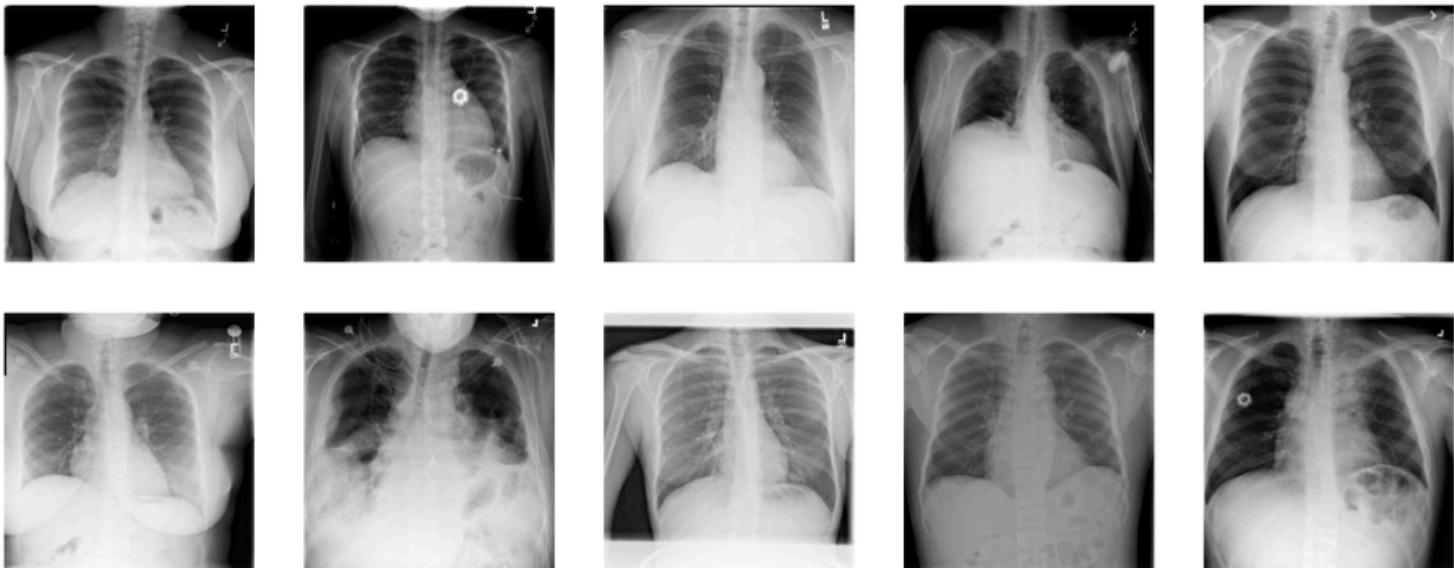
$$L_{FL} = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^{N_c} \alpha_c (1 - p_{i,c})^\gamma y_{i,c} \log(p_{i,c})$$

[\*] Lin, T.Y., Goyal, P., Girshick, R., He, K., Dollár, P.: Focal loss for dense object detection. In: Proceedings of the IEEE international conference on computer vision. pp. 2980–2988 (2017)

# 4. Experiment

# Dataset: ChestXray14\*

- **112,120** frontal-view X ray images from **30,805** unique patients.
- Each image labeled for the presence of **14** thoracic pathologies.



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[\*] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., Summers, R.M.: Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 2097–2106 (2017)

# Imbalance Dataset

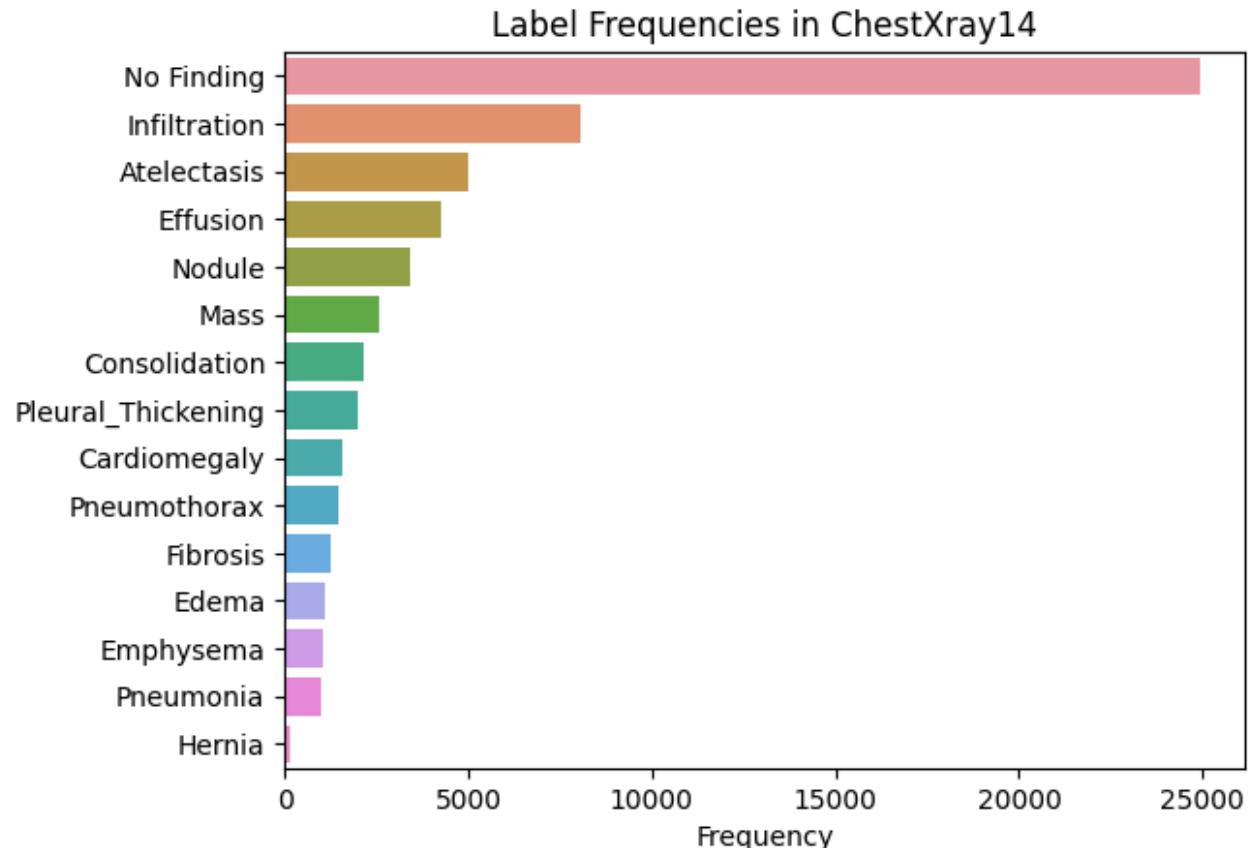


Fig: Diseases Frequencies

# Setting Training

- **Metric:** AUC
- **Preprocessing:**
  - **Image resizing:** All images resized to 224×224 pixels.
  - **Normalization:** Normalized using ImageNet statistics.
  - **Data Augmentation:** Applied during training to improve generalization:
    - Random rotation ( $\pm 10^\circ$ )
    - Horizontal flipping
    - Random cropping and zooming
    - Patient-wise splitting: Ensured no patient appears in both training and test sets to avoid data leakage, divide into 70-10-20.
- **Accelerator:** P100 on Kaggle

# Splitting Dataset

<b>Stage</b>	<b>Training Set</b>	<b>Validation Set</b>	<b>Test Set</b>
<b>Stage 1</b>	36,506 images	5,215 images	-
<b>Stage 2</b>	78,544 images	11,220 images	22,356 images

# Performance Comparison SOTA

TABLE I: Comparison of AUC scores with state-of-the-art methods on ChestXray14 dataset.

Pathology	Wang et al. [1]	CheXNet [2]	SynthEnsemble [3]	AG-CNN (ResNet-50) [4]	AG-CNN (DenseNet-121) [4]	Ours (BCELoss 2 Stage)	Ours (BCELoss + FocalLoss)
Atelectasis	0.716	0.8094	0.83390	0.844	<b>0.853</b>	<b>0.853</b>	<b>0.858</b>
Cardiomegaly	0.807	0.9248	0.91954	0.937	0.939	<b>0.941</b>	<b>0.945</b>
Effusion	0.784	0.8638	0.88977	<b>0.904</b>	0.903	<b>0.909</b>	<b>0.909</b>
Infiltration	0.609	0.7345	0.74102	0.753	<b>0.754</b>	0.749	<b>0.755</b>
Mass	0.706	0.8676	0.87315	0.893	<b>0.902</b>	0.899	<b>0.907</b>
Nodule	0.671	0.7802	0.80611	0.827	0.828	<b>0.836</b>	<b>0.838</b>
Pneumonia	0.633	0.7680	0.77648	0.776	0.774	<b>0.807</b>	<b>0.815</b>
Pneumothorax	0.806	0.8887	0.90164	0.919	0.921	<b>0.93</b>	<b>0.932</b>
Consolidation	0.708	0.7901	0.81575	<b>0.842</b>	<b>0.842</b>	0.832	<b>0.833</b>
Edema	0.835	0.8878	0.91034	0.919	<b>0.924</b>	<b>0.935</b>	<b>0.935</b>
Emphysema	0.815	0.9371	0.92946	0.941	0.932	<b>0.955</b>	<b>0.956</b>
Fibrosis	0.769	0.8047	0.83347	<b>0.857</b>	<b>0.864</b>	0.841	<b>0.856</b>
Pleural Thickening	0.708	0.8062	0.81270	0.836	0.837	<b>0.846</b>	<b>0.853</b>
Hernia	0.767	0.9164	0.91723	0.903	0.921	<b>0.942</b>	<b>0.954</b>
<b>Mean AUC</b>	0.738	0.841	0.85433	0.868	0.871	<b>0.8768</b>	<b>0.8818</b>

Magenta indicates the highest value, and Cyan indicates the second-highest value for each pathology.

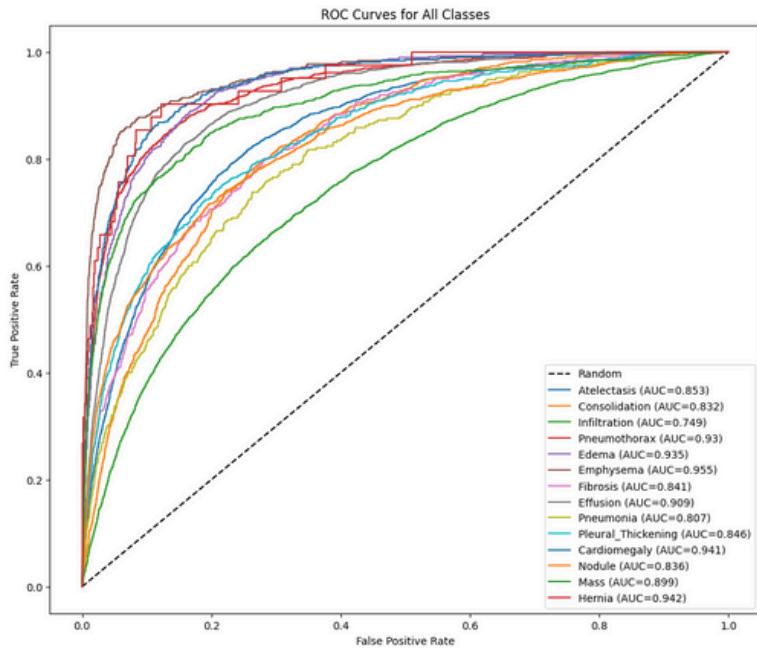
[1] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., Summers, R.M.: Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 2097–2106 (2017)

[2] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., et al.: Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225 (2017)

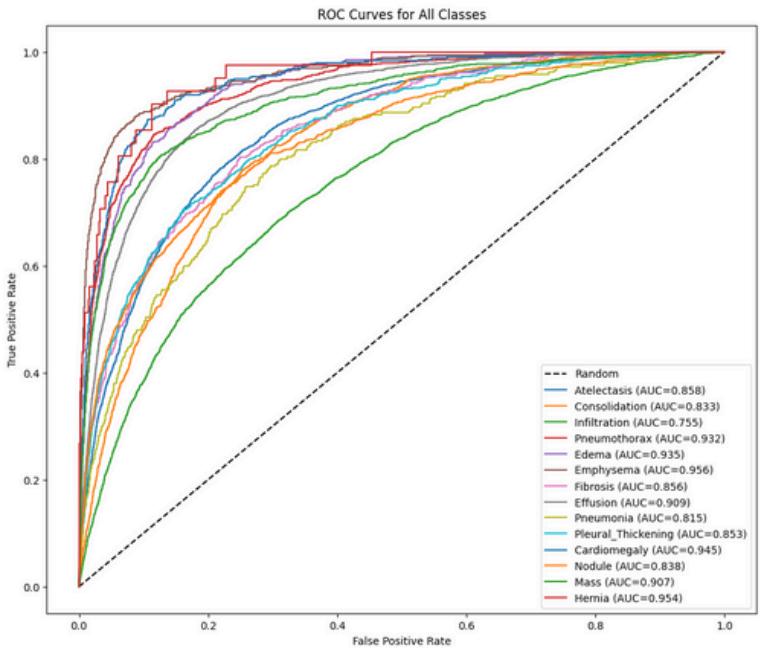
[3] Ashraf, S.N., Mamun, M.A., Abdullah, H.M., Alam, M.G.R.: Synthensemble: a fusion of cnn, vision transformer, and hybrid models for multi-label chest x-ray classification. In: 2023 26th International Conference on Computer and Information Technology (ICCIT). pp. 1–6. IEEE (2023)

[4] Guan, Q., Huang, Y., Zhong, Z., Zheng, Z., Zheng, L., Yang, Y.: Diagnose like a radiologist: Attention guided convolutional neural network for thorax disease classification. arXiv preprint arXiv:1801.09927 (2018)

# ROC AUC



(a) ROC AUC of Ours (BCELoss 2 Stage).



(b) ROC AUC of Ours (BCELoss + FocalLoss).

Fig: ROC AUC of Ours.

# Parameters and Training time Compared to SynthEnsemble (1/2)

Ours						
Model variant	Trainable params	Total params	Training stage 1	Training stage 2	Total	GFLOPS
Densenet121+LKA full	9609870	9609870	6563.2s	8588.8s	<b>15152s</b>	<b>3. 64</b>
Densenet121+LKA 2 block	9223054	9223054	6375.6s	8239s	<b>14614.6s</b>	<b>3. 14</b>
Densenet121+LKA after	8095630	8096530	5611.4s	6957.3s	<b>12568.7s</b>	<b>2. 92</b>
VGG16+LKA full	15453966	15453966	14225.2s	10206.1s	<b>24431.3s</b>	<b>16. 70</b>
VGG16+LKA 3 block	15418702	15418702	8628.6s	5682.1s	<b>14310.7s</b>	<b>15. 93</b>
VGG16+LKA after	15031886	15031886	4851.2s	5492.6s	<b>10343.8s</b>	<b>15. 39</b>

# Parameters and Training time

## Compared to SynthEnsemble (2/2)

Synth Ensemble				
Model	Trainable Params	Total Params	FLOPS (GFLOPS)	Training time
CoAtNet	1128320	73904264	14. 55	Stage 1: 21045.6s Stage 2: 6811.2s
DenseNet121	1144512	8014720	2. 87	Stage 1: 40958.1s
MaxViTV2	1122944	116128376	23. 88	Stage 1: 13791.6s
SwinV2	842240	49725140	9. 08	Stage 1: 31071.3s
VOLO D2	319872	57923696	14. 24	Stage 1: 32398.5s
convnextv2	1647488	198007040	34. 4	Stage 1: 35538.9 Stage 2: 11597.6s
<b>Total</b>	<b>6205376</b>	<b>503703236</b>	<b>99. 02</b>	<b>~193212.8s</b>

# Ablation Studies (1/3)

- Impact of Loss Function in Single vs Two-Stage Training

Model Variant	One-Stage BCE	One-Stage Focal	Two-Stage
DenseNet121	0.8227	0.8044	0.8402
DenseNet121 + AWBs	0.8340	0.8369	<b>0.8498</b>
VGG16	0.8275	0.8094	0.8401
VGG16 + AWBs	0.8238	0.8247	<b>0.8818</b>

- Statement:** Two-Stage strategy enables the model to better learn and focus on relevant features → improved performance.

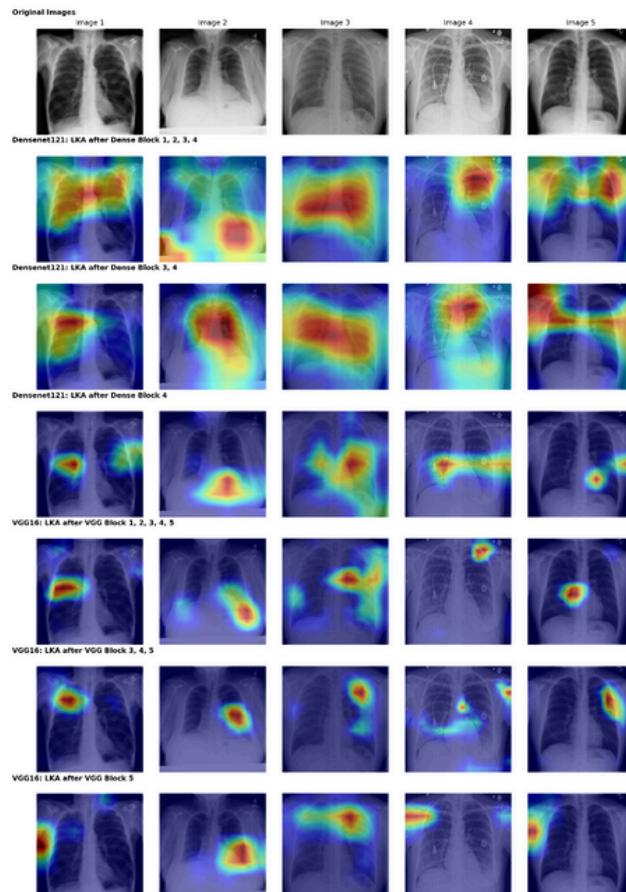
# Ablation Studies (2/3)

- Impact of Attention Module Integration Position

Model	Position	Mean AUC
DenseNet121 + LKA	After	0. 8475
DenseNet121 + LKA	Full Block	0. 8416
DenseNet121 + LKA	Last 2 Block	<b>0. 8498</b>
VGG16 + LKA	After	0. 8470
VGG16 + LKA	Full Block	0. 8666
VGG16 + LKA	Last 3 Block	<b>0. 8818</b>

- Statement:** Optimal placement of attention modules  $\Leftrightarrow$  higher-level features are consolidated  
→ yields the best performance

# Ablation Studies (3/3)



## GRADCAM

- **"Soft segmentation"**
  - The model adaptively focuses on **important areas**
  - Improving the **refine segmentation** process.

Fig: GRADCAM for Illustration of Attention Module based on Different Methods.

# 5. Demo

# System Workflow

- After training we use the best weight for demo, we will highlight important area via GRAD-CAM and give the predicted results of model and ground truth labels.

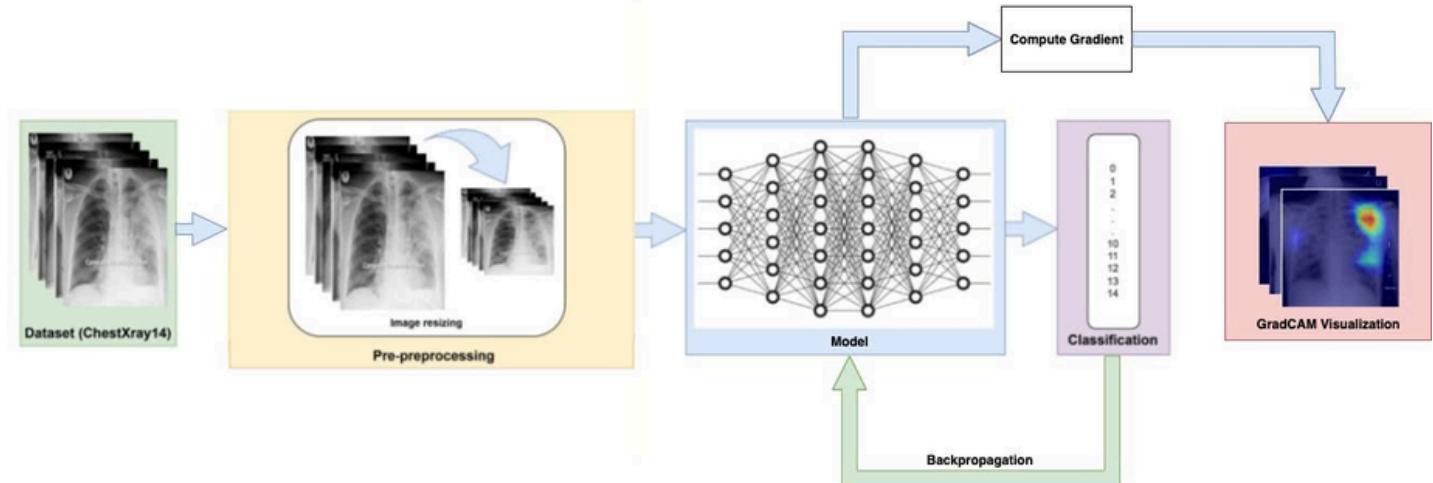


Fig: Our system workflow

# 6. Conclusion

# Our contribution

- **Solutions**

- We proposed an end-to-end model comprising following methods:
  - Apply Attention Modules as Soft Segmentation
  - Block-Wise Attention within CNNs
  - Two-Stage Training Strategy

- **Achievements**

- Achieves 0.8818 average AUC, surpassing state-of-the-art methods
- Computational efficiency.

# 7. References

# References (1/4)

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THANK YOU FOR  
YOUR ATTENTION !

Q&A