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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

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1. Introduction (1/5)

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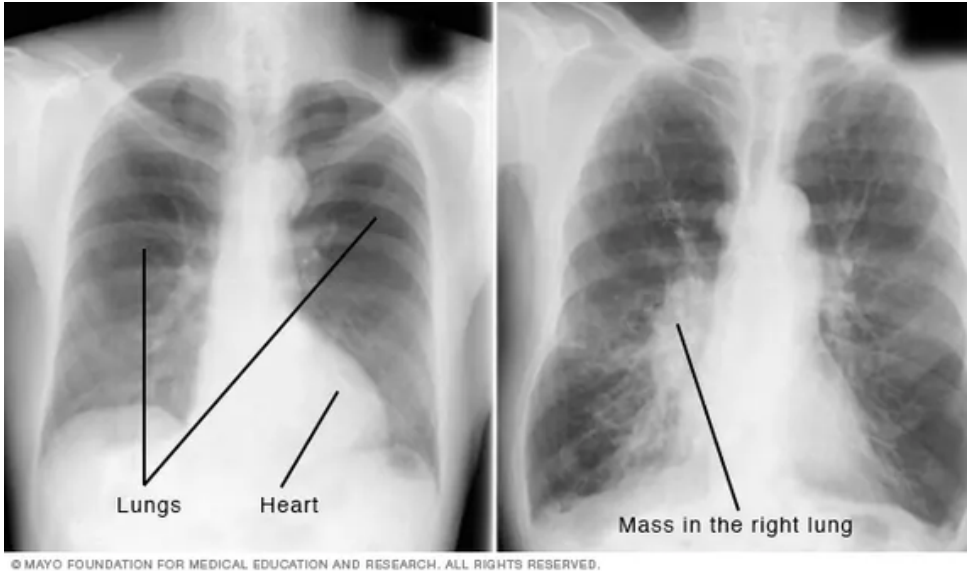
Scenario

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



1. Introduction (2/5)

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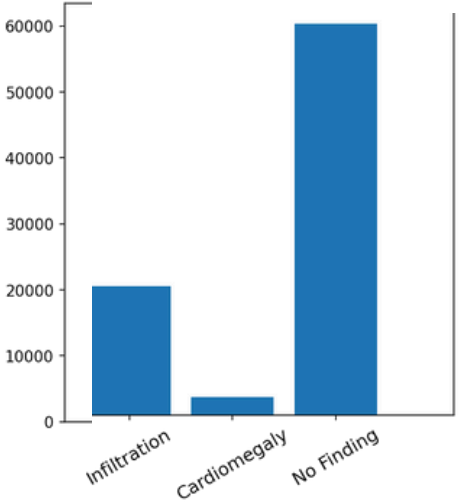
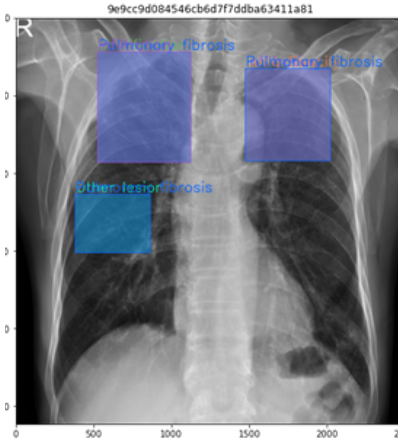
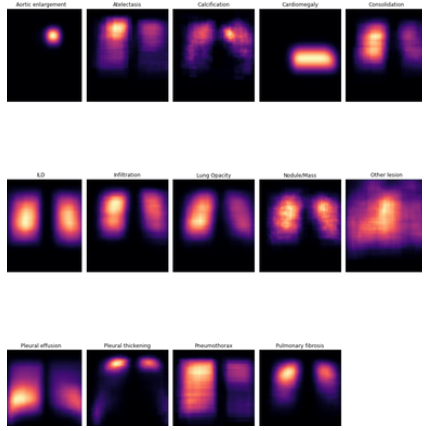
Problems



Class Imbalance



Annotation Limitations



Feature Discrimination

1. Introduction (3/5)

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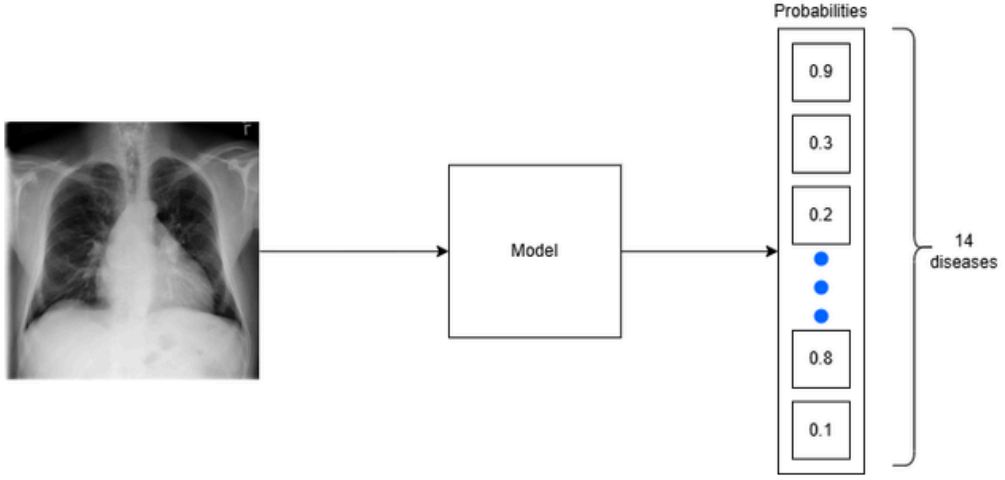
Questions

1. Can lightweight attention modules integrated into CNN backbones improve multi-label thoracic disease classification?
2. Can a two-stage training process using Focal Loss improve classification performance in class-imbalanced datasets like ChestXray14?



1. Introduction (4/5)

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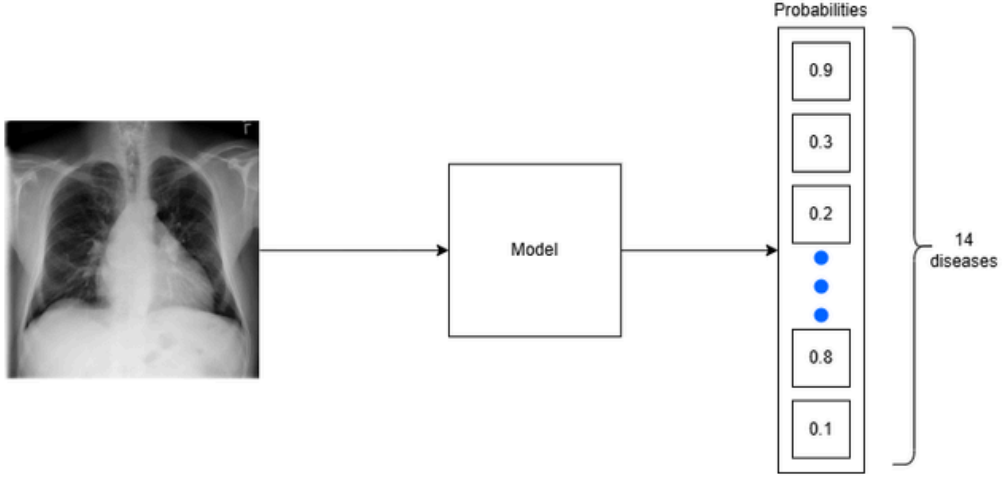
What do we need to do ...

- To implement and integrate Attention-Wise Blocks (AWBs) using Large Kernel Attention (LKA) into the DenseNet121 and VGG16 backbone.
- To design a training pipeline that separates feature learning and class rebalancing using Binary Cross-Entropy and Focal Loss in sequence.
- To evaluate the model on ChestXray14 using appropriate metrics and benchmarks.



1. Introduction (5/5)

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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.**

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2. Related Work (1/7)

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Related Works

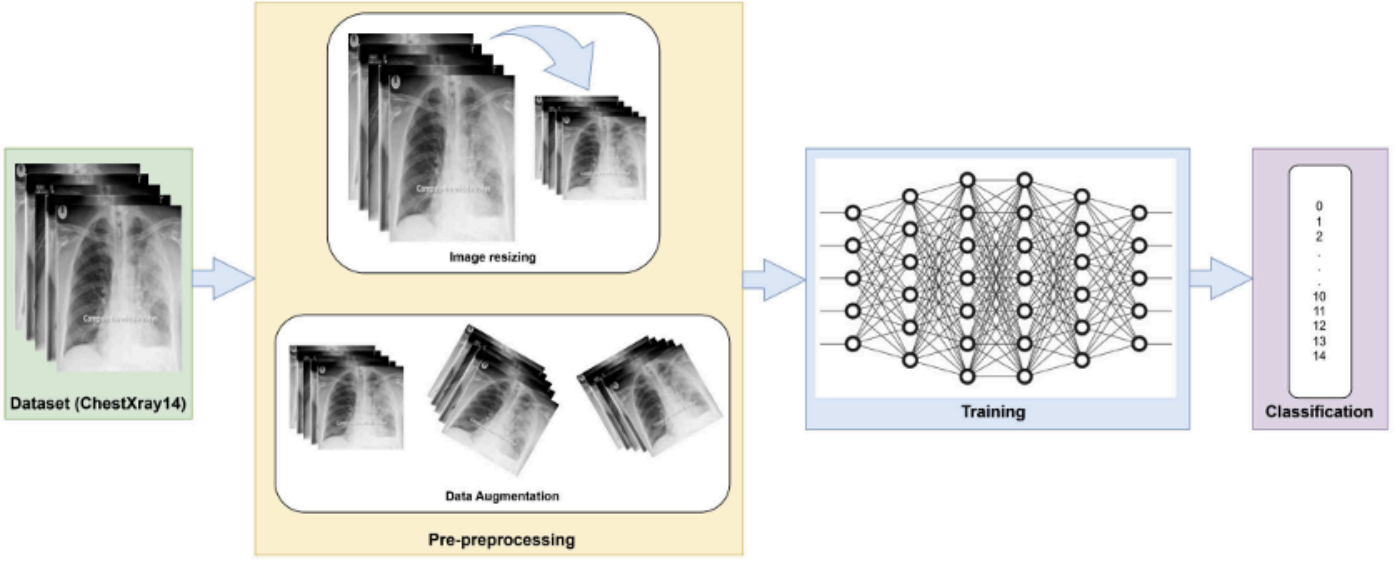

Fig: The workflow of Learning Technique for ChestXray14 multi-label classification.

2. Related Work (2/7)

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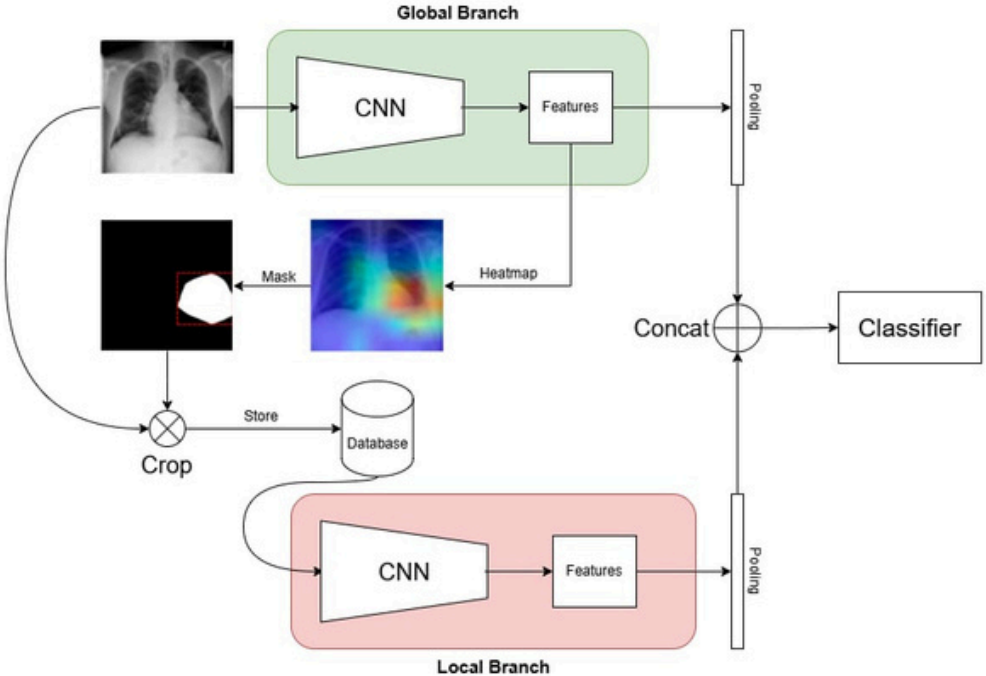
Related Works

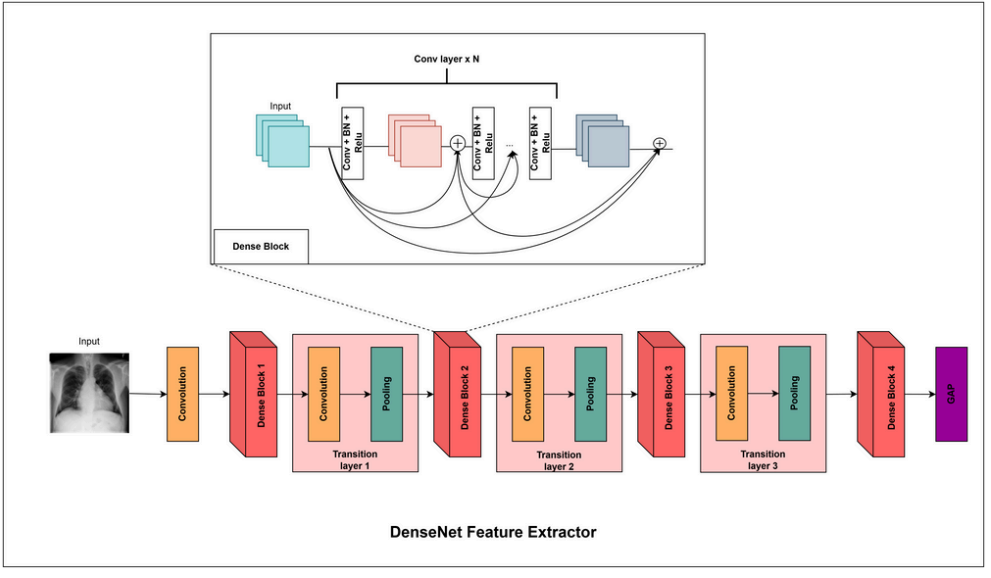


AG-CNN [*] Architecture

[*] L. Guan et al. “AG-CNN: Attention Guided Convolutional Neural Network for Thoracic Disease Classifica tion”. In: IEEE Transactions on Medical Imaging 37.6 (2018), pp. 1324–1333.

2. Related Work (3/7)

Feature Extractor: DenseNet121



Dense block: Contains multiple Convolution layer, Batch Normalization and ReLu function. Each layer in dense block concatenate output from all the preceding layers as its input

Transition layer: Use to connect dense blocks, has 2 main purpose: reduce number of feature map and downsampling the dimension of feature map

Advantages:

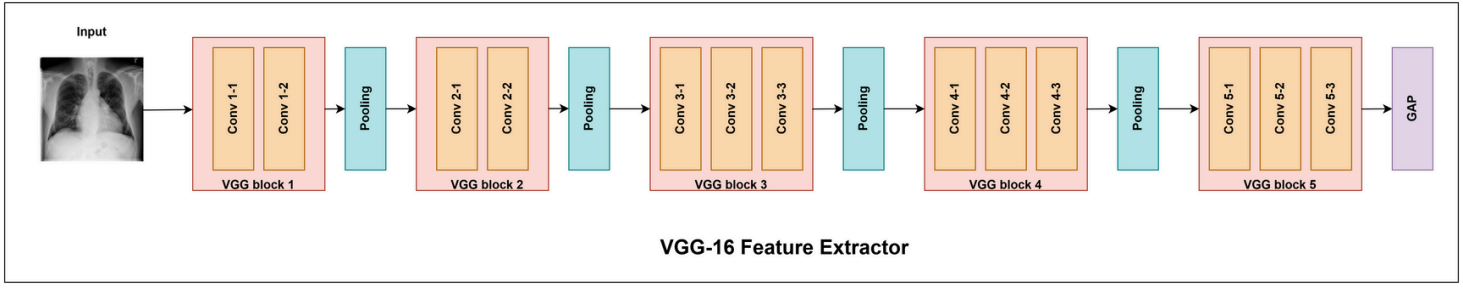
- Reduce vanishing gradient
- Feature reuse
- Fewer parameters

Limitations:

- High Memory Consumption
- Computational Complexity
- Implementation Complexity

2. Related Work (4/7)

Feature Extractor: VGG16



Contains 16 weight layers, when it get through each Convolution block, it use 2x2 Max Pooling to keep the important feature. Use Flatten to become 1D vector and finally get through 3 last FC layers to give prediction

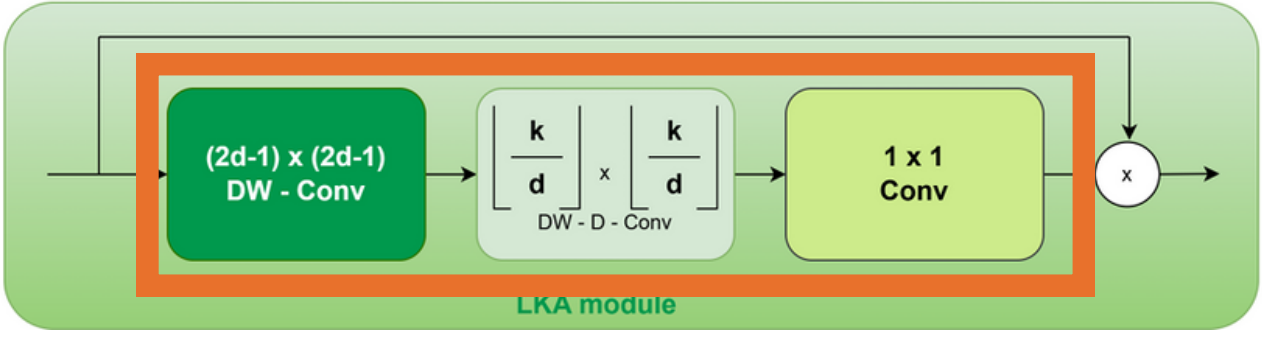
Advantages:
- Basic architecture
- Strong in feature extractor
- Suitable for pretraining

Limitations:
- Lots of parameter (138M)
- High risk of overfitting because of not having skip connection

2. Related Work (5/7)

Large Kernel Attention (LKA) as Soft Segmentation

- 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.

[*] Guo, M.H., Lu, C.Z., Liu, Z.N., Cheng, M.M., Hu, S.M.: Visual attention network. Computational visual media 9(4), 733–752 (2023)

2. Related Work (6/7)

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Large Kernel Attention (LKA) as Soft Segmentation

- Receptive Field Analysis for Soft Segmentation
- The **receptive field** of LKA is

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

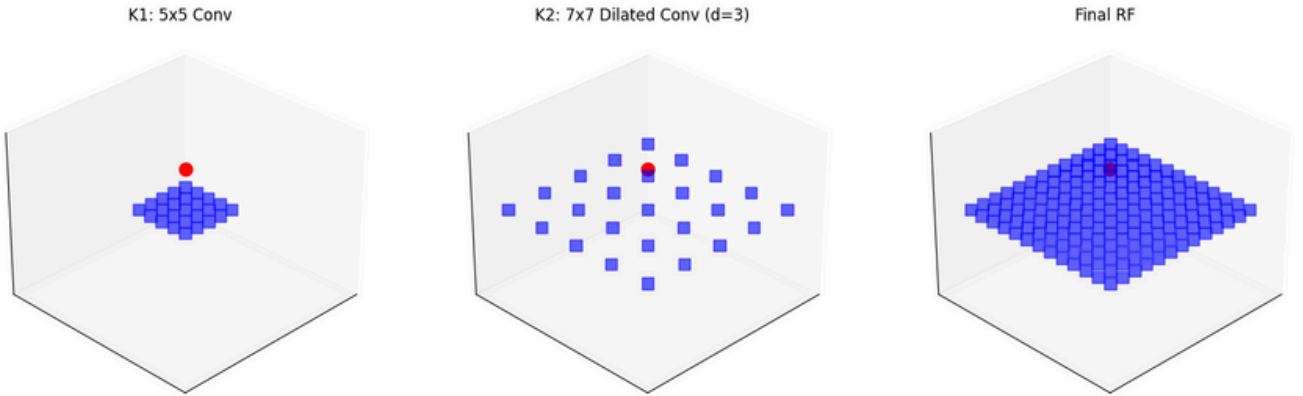

Fig. 2: Illustration of the receptive field of the LKA modules.

2. Related Work (7/7)

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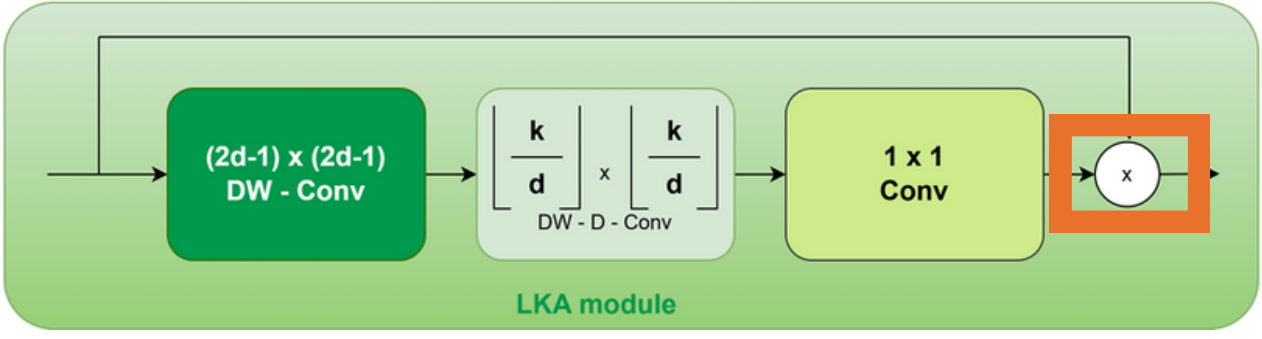
Large Kernel Attention (LKA) as Soft Segmentation



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

Soft Mask

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3. Main Contributions (1/5)

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Block-Wise Attention for Hierarchical Soft Segmentation

$$x^{(k)} = \begin{cases} B_k(x^{(k-1)}), & k \notin S, \\ A_k(B_k(x^{(k-1)})), & k \in S, \end{cases}$$

where Ak is LKA with dimension Ck. For our implementation, **S = {3, 4}**, corresponding to **C3 = 1024, C4 = 1024**

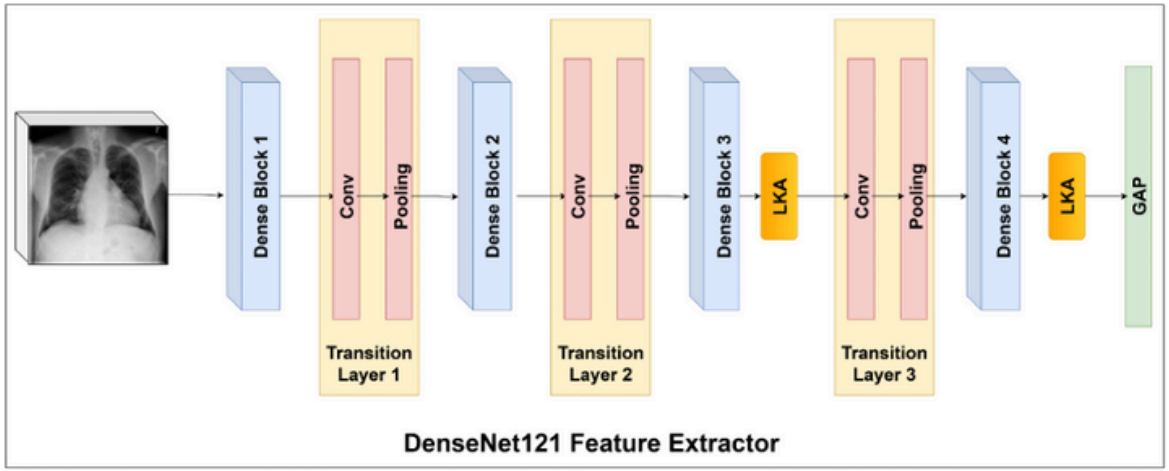

Fig: Architecture with AWBs in DenseNet121

3. Main Contributions (2/5)

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Block-Wise Attention for Hierarchical Soft Segmentation

$$x^{(k)} = \begin{cases} B_k(x^{(k-1)}), & k \notin S, \\ A_k(B_k(x^{(k-1)})), & k \in S, \end{cases}$$

where Ak is LKA with dimension Ck. For our implementation, **S = {3,4,5}**, corresponding to **C3 = 256, C4 =512, C5 = 512**.

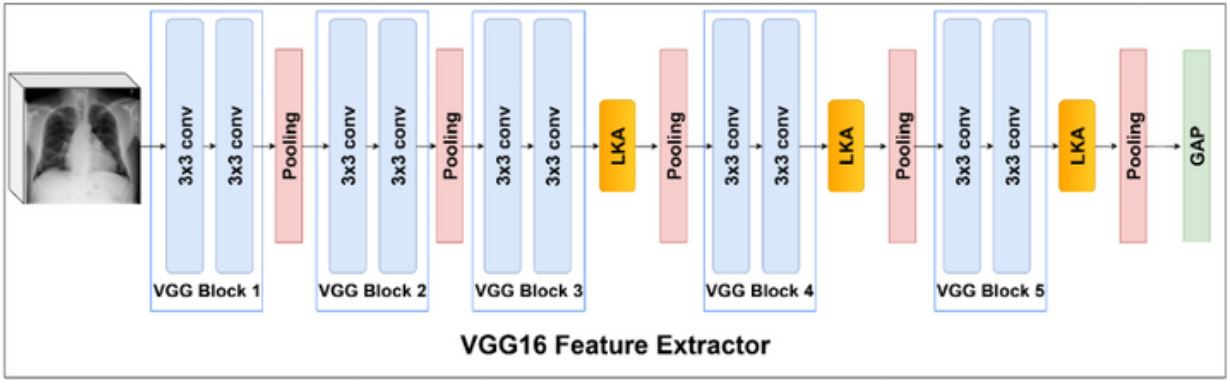

Fig : Architecture with AWBs in VGG16

3. Main Contributions (3/5)

Training Strategy for Imbalanced Data

- 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

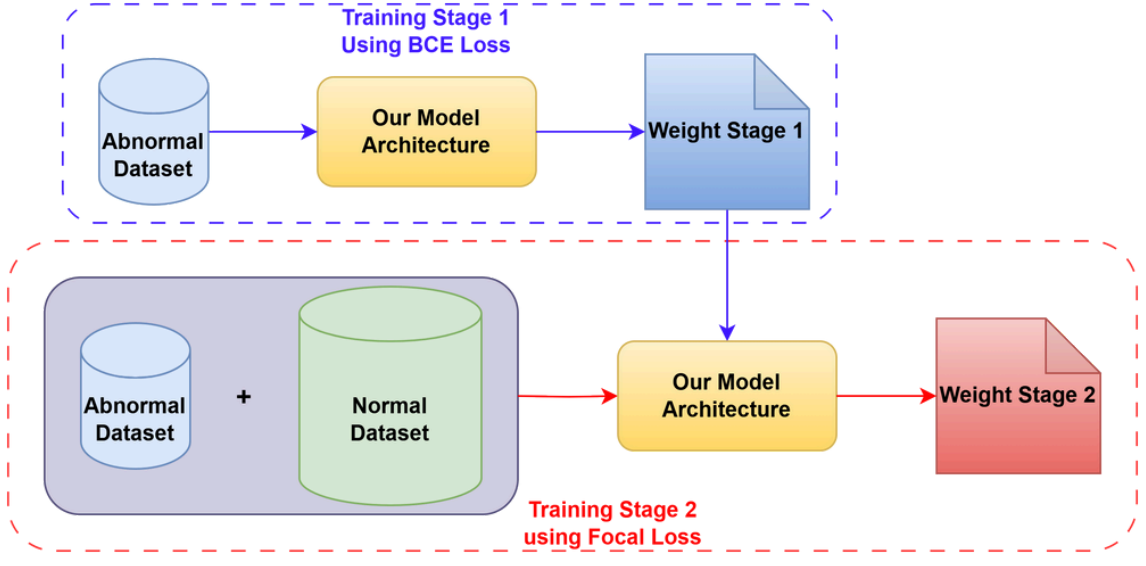

Fig. 3: Training Strategy for Imbalanced Data.

[*] 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)

3. Main Contributions (4/5)

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Training Strategy for Imbalanced Data

- **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., Doll´ar, P.: Focal loss for dense object detection. In: Proceedings of the IEEE international conference on computer vision. pp. 2980–2988 (2017)

3. Main Contributions (5/5)

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Focal Loss Analysis

- For hard examples, the steep slope → strong gradient.
- For easy examples, the shallow slope → small gradient, so it's not distracted by easy examples.

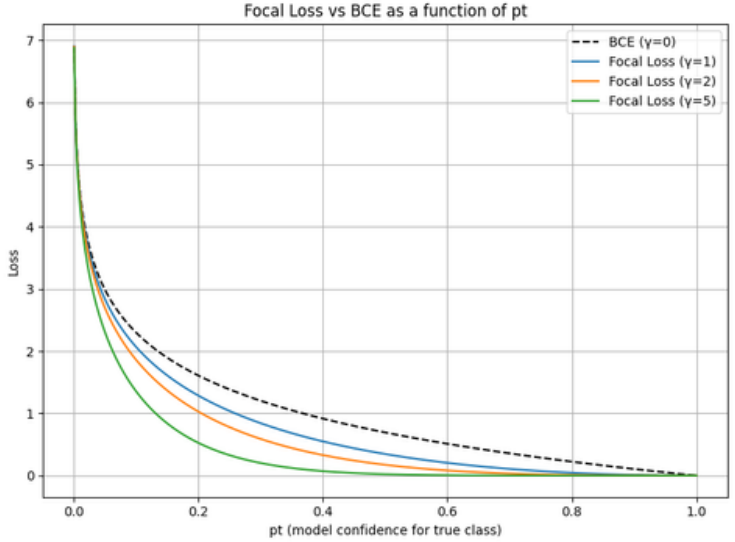

Fig: Focal Loss vs BCE Loss

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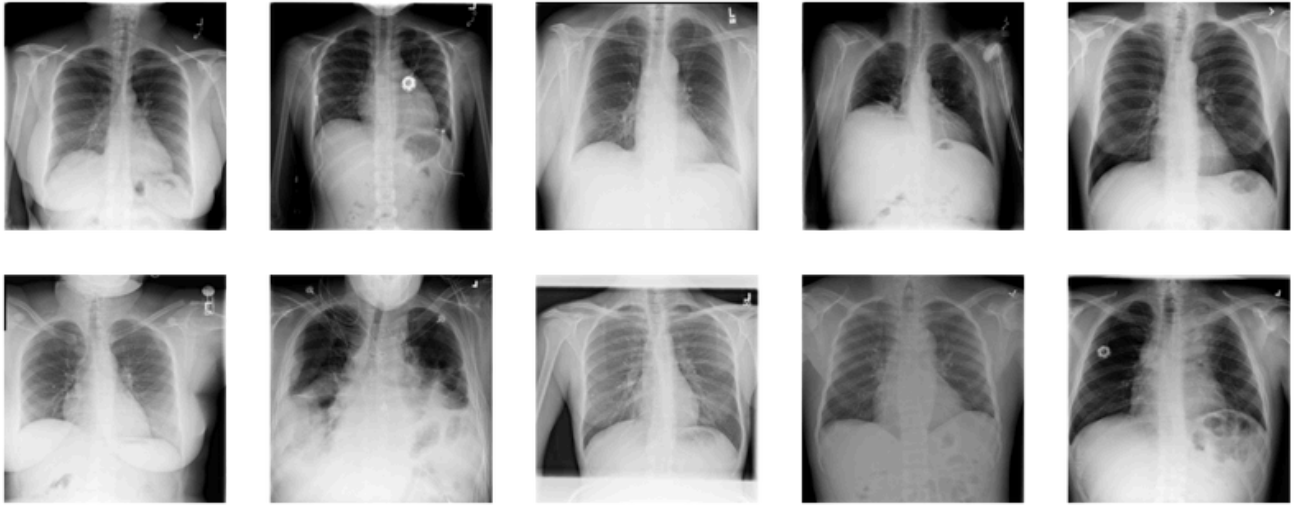
4. Experiment (1/11): Dataset

Benchmark Dataset: ChestXray14*

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



[*] 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)

4. Experiment (2/11): Dataset

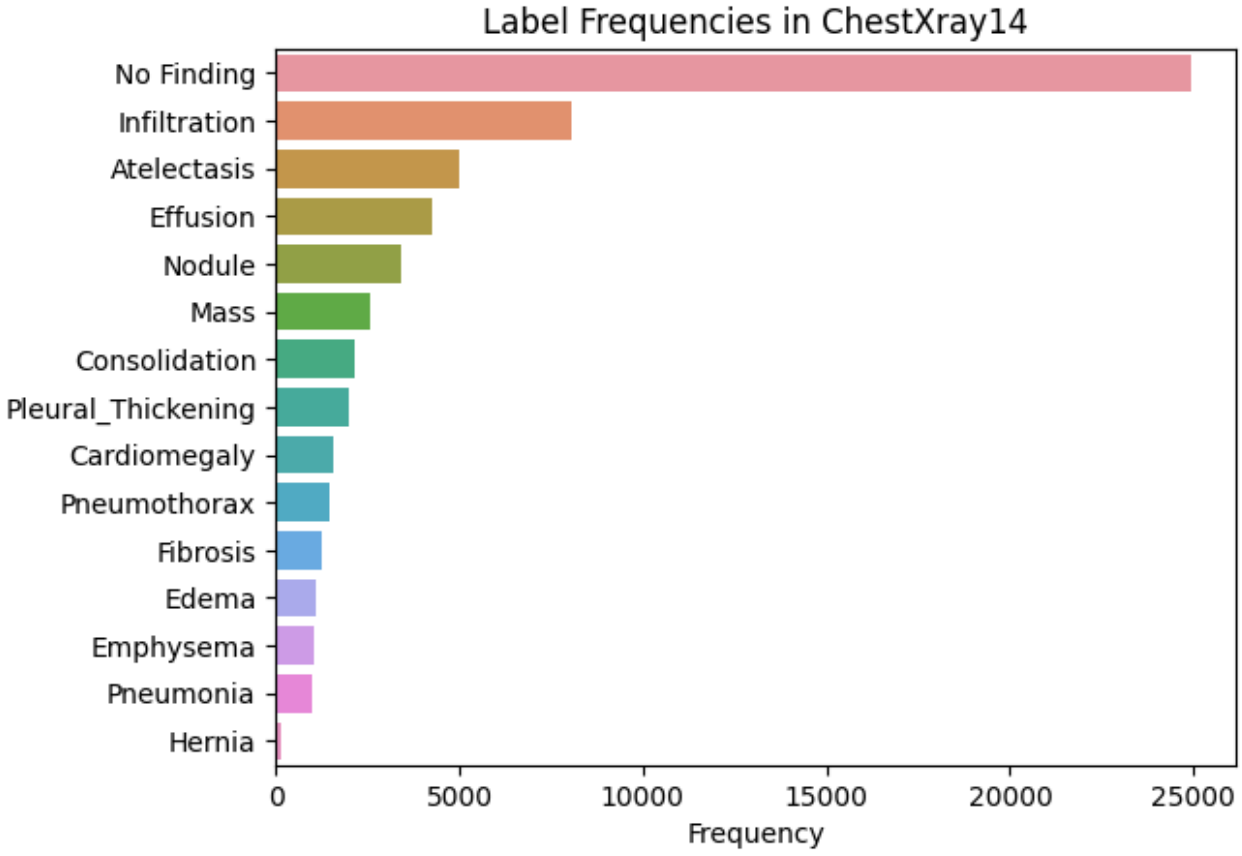


Fig: Diseases Frequencies

4. Experiment (3/11):

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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 (±10°)
    - 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

4. Experiment (4/11):

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Train&Valid Set and Test Set

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

4. Experiment (5/11):

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Results & Discussion

Performance Comparison State-of-the-Art Methods

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	0.853	0.853	0.858
Cardiomegaly	0.807	0.9248	0.91954	0.937	0.939	0.941	0.945
Effusion	0.784	0.8638	0.88977	0.904	0.903	0.909	0.909
Infiltration	0.609	0.7345	0.74102	0.753	0.754	0.749	0.755
Mass	0.706	0.8676	0.87315	0.893	0.902	0.899	0.907
Nodule	0.671	0.7802	0.80611	0.827	0.828	0.836	0.838
Pneumonia	0.633	0.7680	0.77648	0.776	0.774	0.807	0.815
Pneumothorax	0.806	0.8887	0.90164	0.919	0.921	0.93	0.932
Consolidation	0.708	0.7901	0.81575	0.842	0.842	0.832	0.833
Edema	0.835	0.8878	0.91034	0.919	0.924	0.935	0.935
Emphysema	0.815	0.9371	0.92946	0.941	0.932	0.955	0.956
Fibrosis	0.769	0.8047	0.83347	0.857	0.864	0.841	0.856
Pleural Thickening	0.708	0.8062	0.81270	0.836	0.837	0.846	0.853
Hernia	0.767	0.9164	0.91723	0.903	0.921	0.942	0.954
Mean AUC	0.738	0.841	0.85433	0.868	0.871	0.8768	0.8818

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)

4. Experiment (6/11):

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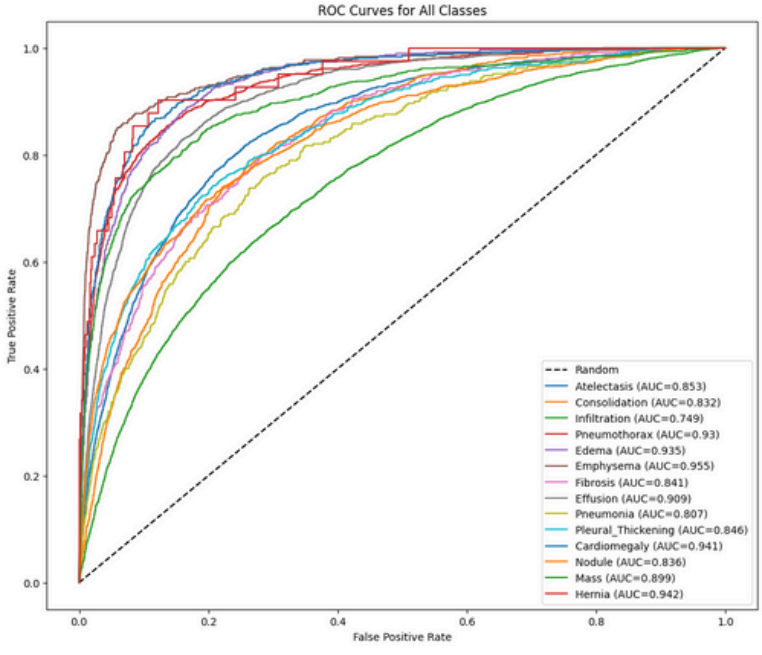
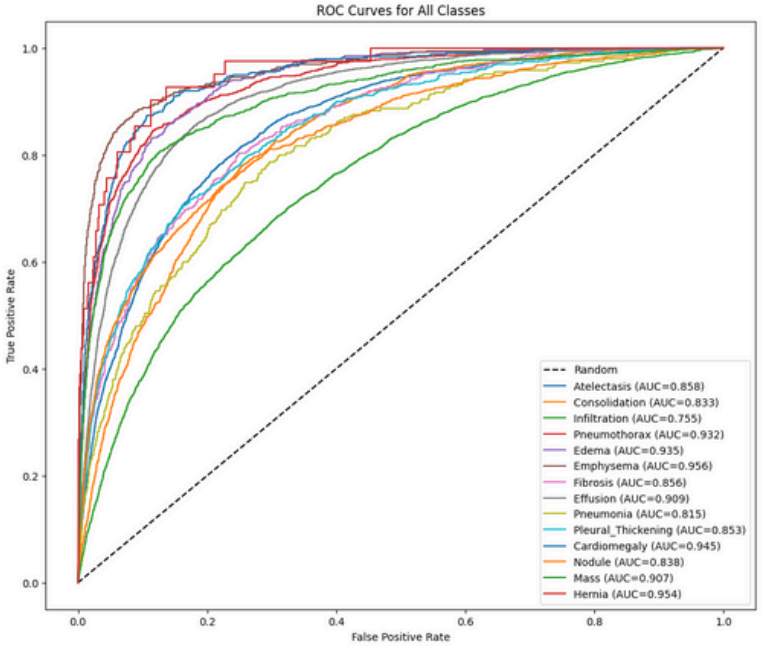
Results & Discussion



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



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

Fig: ROC AUC of Ours.

4. Experiment (7/11):

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Results & Discussion

Parameters and Training time Compared to SynthEnsemble

Ours						
Model variant	**Trainable params**	**Total params**	**Training stage 1**	**Training stage 2**	**Total**	**GFLOPS**
Densenet121+LKA full	9609870	9609870	6563.2s	8588.8s	**15152s**	**3. 64**
Densenet121+LKA 2 block	9223054	9223054	6375.6s	8239s	**146.146**	**3. 14**
Densenet121+LKA after	8095630	8096530	5611.4s	6957.3s	**12568.7s**	**2. 92**
VGG16+LKA full	15453966	15453966	14225.2s	10206.1s	**24431.3s**	**16. 70**
VGG16+LKA 3 block	15418702	15418702	8628.6s	5682.1s	**14310.7s**	**15. 93**
VGG16+LKA after	15031886	15031886	4851.2s	5492.6s	**10343.8s**	**15. 39**

4. Experiment (8/11):

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Results & Discussion

Parameters and Training time Compared to SynthEnsemble

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
Total	**6205376**	**503703236**	**99. 02**	**~193212.8s**

4. Experiment (9/11):

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Ablation Studies: 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	**0. 8498**
VGG16	0. 8275	0. 8094	0. 8401
VGG16 + AWBs	0. 8238	0. 8247	**0. 8818**

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

4. Experiment (10/11):

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Ablation Studies: 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	**0. 8498**
VGG16 + LKA	After	0. 8470
VGG16 + LKA	Full Block	0. 8666
VGG16 + LKA	Last 3 Block	**0. 8818**

Statement:

Optimal placement of attention modules <=> **higher-level features** are consolidated

→ yields the best performance

4. Experiment (11/11):

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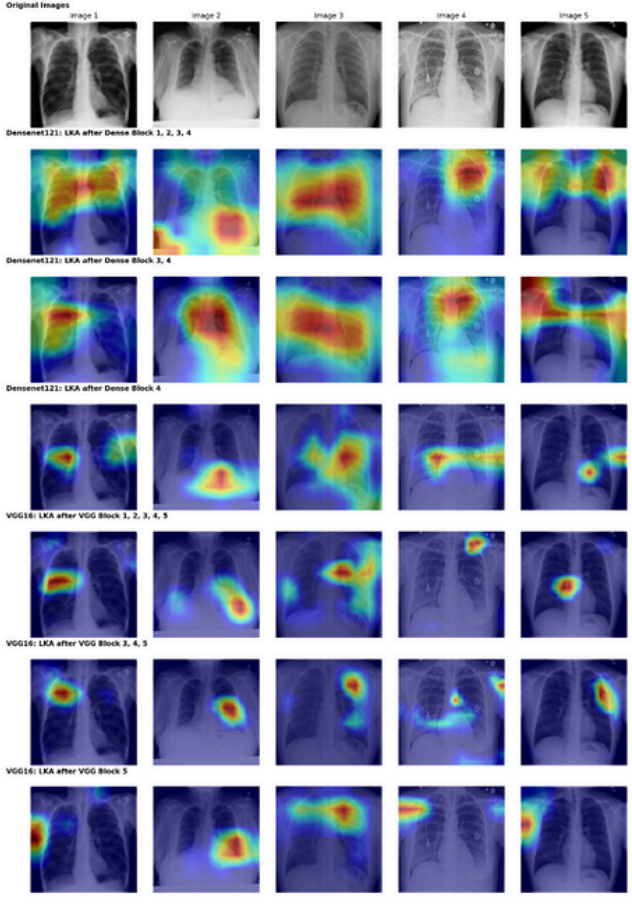
Ablation Studies:
GRADCAM for Illustration of Different Methods



”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.

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Outlines

1.Introduction

2.Related Work

3.Main Contribution

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5.Demo

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5. Demo (1/1)

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System Workflow

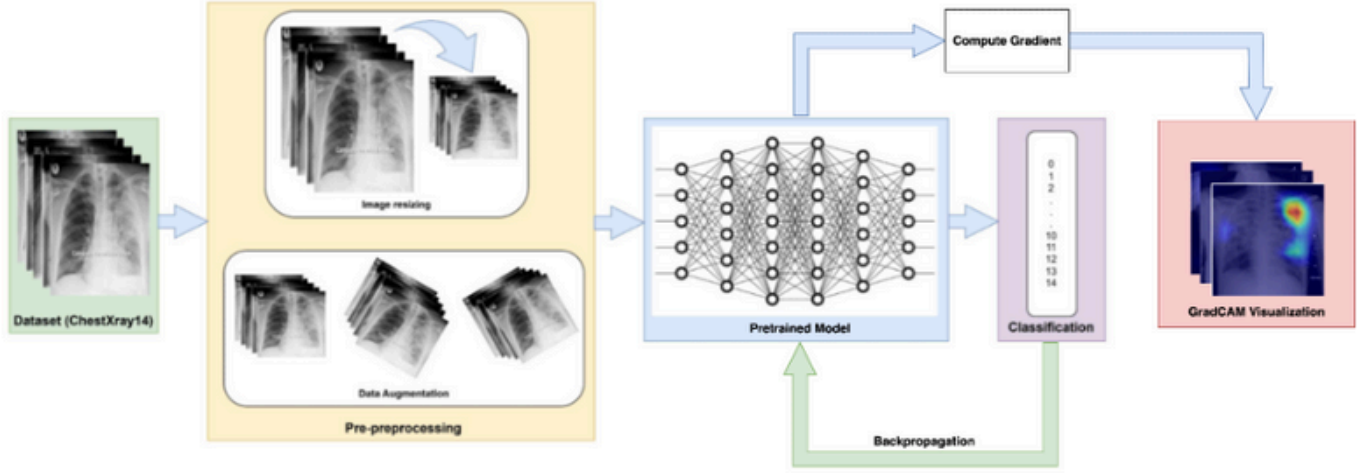

Fig: Our system workflow

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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.**

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7. References (1/3)

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THANK YOU FOR YOUR ATTENTION !

Q&A