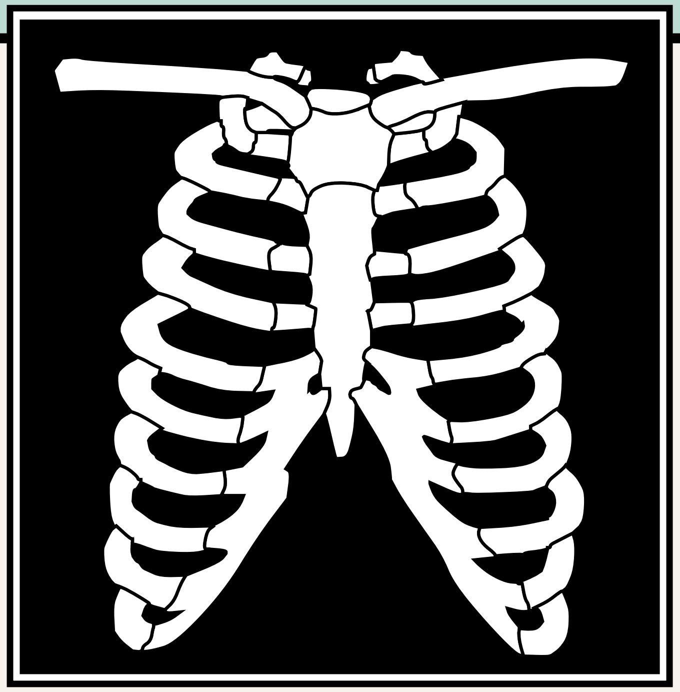


Machine Learning and Pattern Recognition : AI3011

PNEUMONOTHORAX SEGMENTATION OF CHEST RADIOGRAPHS

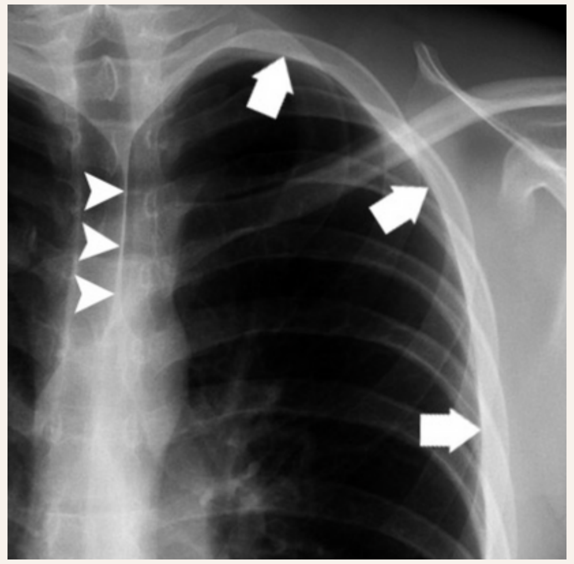
Pneumothorax

Pneumothorax, also known as a **collapsed lung**, is a condition in which air builds up outside the lung but within the pleural cavity, or space between the lung and chest wall. This can cause pressure on the lung and lead to collapse.

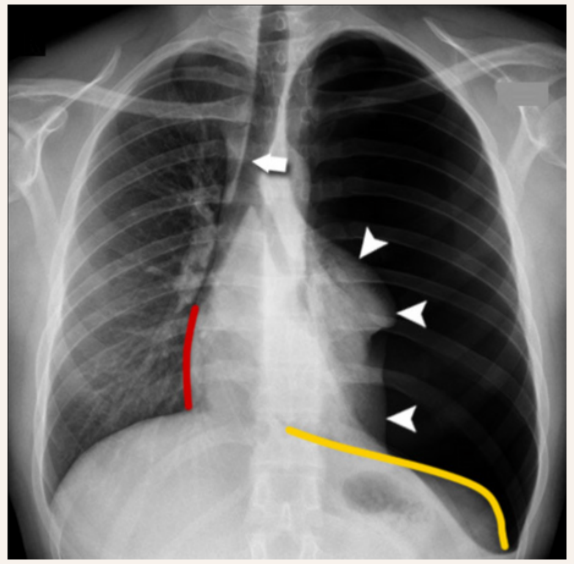
Pneumothorax can be caused by:

- Chest Trauma
- Excess Pressure
- Lung disease, such as Asthma, Chronic Obstructive Pulmonary Disease (COPD), Cystic Fibrosis, Tuberculosis, or Whooping Cough
- Cystic Lung Diseases

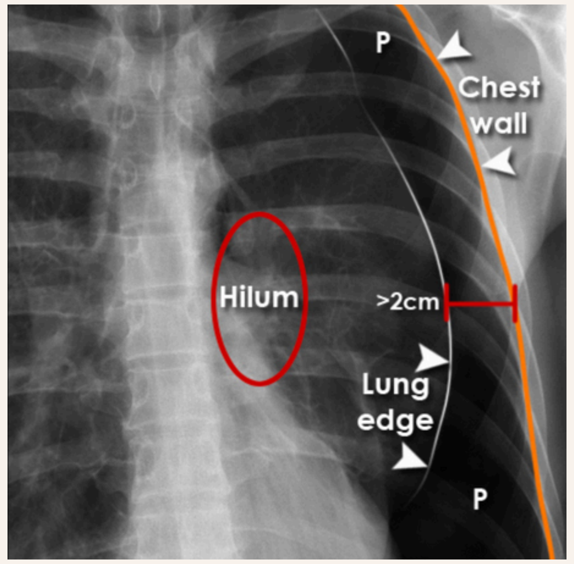
! Primary spontaneous pneumothorax mainly occurs at 20-30 years of age. Treatements costing upwards of $6,000 and 3 Lakh INR.



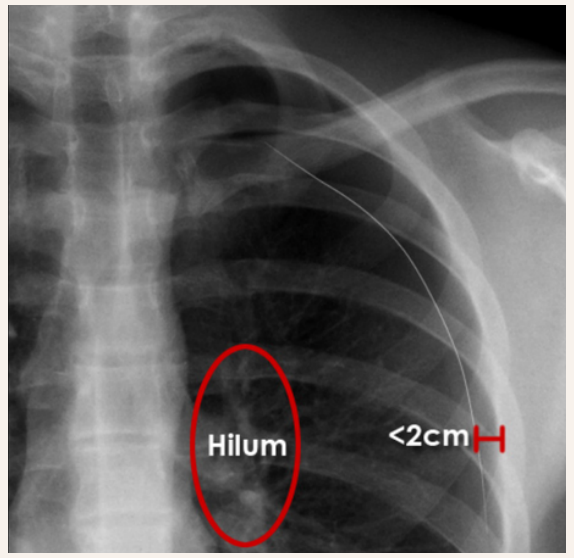
Normal Lung



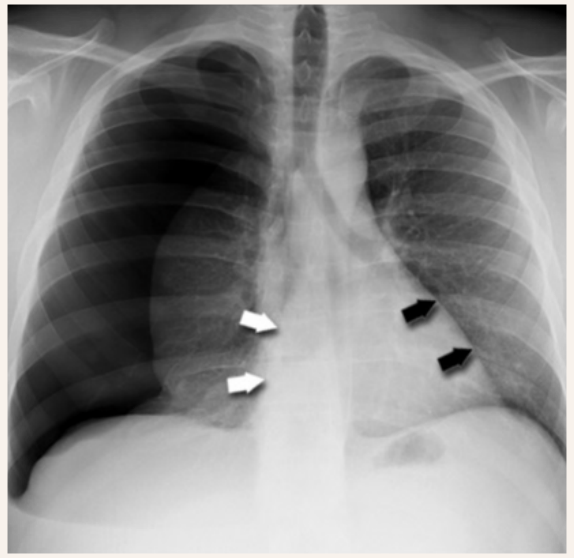
Tension Pneumothorax



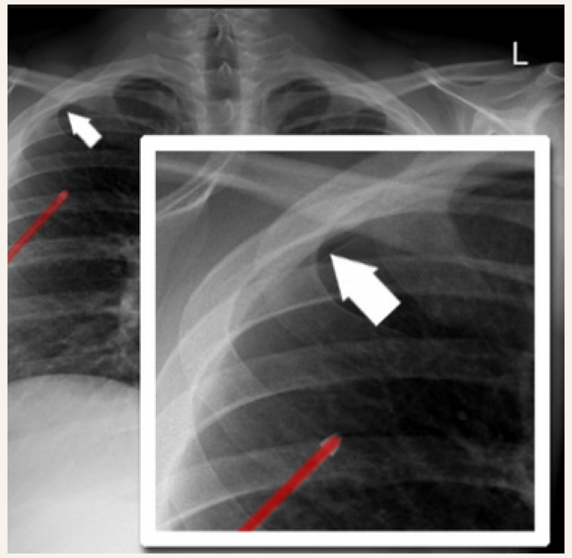
Large Pneumothorax



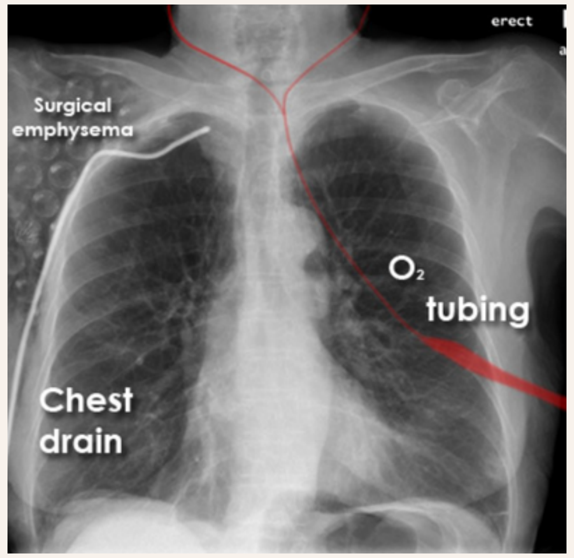
Subtle Pneumothorax



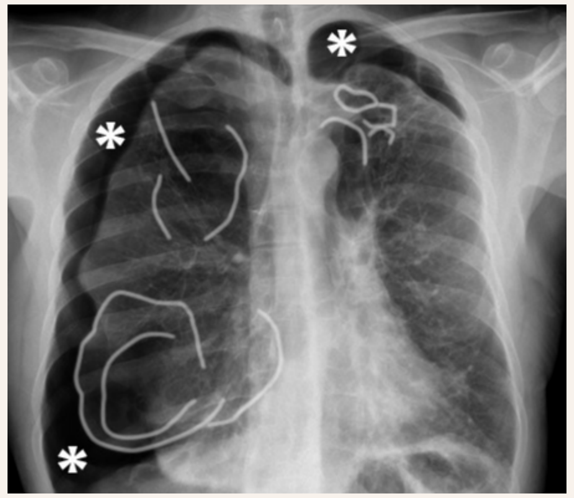
Large Pneumothorax Early Tension

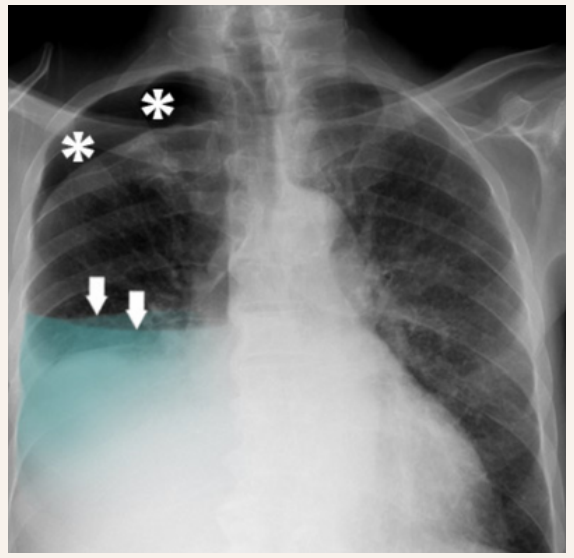


Chest Drain



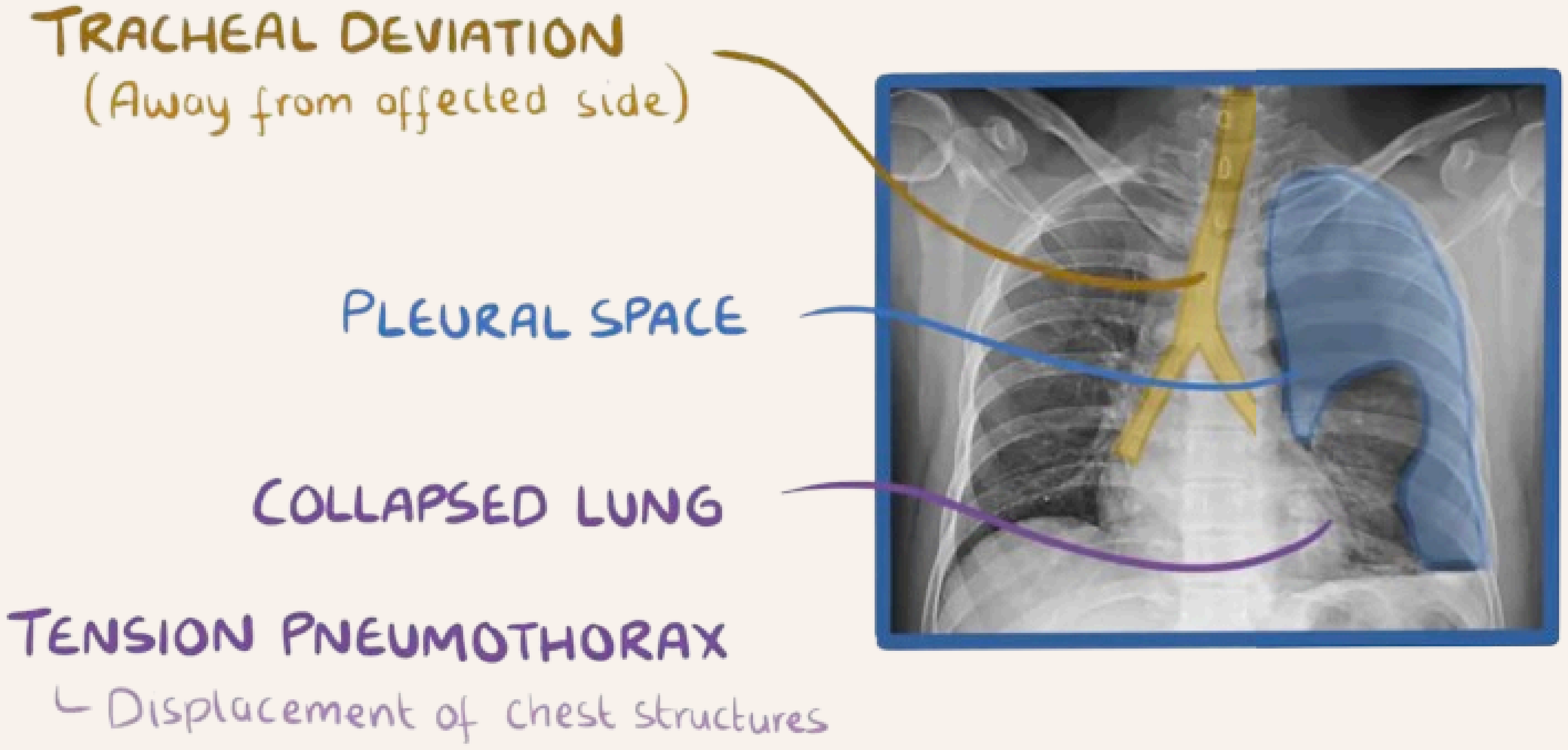
Drain/Surgical Emphysema

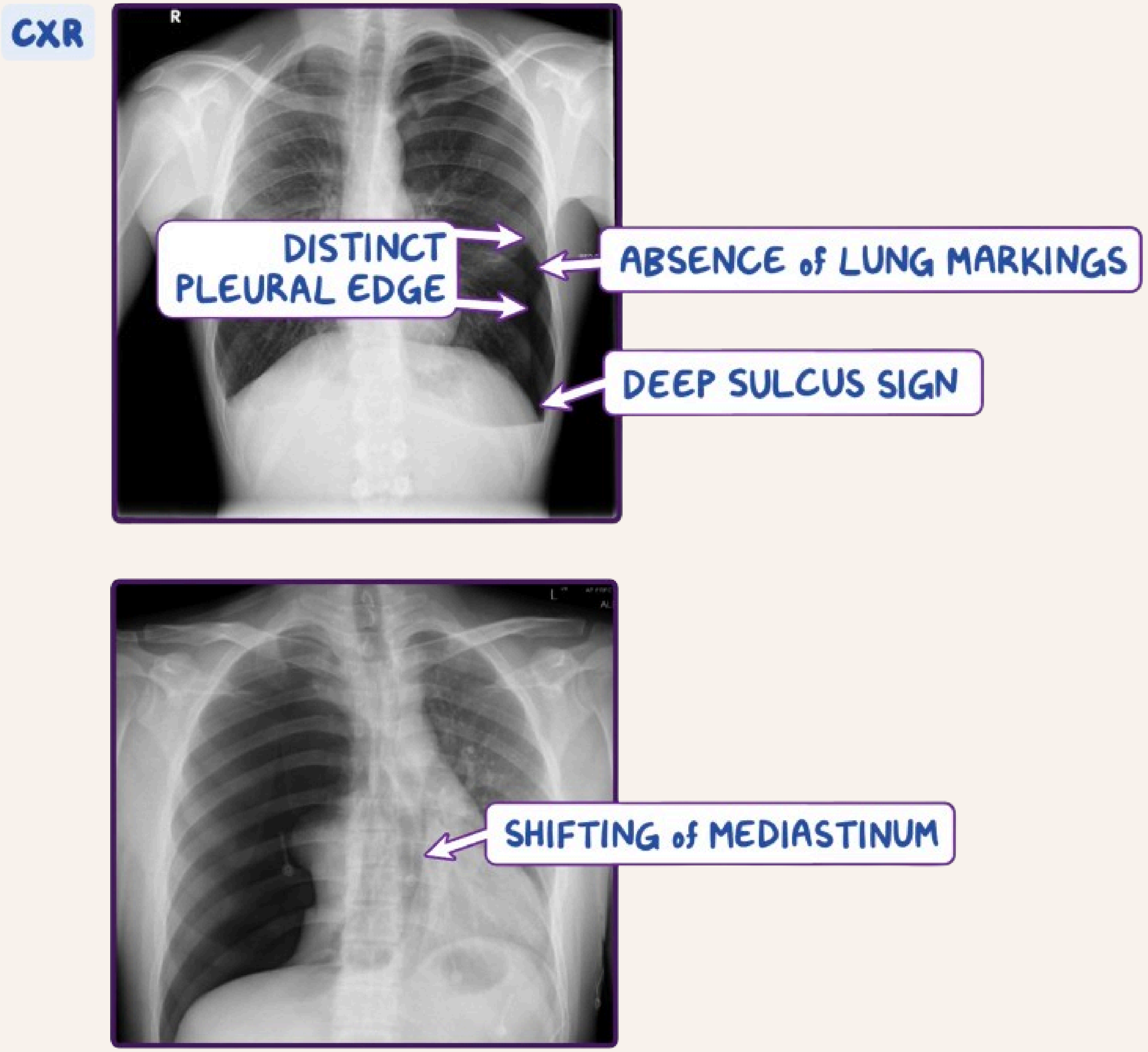




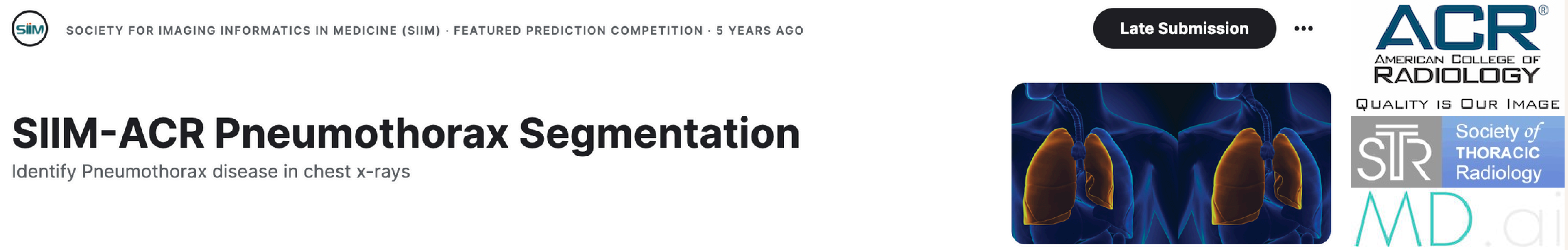
Latrogenic Pneumothorax

Pneumothorax : Radiography





Problem Statement

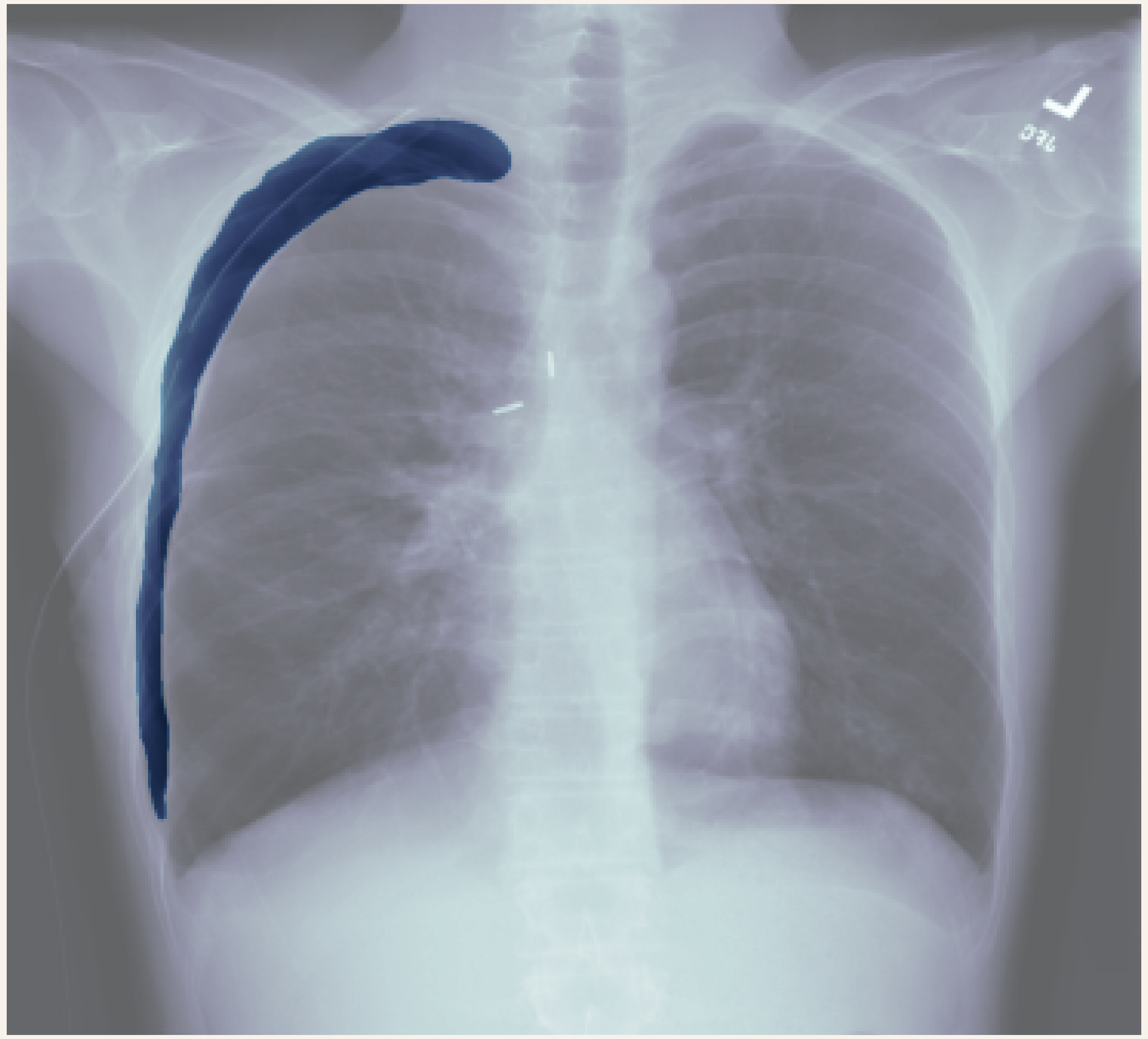


Problem Statement: Develop a segmentation model that indicates the location and extent of pneumothorax using binary masks (encoded by RLE) for a set of chest radio-graphic images from the SIIM-ACR Pneumothorax Segmentation Challenge on Kaggle.

Input (training): X-Ray Image, Ground Truth Mask
Output (training): Predicted Mask

Input (test): X-Ray Image
Output (test): Predicted Mask

Applications and Impact



Sometimes, fatigued doctors will make incorrect judgments. The diagnostic accuracy of pneumothorax highly depends on the **expertise of the attending radiologist**.

Automated methods of pneumothorax detection may allow earlier diagnosis and treatment because the signs of pneumothorax on chest radiographs can be subtle, and up to **20% of occult pneumothoraces are missed at the time of presentation**.

Literature Review : Competition Leaderboard

#	△	Team	Members	Score	Entries	Last	Solution
1	▲ 205	[dsmlkz] Aimoldin Anuar		0.8679	15	5y	
2	▲ 112	X5		0.8665	3	5y	
3	▲ 16	bestfitting		0.8651	7	5y	
4	▲ 233	[ods.ai] amirassov		0.8644	2	5y	
5	▲ 125	earhian		0.8643	5	5y	

Rank	Network	Encoder	Techniques	Score
1	U-Net	ResNet (34, 50), SE-ResNext 50	Triplet Scheme Thresholding (Inference), Destructive Augmentation, High Resolution (512 - 1024) Uptraining, Gradient Accumulation	0.8679
2	Deeplabv3+, U-Net	SE-ResNext (50, 101), EfficientNet (B3, B5)	Stochastic Weight Averaging (SWA), Motion-Blurring Augmentation	0.8665
3	U-Net	ResNet-34, SE-ResNext-50	Lung segmentation and CBAM Attention, External Dataset : NIH Chest X-Ray, CheXpert. Montgomery County X-ray	0.8651
4	U-Net	ResNet-34	Frozen Batch-Normalization, Deep Supervision Model	0.8644
5	U-Net	SE-ResNext (50, 101)	ASPP and Semi-Supervision Model,	0.8643

Pneumothorax Recognition Neural Network Based on Feature Fusion of Frontal and Lateral Chest X-Ray Image

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Multidisciplinary | Rapid Review | Open Access Journal

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Pneumothorax Recognition Neural Network Based on Feature Fusion of Frontal and Lateral Chest X-Ray Images

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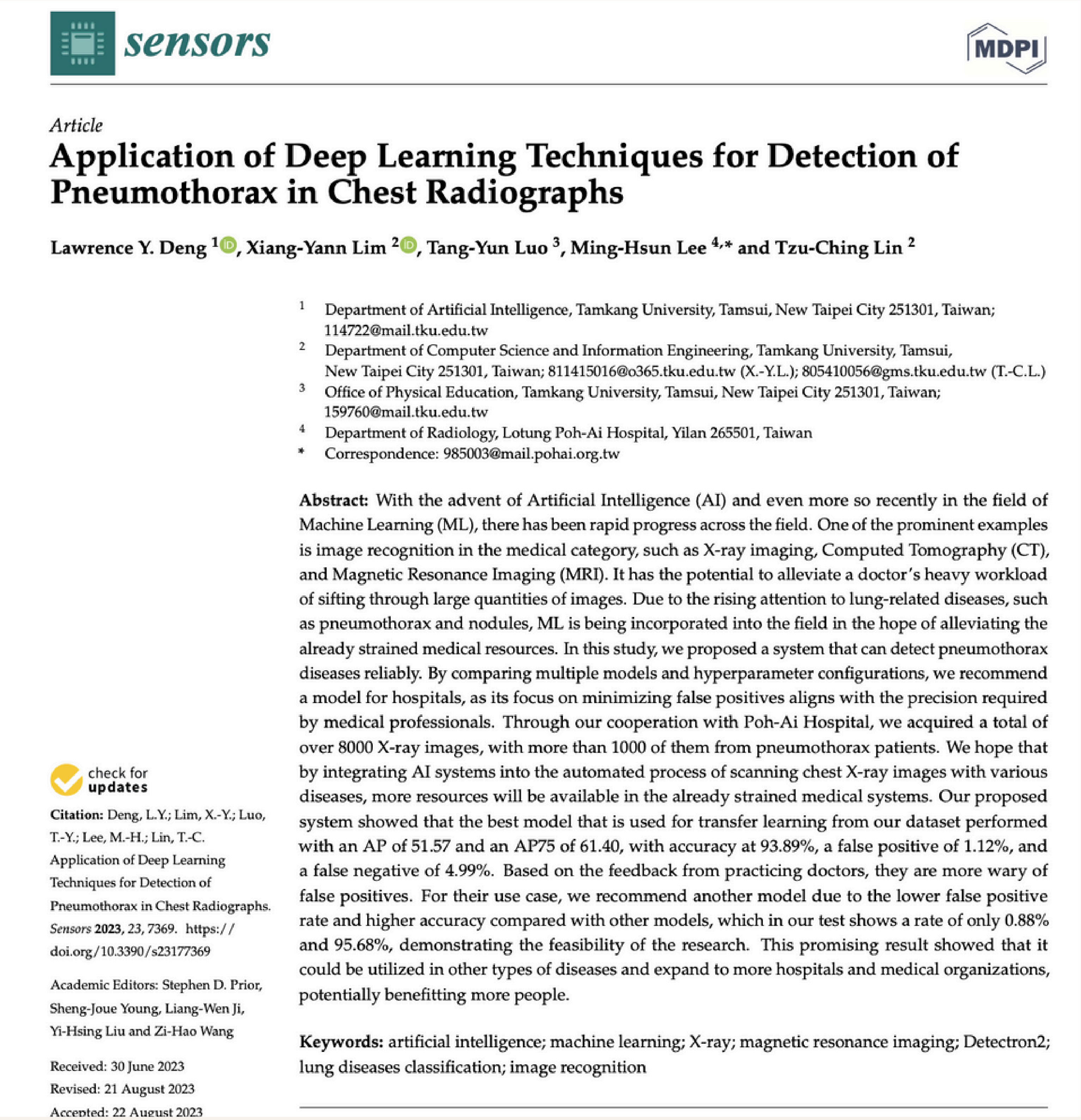
ABSTRACT Pneumothorax is a potentially life-threatening disease that requires urgent diagnosis and treatment. Clinically, a chest X-ray examination is the first choice for diagnosing pneumothorax. However, it is difficult to diagnose pneumothorax by only frontal chest X-ray imaging when the lesion area is only composed of a small amount of air. Therefore, we propose a pneumothorax diagnosis neural network based on feature fusion, where frontal and lateral X-ray information are fused. In this network, there are two inputs and three outputs. The two inputs are the frontal chest X-ray image and the lateral chest X-ray image. The three outputs are the classification results of the frontal chest X-ray image, the classification results of the lateral chest X-ray image, and the classification results integrating the characteristics of the fused frontal chest X-ray image and lateral chest X-ray image. Our algorithm considers the vanishing gradient problem in the pneumothorax recognition model and introduces the residual block to alleviate this problem. Because of the large number of channels in this model, we also utilize channel attention mechanisms to improve the model's performance. Our comparative experiments show that neural network fusion of frontal and lateral chest image features can achieve higher accuracy than the single task model. Using only image-level annotation, our pneumothorax model can achieve high recognition accuracy.

INDEX TERMS Convolutional neural network, pneumothorax, chest X-ray images, computer-aided diagnosis, multiple input network.

Architecture Inferences (Developed Solution)	**Feature Fusion Technique :** Multi-input multi-output neural network that fuses information from frontal and lateral chest X-ray images. **Residual block and Channel Attention Mechanism :** Residual block alleviates the vanishing gradient problem, while channel attention mechanism gives different weights to different feature maps. **Image-level Annotation**
Evaluation Metrics	AUC, Accuracy, Recall, Precision, Macro avg, F1–Score, Weighted avg
Performance Scores (AUC)	Resnet50 (frontal branch) -0.956 Resnet50 (lateral branch) - 0.950 **Resnet50 (fused branch) - 0.975** EfficientNet-b4 (frontal branch) - 0.952 EfficientNet-b4 (lateral branch) - 0.943 **EfficientNet-b4 (fused branch) - 0.961** DenseNet-121 (frontal branch) - 0.956 DenseNet-121 (lateral branch) - 0.948 **DenseNet-121 (fused branch) - 0.974**
Limitations	**Data Limitations :** Requirement of pairs of image-level annotations (frontal annotation + lateral annotation) rather than only front images. **Data Annotations :** Paired image-level annotations over pixel-level annotations.

Application of Deep Learning Techniques for Detection of Pneumothorax in Chest Radiographs



sensors

MDPI

Article

Application of Deep Learning Techniques for Detection of Pneumothorax in Chest Radiographs

Lawrence Y. Deng [1], Xiang-Yann Lim [2], Tang-Yun Luo [3], Ming-Hsun Lee [4,*] and Tzu-Ching Lin [2]

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Abstract: With the advent of Artificial Intelligence (AI) and even more so recently in the field of Machine Learning (ML), there has been rapid progress across the field. One of the prominent examples is image recognition in the medical category, such as X-ray imaging, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI). It has the potential to alleviate a doctor's heavy workload of sifting through large quantities of images. Due to the rising attention to lung-related diseases, such as pneumothorax and nodules, ML is being incorporated into the field in the hope of alleviating the already strained medical resources. In this study, we proposed a system that can detect pneumothorax diseases reliably. By comparing multiple models and hyperparameter configurations, we recommend a model for hospitals, as its focus on minimizing false positives aligns with the precision required by medical professionals. Through our cooperation with Poh-Ai Hospital, we acquired a total of over 8000 X-ray images, with more than 1000 of them from pneumothorax patients. We hope that by integrating AI systems into the automated process of scanning chest X-ray images with various diseases, more resources will be available in the already strained medical systems. Our proposed system showed that the best model that is used for transfer learning from our dataset performed with an AP of 51.57 and an AP75 of 61.40, with accuracy at 93.89%, a false positive of 1.12%, and a false negative of 4.99%. Based on the feedback from practicing doctors, they are more wary of false positives. For their use case, we recommend another model due to the lower false positive rate and higher accuracy compared with other models, which in our test shows a rate of only 0.88% and 95.68%, demonstrating the feasibility of the research. This promising result showed that it could be utilized in other types of diseases and expand to more hospitals and medical organizations, potentially benefitting more people.

Keywords: artificial intelligence; machine learning; X-ray; magnetic resonance imaging; Detectron2; lung diseases classification; image recognition

check for updates

Citation: Deng, L.Y.; Lim, X.-Y.; Luo, T.-Y.; Lee, M.-H.; Lin, T.-C. Application of Deep Learning Techniques for Detection of Pneumothorax in Chest Radiographs. *Sensors* **2023**, *23*, 7369. https://doi.org/10.3390/s23177369

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Received: 30 June 2023
Revised: 21 August 2023
Accepted: 22 August 2023

Architecture Inferences (Developed Solution)	**Model Selection :** Utilized Detectron2 for pneumothorax detection. Model choices include ResNet and ResNeXt. ResNet models employed Feature Pyramid Network (FPN) for COCO instance segmentation. ResNeXt model used X101-FPN. **Training :** Training set consists of 784 pneumothorax images. Test run with various configurations from R101-FPN baseline. Selected configuration: 26-1501, with 100,000 iterations, learning rate of 0.001, weight decay of 0.0001, batch size of 512. Decay steps at 25k, 40k, 50k, 60k, 70k, 80k, 85k, and 95k iterations. **Augmentations :** Various augmentations applied during training, including random brightness, contrast, rotation, and saturation adjustments to reduce overfitting.
Evaluation Metrics	False Positive (%), False Negative (%), Accuracy (%), AP (%), AP50 (%), AP75 (%)
Performance Scores (AUC)	**ResNet50 (COCO)** **False Positive (%) -** 1.33 **False Negative (%) -** 4.38 **Accuracy (%) -** 94.29 **ResNeXt101 (COCO)** **False Positive (%) -** 0.88 **False Negative (%) -** 3.44 **Accuracy (%) -** 95.68
Limitations	**Limited Dataset :** The dataset used in the study was collected from a local hospital, which may not represent diverse populations or imaging protocols. **Limited Clinical Validation:** While the model shows promising results, there's a lack of comprehensive clinical validation in real-world settings. Further validation studies involving radiologists and healthcare professionals are necessary to assess the model's performance and reliability in clinical practice

Deep Learning Systems for Pneumothorax Detection on Chest Radiographs: A Multicenter External Validation Study

Radiology: Artificial Intelligence

ORIGINAL RESEARCH

Deep Learning Systems for Pneumothorax Detection on Chest Radiographs: A Multicenter External Validation Study

Yee Liang Thian, MBBS, FRCR • Dianwen Ng, MSc, BSc Hons* • James Thomas Patrick Decourcy Hallinan, MBBS, FRCR • Pooja Jagmohan, MBBS, FRCR, MD • Soon Yiew Sia, MBBS, FRCR • Cher Heng Tan, MBBS, FRCR, MBA • Yong Han Ting, MBBS, FRCR • Pin Lin Kei, MBBS, FRCR • Geoiphy George Pulickal, MBBS, FRCR • Vincent Tze Yang Tiong, MBBS, FRCR • Swee Tian Quek, MBBS, FRCR • Mengling Feng, PhD*

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*Y.L.T. and D.N. contributed equally to this work.

Conflicts of interest are listed at the end of this article.

See also commentary by Jacobson and Krupinski in this issue.

Radiology: Artificial Intelligence 2021; 3(4):e200190 • https://doi.org/10.1148/ryai.2021200190 • Content codes: AI CH

Purpose: To assess the generalizability of a deep learning pneumothorax detection model on datasets from multiple external institutions and examine patient and acquisition factors that might influence performance.

Materials and Methods: In this retrospective study, a deep learning model was trained for pneumothorax detection by merging two large open-source chest radiograph datasets: ChestX-ray14 and CheXpert. It was then tested on six external datasets from multiple independent institutions (labeled A–F) in a retrospective case-control design (data acquired between 2016 and 2019 from institutions A–E; institution F consisted of data from the MIMIC–CXR dataset). Performance on each dataset was evaluated by using area under the receiver operating characteristic curve (AUC) analysis, sensitivity, specificity, and positive and negative predictive values, with two radiologists in consensus being used as the reference standard. Patient and acquisition factors that influenced performance were analyzed.

Results: The AUCs for pneumothorax detection for external institutions A–F were 0.91 (95% CI: 0.88, 0.94), 0.97 (95% CI: 0.94, 0.99), 0.91 (95% CI: 0.85, 0.97), 0.98 (95% CI: 0.96, 1.0), 0.97 (95% CI: 0.95, 0.99), and 0.92 (95% CI: 0.90, 0.95), respectively, compared with the internal test AUC of 0.93 (95% CI: 0.92, 0.93). The model had lower performance for small compared with large pneumothoraces (AUC, 0.88 [95% CI: 0.85, 0.91] vs AUC, 0.96 [95% CI: 0.95, 0.97]; $P = .005$). Model performance was not different when a chest tube was present or absent on the radiographs (AUC, 0.95 [95% CI: 0.92, 0.97] vs AUC, 0.94 [95% CI: 0.92, 0.05]; $P > .99$).

Conclusion: A deep learning model trained with a large volume of data on the task of pneumothorax detection was able to generalize well to multiple external datasets with patient demographics and technical parameters independent of the training data.

Supplemental material is available for this article.

Architecture Inferences (Developed Solution)	• The research proposes usage of convolutional neural networks **(CNNs)** and recurrent neural networks **(RNNs)** used for feature extraction and capturing spatial dependencies in segmentation tasks. **Attention Mechanisms** were incorporated to focus on relevant regions during segmentation, enhancing accuracy. • Lower performance for detection of small compared with large pneumothoraces **(AUC - 0.88 vs 0.96; P = 0.005)** • No model performance influence due to presence of a chest tube **(AUC - 0.95 [with tube] vs 0.94 [without tube]; P = 0.99)**
Evaluation Metrics	Sensitivity, Specificity, F1 Score, AUC, P Value
Performance Scores (AUC)	**EfficientNet B3** **Sensitivity (%)** - 98 **Specificity (%)** - 92 **Positive predictive value (%)** - 80 **Negative predictive value (%)** - 99 **F1 score (%)** - 88
Limitations	**Dependency on large annotated datasets:** The effectiveness of the proposed architecture heavily relies on access to large and diverse datasets for training. Computational complexity: Integrating both Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) increases the computational burden.

Dataset: Source, Modality and Ethical Concerns

Source: Society for Imaging Informatics in Medicine (SIIM)
Data Provided:

- DICOM Files (encapsulate patient data and image)
- CSV File (includes Run Length Encoded mask information)

Modality of Image: X-Ray (Greyscale)
Ethical Concerns: None, as it's a publicly available dataset
Missing Files: 42 files of Stage 1 & 2 train set don't have annotations

1. Stage 1 and Stage 2 Training and Test Data

	Train	**Test**
Stage 1 & 2	12089	3205

2. Stage 1 and Stage 2 Pneumothorax Distribution

	Pneumothorax	**Non-Pneumothorax**
Stage 1 & 2	2669(22.15%)	9378(77.84%)

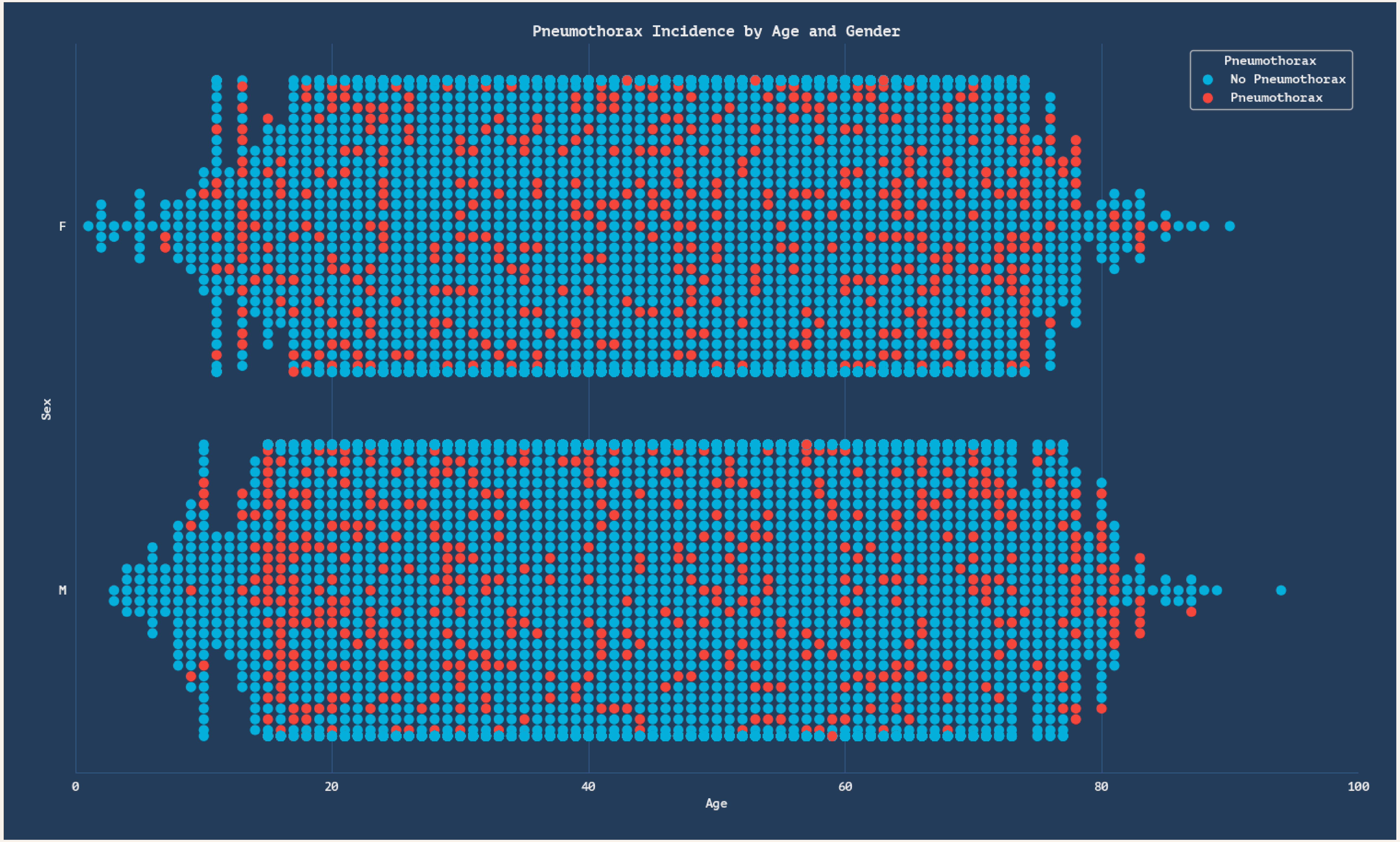
3. Stage 1 and Stage 2 Gender Distribution

	Male	**Female**
Stage 1 & 2	6626 (55.001)	5421 (44.998%)

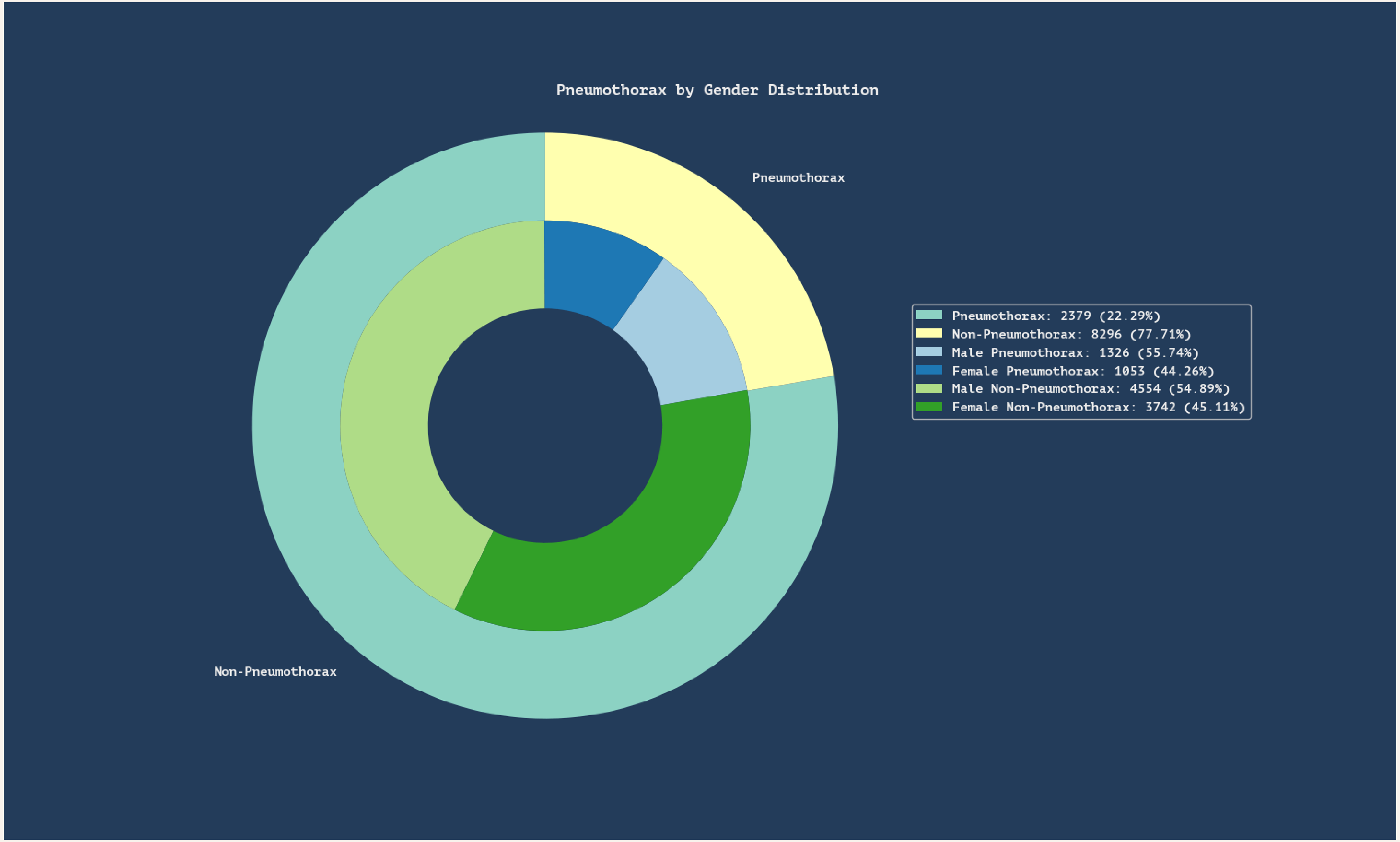
4. Stage 1 and Stage 2 View Position Distribution

	AP	**PA**	**AP/PA**
Stage 1 & 2	4773	7274	**0.6562**

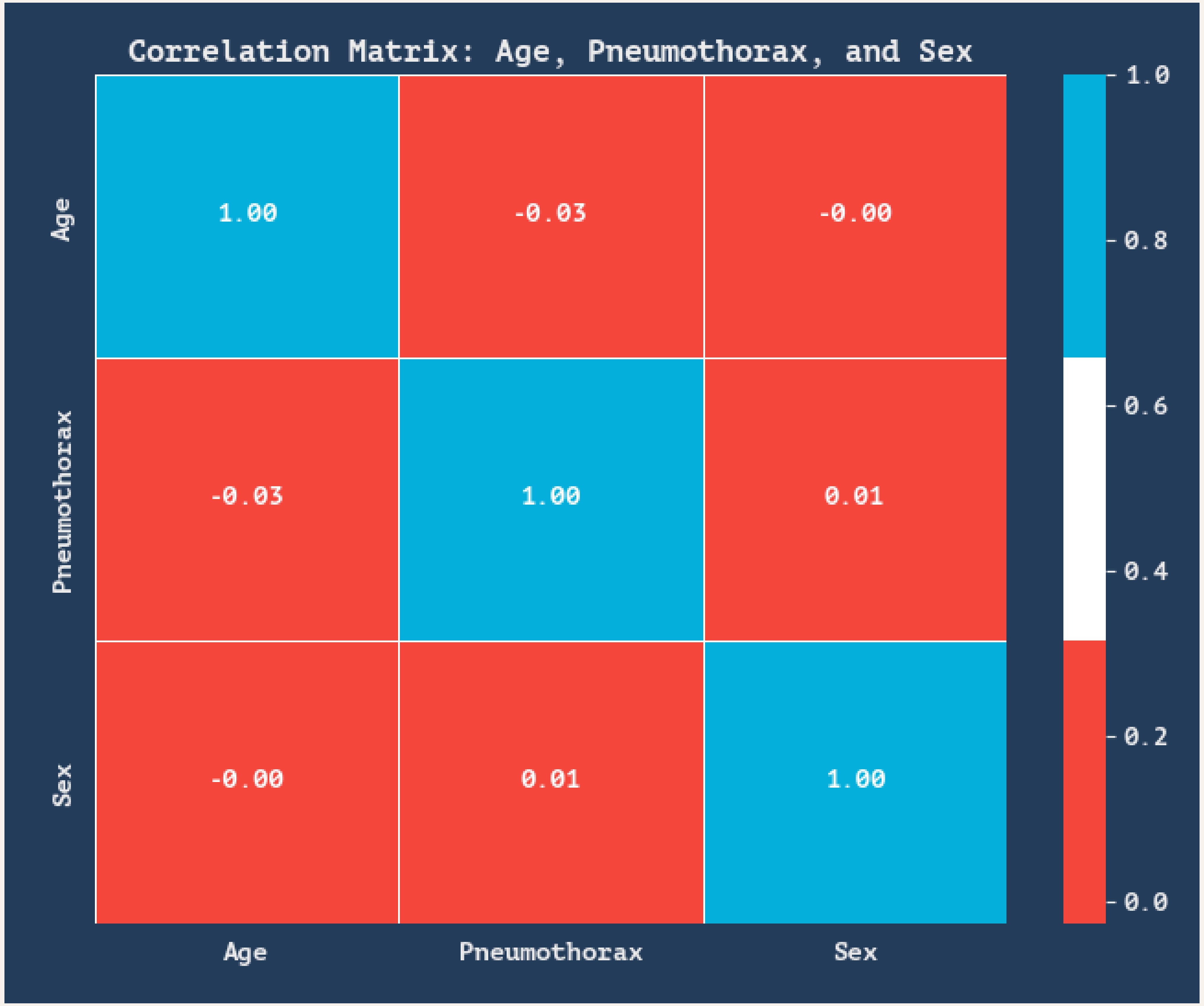
Dataset Statistics and Visualisation



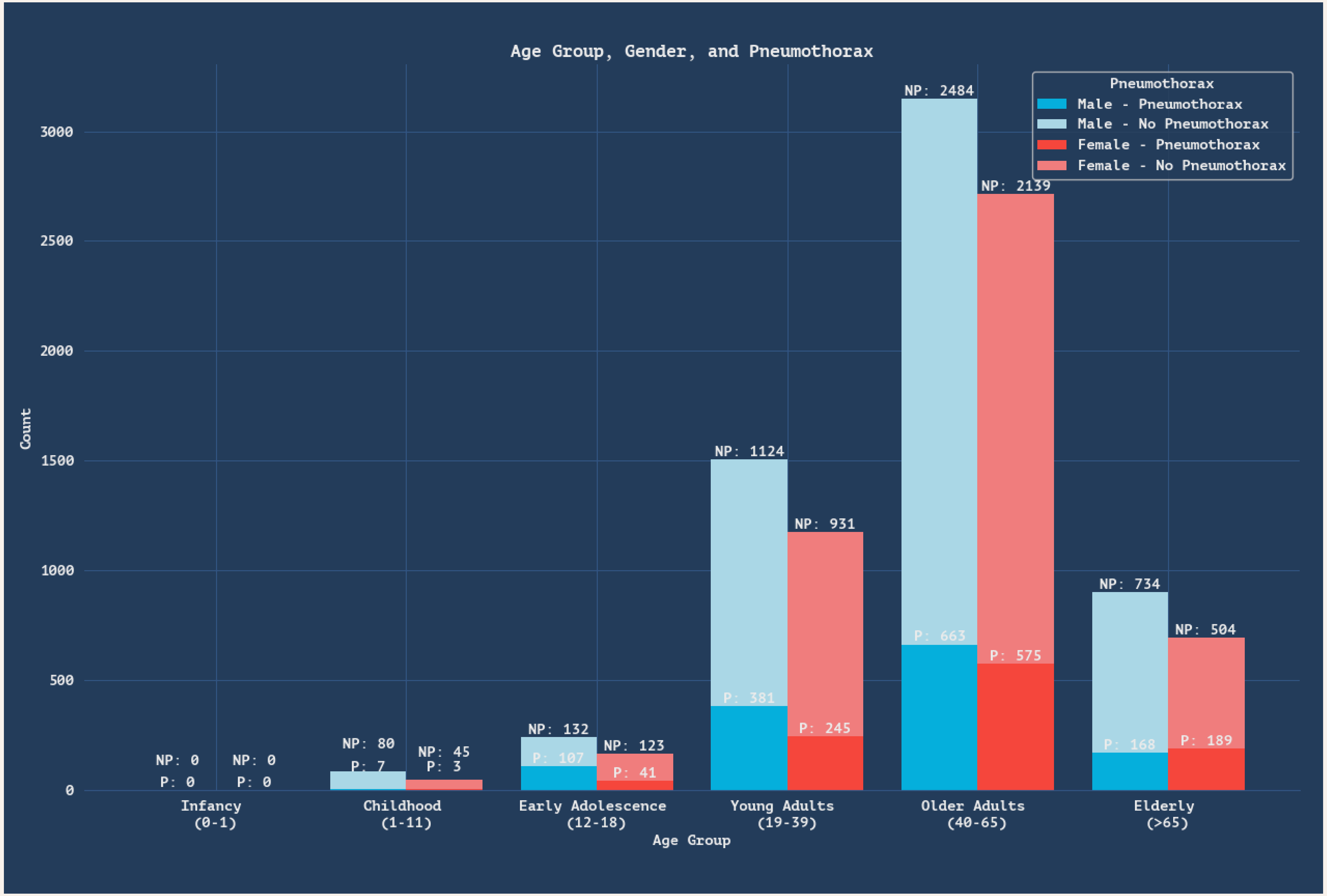
Dataset Statistics and Visualisation



Dataset Statistics and Visualisation



Dataset Statistics and Visualisation



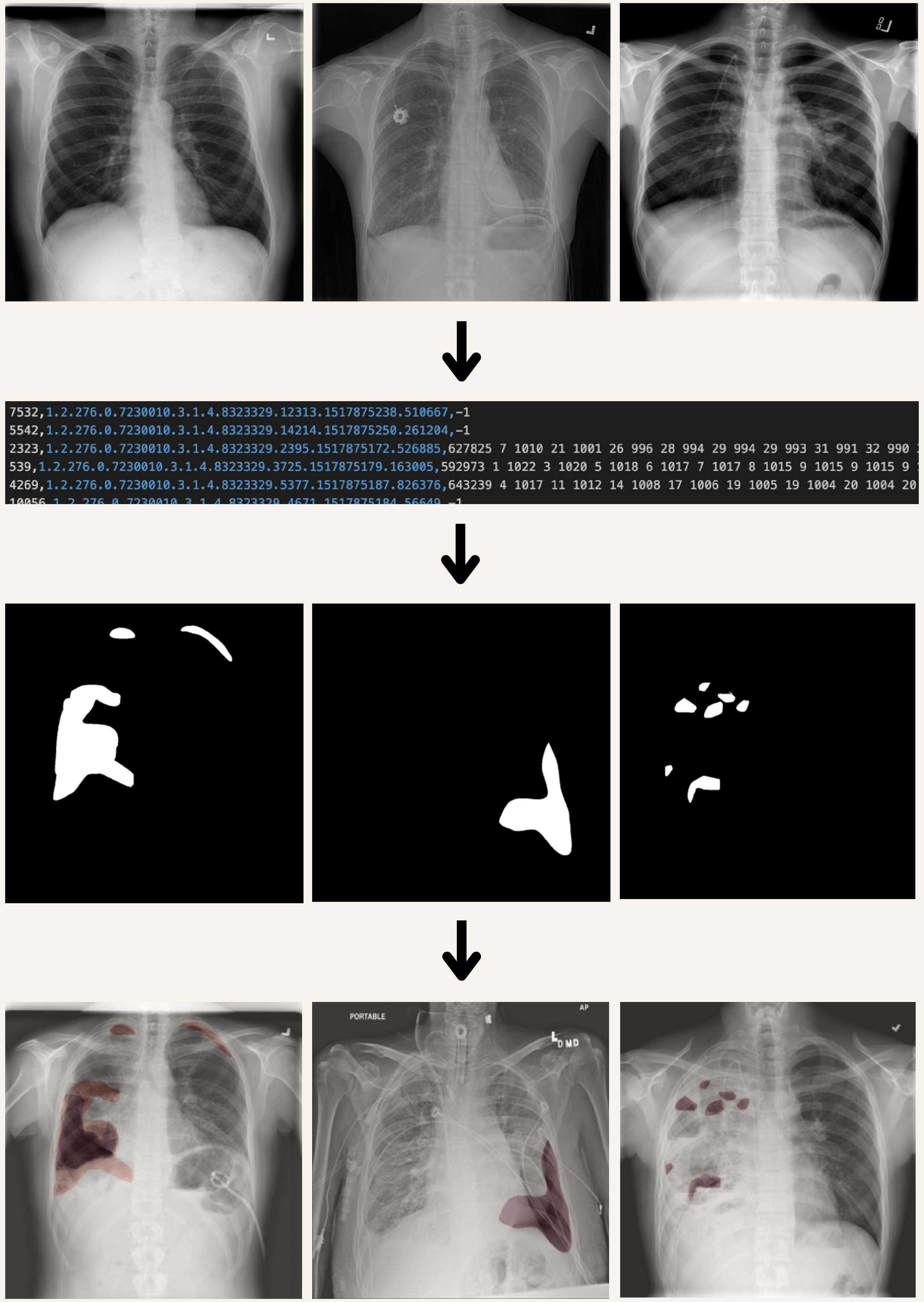
Data Preprocessing

01 Extract X-Ray images (.png) and patient metadata from DICOM files

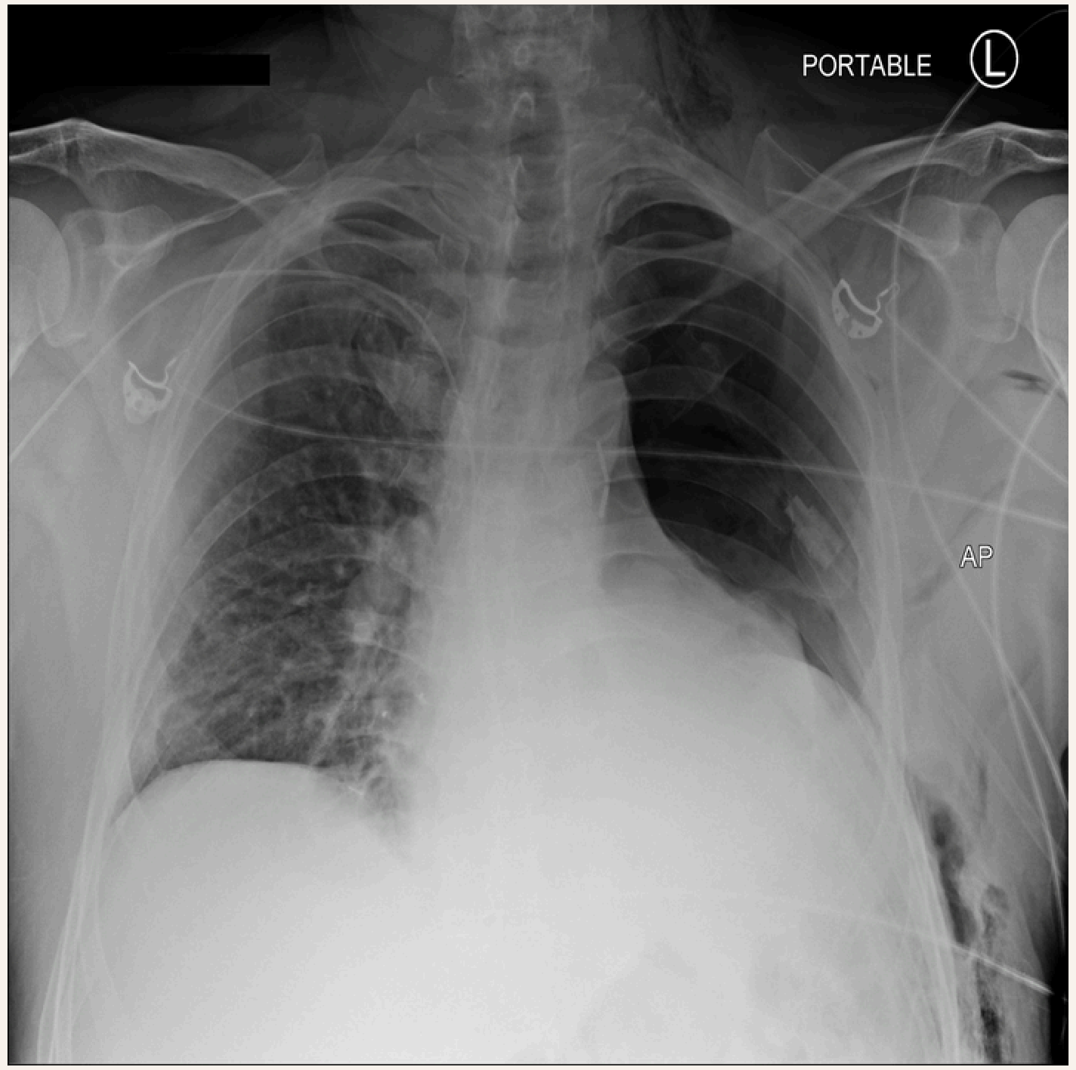
02 Decode and generate Run Length Encoded (RLE) Masks

03 Merge multiple masks for the same file into a single mask

04 Perform augmentation techniques to reduce data imbalance by approximating 1:1 true positive and true negative instances



Data Preprocessing: Radiographs, Segmentation Masks and Groundtruth

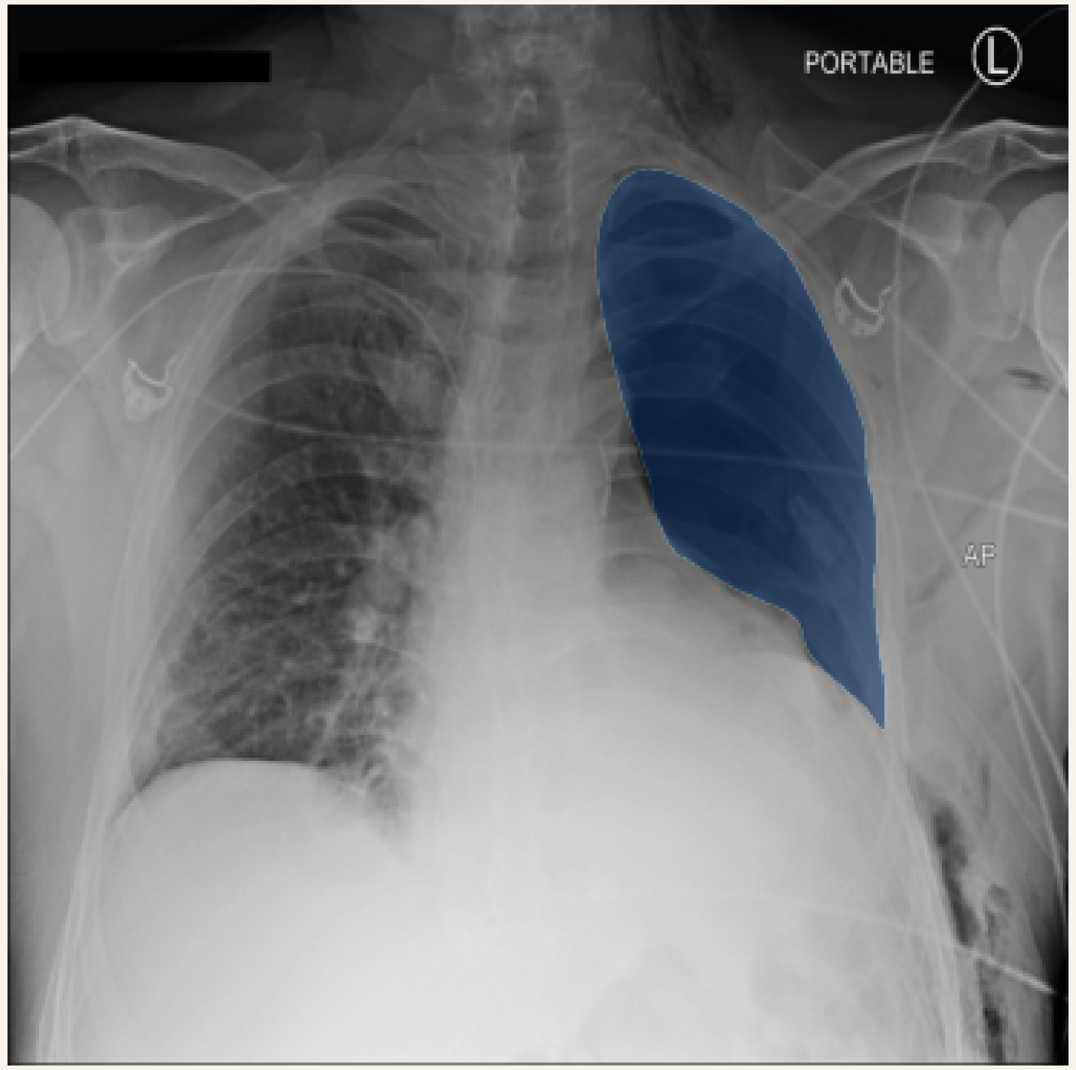


EXTRACTED IMAGE

DICOM FILES

DECODED MERGED MASK

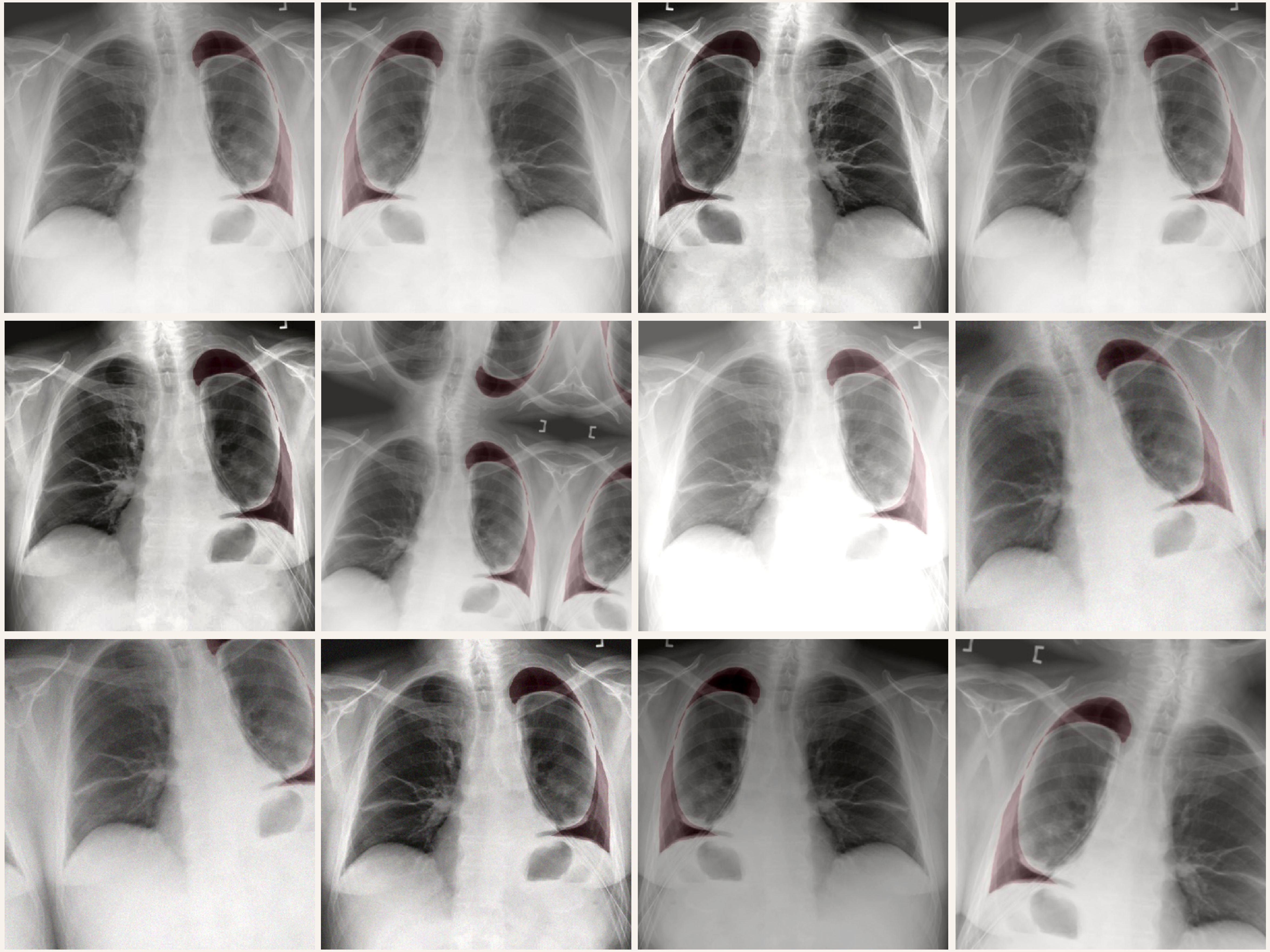
580842 33 986 48 966 ...



OVERLAYED IMAGE

Overlayed on Alpha Channels

Data Preprocessing : Dynamic Augmentation



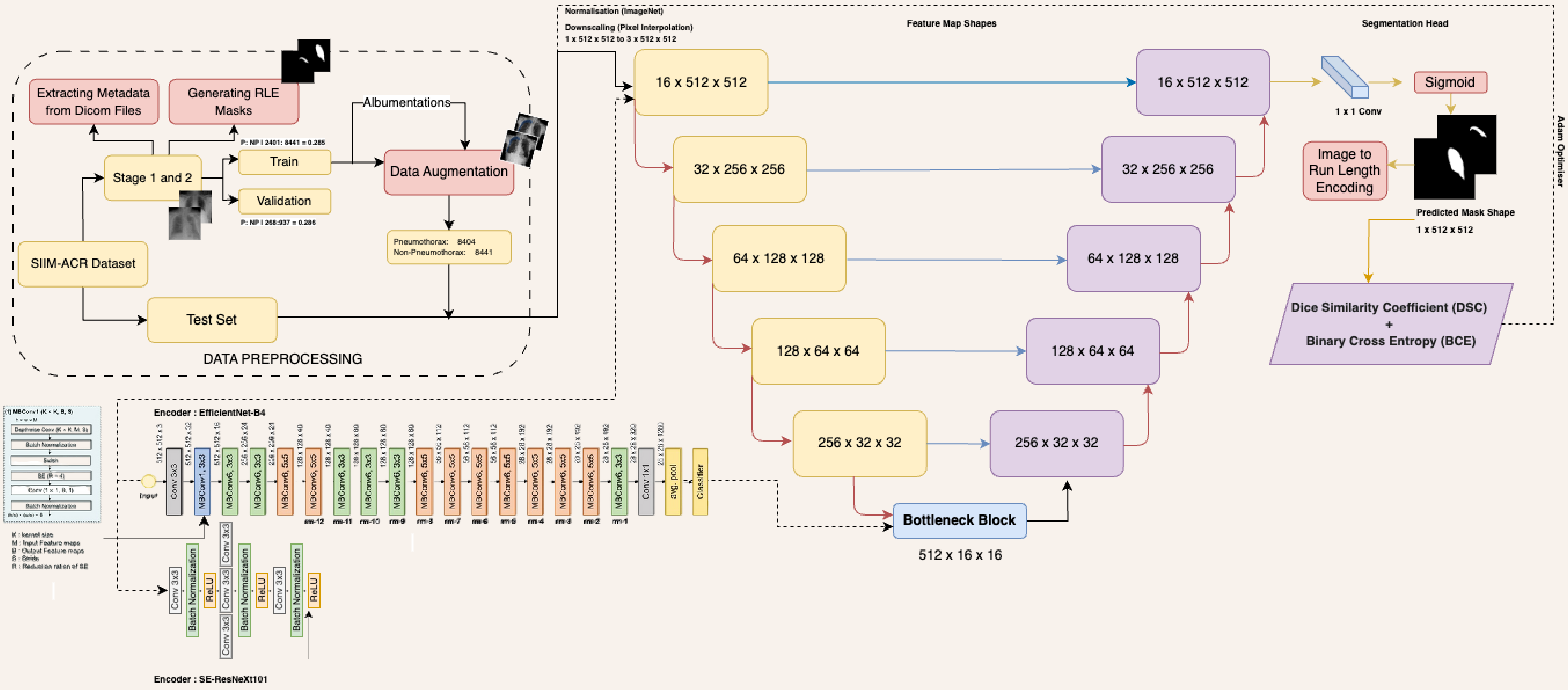
Pure Augmentations

1. Horizontal Flip
2. Random Brightness Contrast
3. Random Gamma
4. CLAHE (Contrast Limited Adaptive Histogram Equalization)
5. Optical Distortion
6. Shift Scale Rotate (± 15°)
7. Gaussian Noise

Mixed Augmentations

1. Horizontal Flip + Random Brightness Contrast + Random Gamma/CLAHE/Optical Distortion/Gaussian Noise
2. Shift Scale Rotate + Gaussian Noise
3. CLAHE + Gaussian Noise/Random Gamma/Optical Distortion
4. Random Gamma + Optical Distortion
5. Random Brightness Contrast + Gaussian Noise
6. Shift Scale Rotate + Random Gamma/Horizontal Flip/Gaussian Noise/Optical Distortion

Methodology



Hyper Parameters

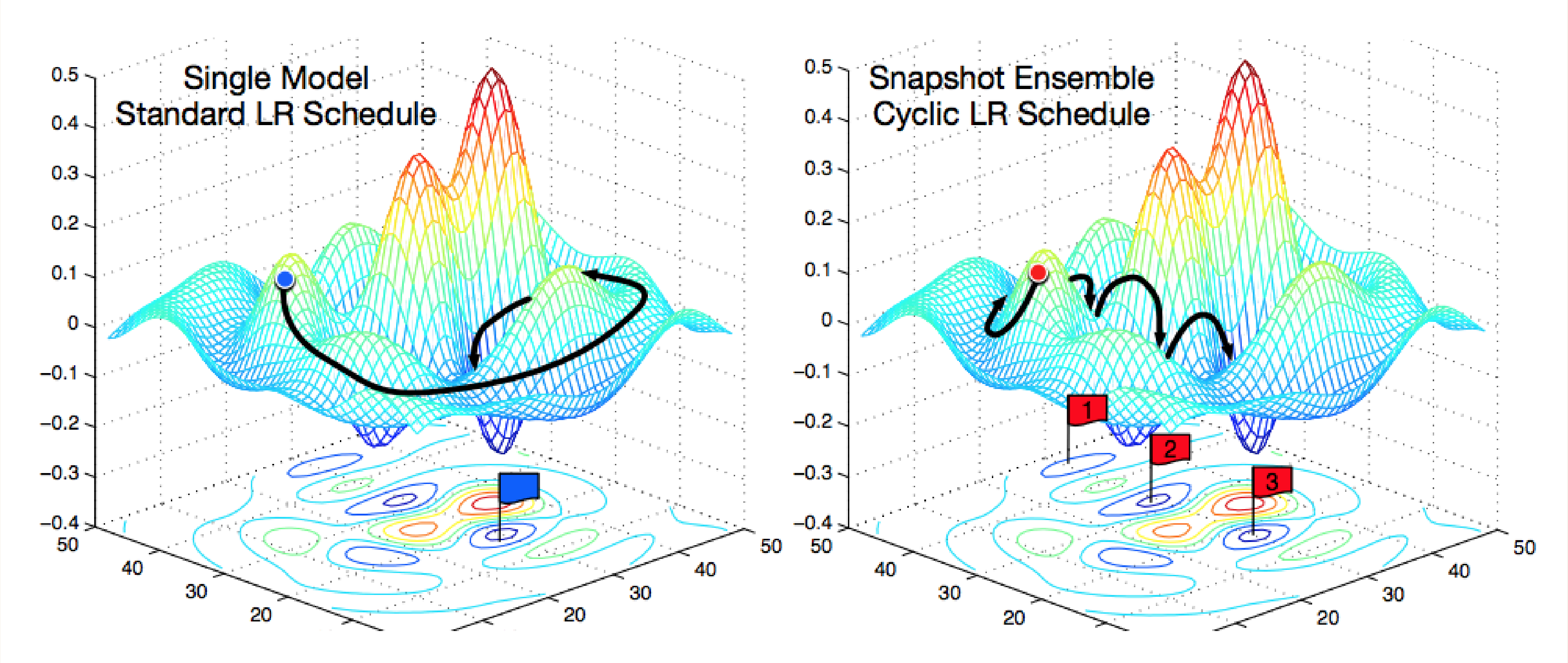
Parameter	Value
Input size	512 x 512 x 3
Batch Size	8
Loss Function	Combination Loss of Dice and Binary Cross Entropy
CNN Activation Functions	ReLU
Segmentation Head Activation Function	Sigmoid
Encoder Depth	5

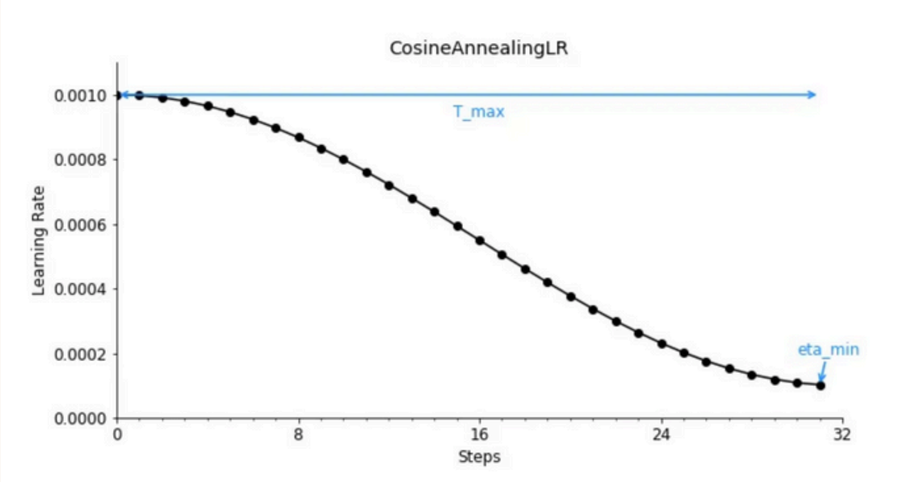
Hyper Parameters

Parameter	Value
Scheduler	Cosine Annealing with Warm Restarts (Iterations for Restart = 10) / Reduce Learning Rate on Plateau (Patience = 2, Threshold = 0.01, Factor = 0.8)
Optimizer	Adam
Initial Learning Rate	1e-4
Kernel Size	3x3
Encoder Weights Initialization	ImageNet

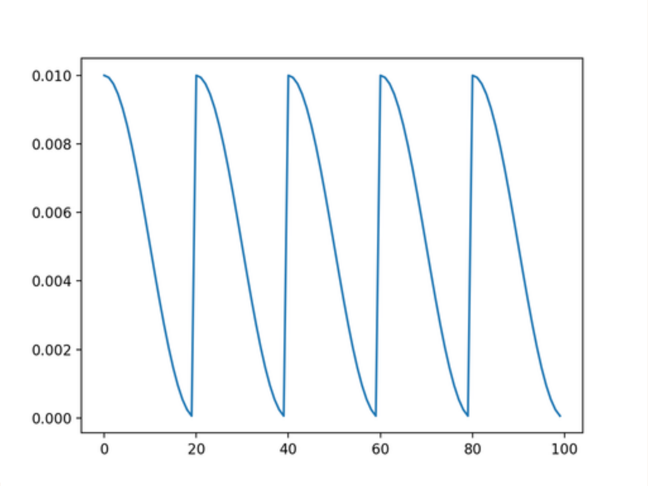
Hyper Parameters - Learning Rate Schedulers

Cosine Annealing





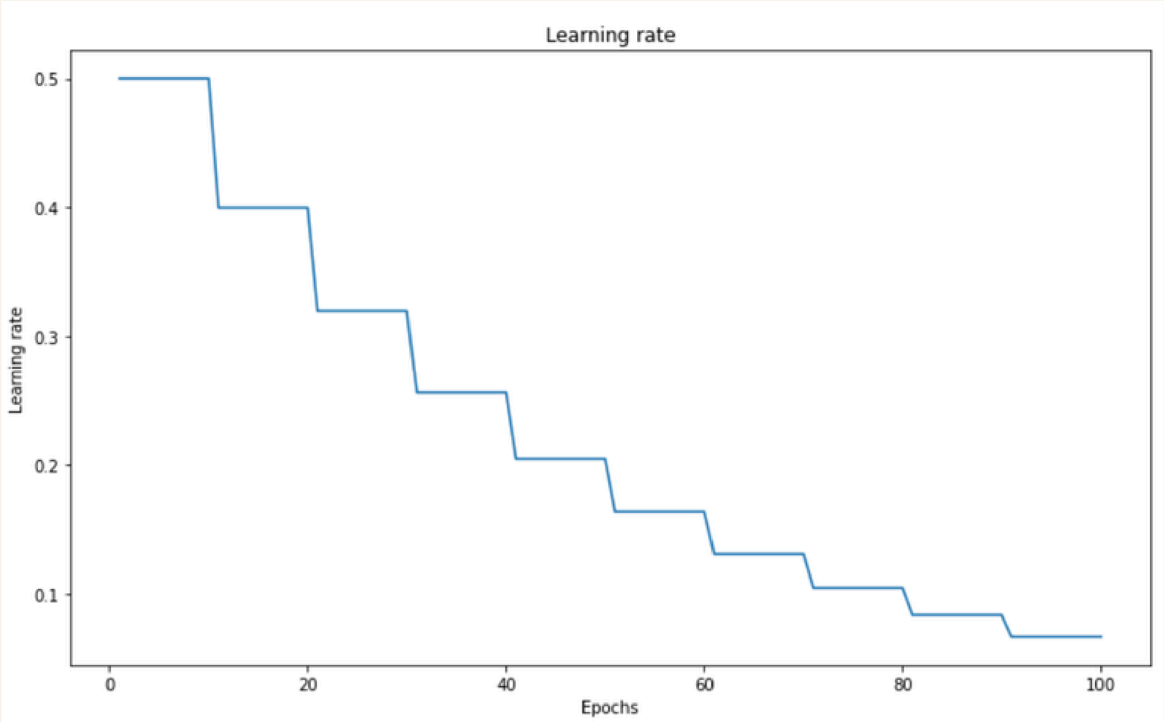
Regular



Warm Restarts

- Expected **better convergence** and thereby provide **better accuracy**
- However, the expected number of epochs are much higher for convergence!

ReduceLROnPlateau



Reducing the learning rate if the performance metric (**Validation IoU**) does not cross the **dynamic absolute threshold.**

“Patience Value” waits for a certain number of epochs before reducing the learning rate

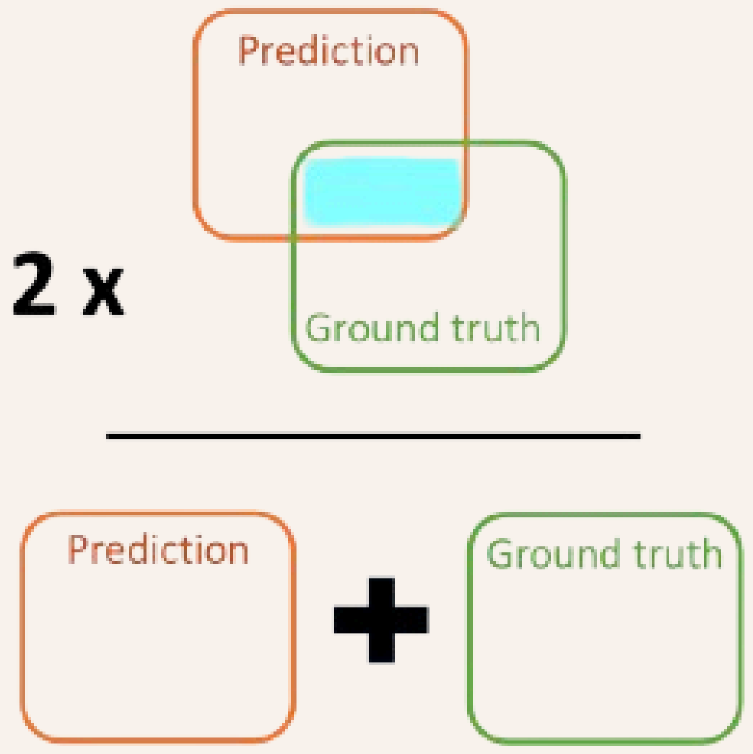
Dice Loss

Region Based Loss

It is a **measure of the dissimilarity** between the **predicted segmentation** and the **true segmentation** of an image.

Dice Loss is particularly useful when dealing with **imbalanced datasets**, where the positive and negative classes are not evenly distributed. Since Dice Loss takes into account both the predicted and true segmentation values, it can help prevent the model from favouring one class over the other.

$$\text{Dice} = \frac{2\ X\ Area\ of\ overlap}{Total\ area} =$$



Loss = 1 - Dice

Binary Cross Entropy Loss

Distribution Based Loss

Binary cross entropy measures the **difference between the predicted probabilities and the true labels, penalizing incorrect predictions more heavily as the confidence in the prediction increases.**

This loss function is particularly useful in scenarios where the classes are imbalanced, as it can help the model learn to make better predictions for the minority class.

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Weighted Combo Loss

Penalise both Regions and Edges

Combo loss is defined as a weighted sum of Dice Loss and Binary Cross-Entropy. It attempts to leverage the flexibility of Dice Loss of class imbalance and at the same time use Cross-Entropy for curve smoothing.

It's defined as:

$$L_{m-bce} = -\frac{1}{N}\sum_i \beta(y - log(\hat{y})) + (1-\beta)(1-y)log(1-\hat{y}) \tag{17}$$

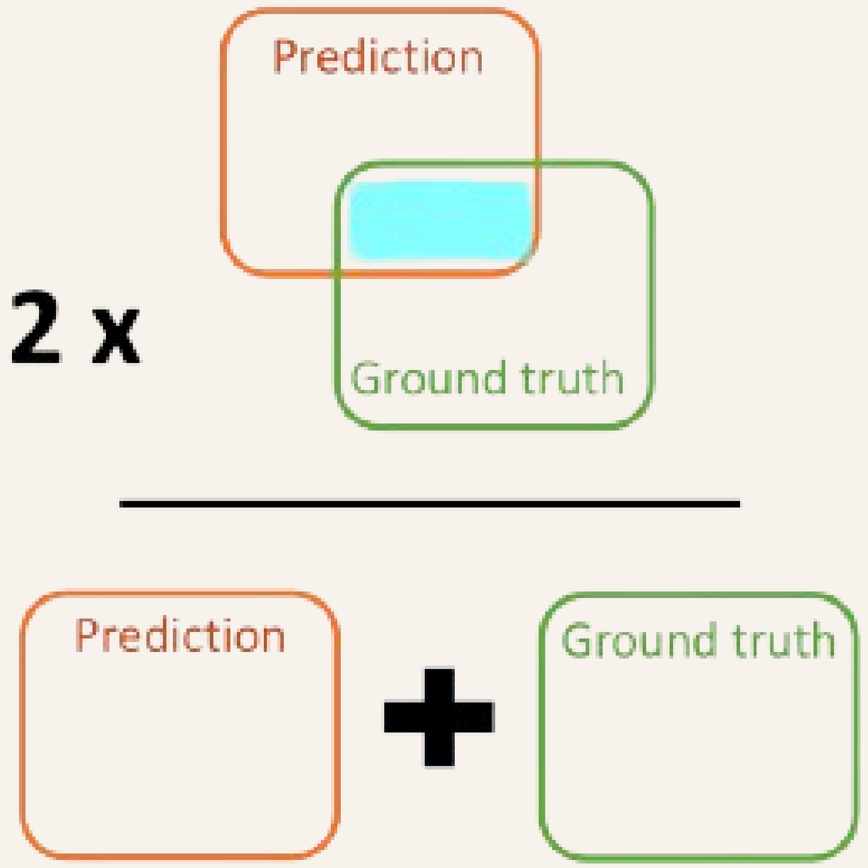
$$CL(y,\hat{y}) = \alpha L_{m-bce} - (1-\alpha)DL(y,\hat{y}) \tag{18}$$

Here DL is Dice Loss.

$$\text{Loss} = 1 \times \text{Dice} + 0.5 \times \text{BCE}$$

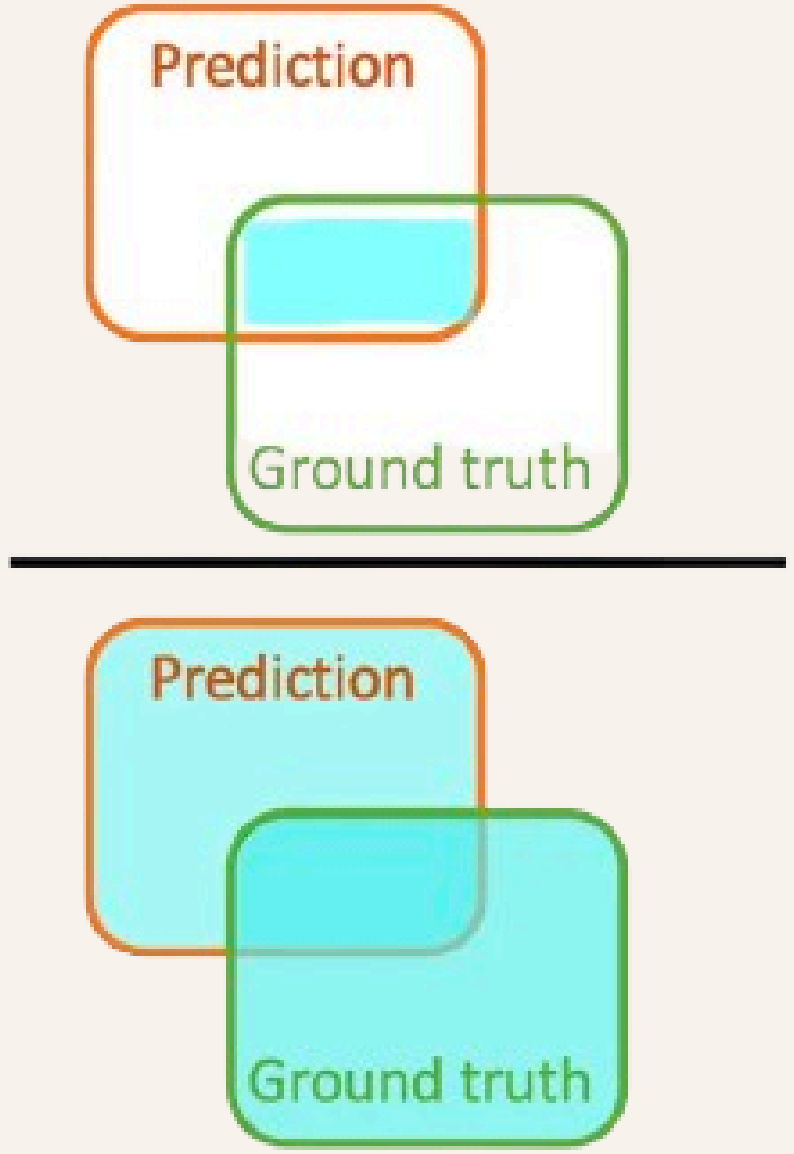
Performance Metrics

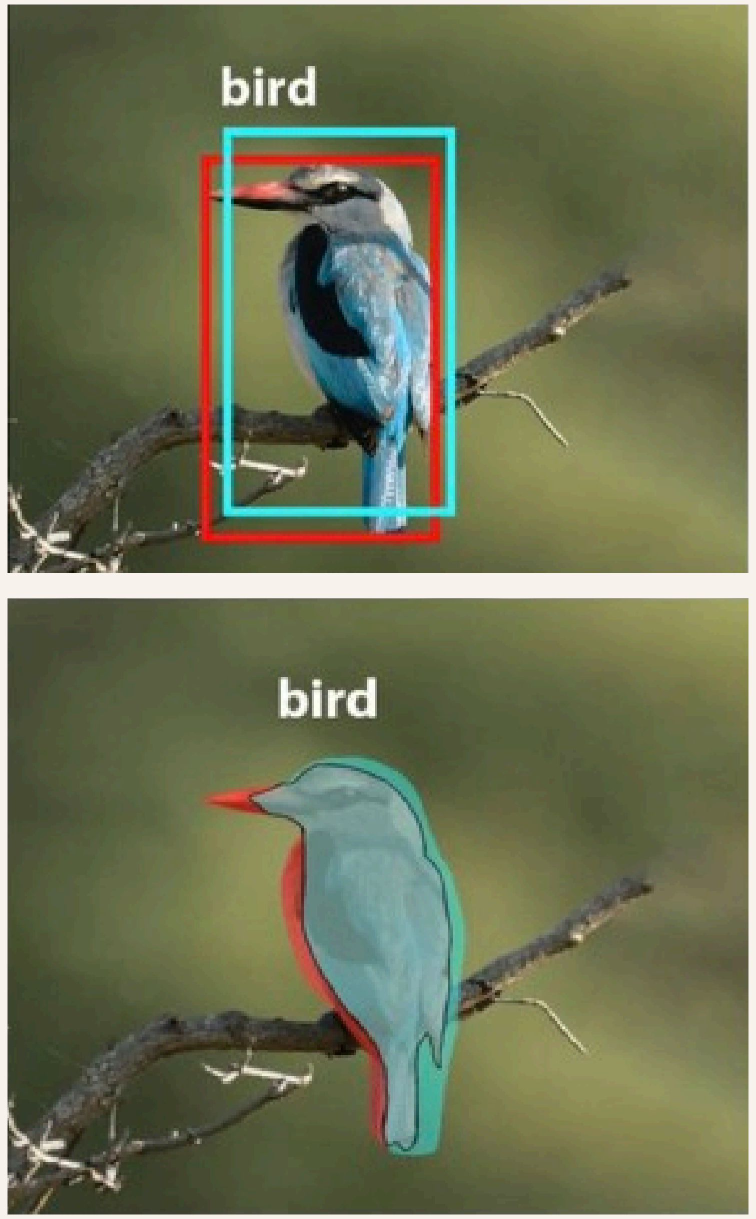
$$\text{Dice} = \frac{2\ X\ Area\ of\ overlap}{Total\ area} =$$



Performance Metrics

$$\mathrm{IoU} = \frac{Area\ of\ overlap}{Area\ of\ union} =$$





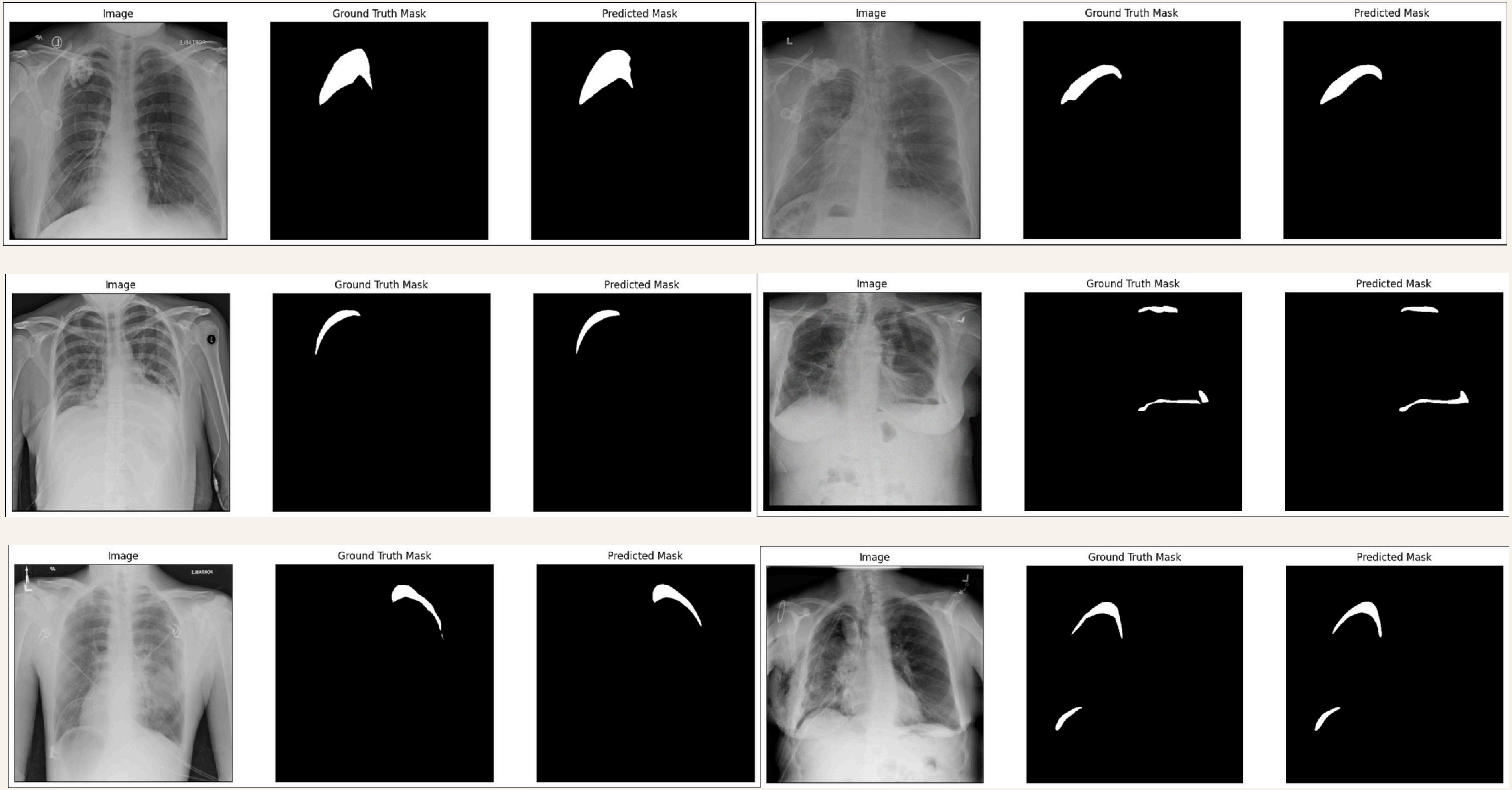
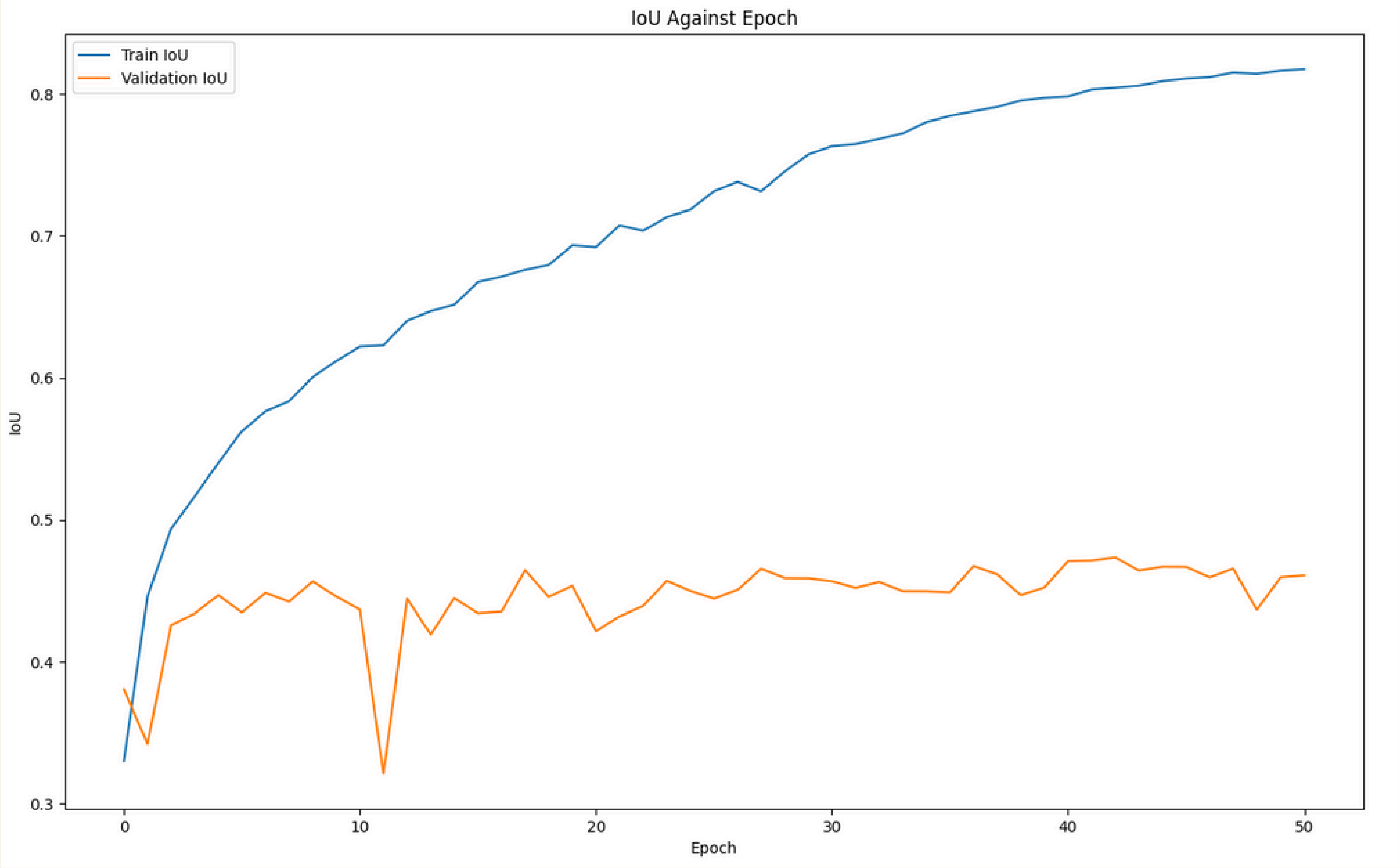


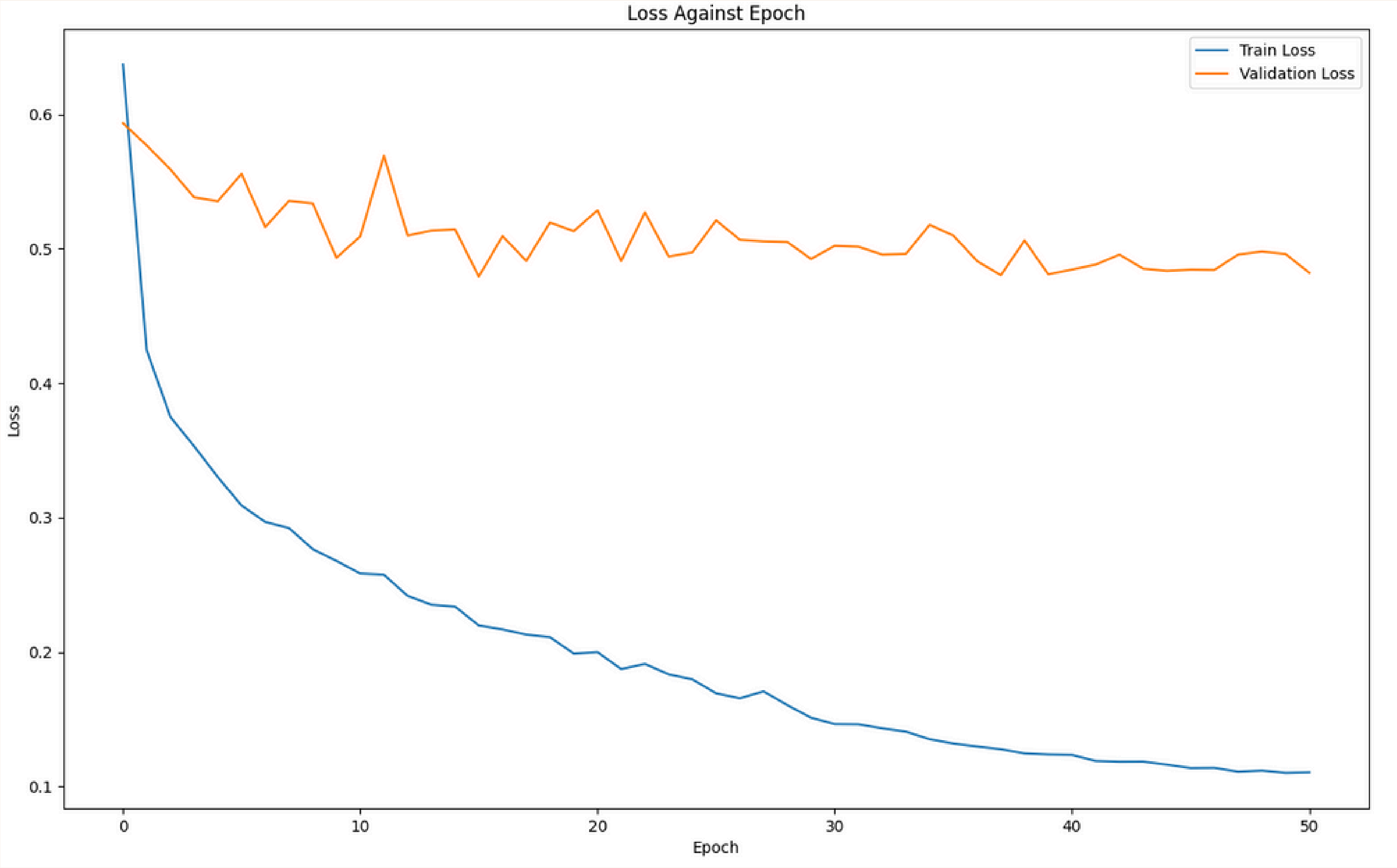
Image
Ground Truth Mask
Predicted Mask
Image
Ground Truth Mask
Predicted Mask
Image
Ground Truth Mask
Predicted Mask
Image
Ground Truth Mask
Predicted Mask
Image
Ground Truth Mask
Predicted Mask
Image
Ground Truth Mask
Predicted Mask

Results

Core Architecture	Encoder	Scheduler	Optimizer	Initial LR	Test DSC
UNet	EfficientNet-B4	Reduce LR on Plateau	Adam	0.0001	0.7600

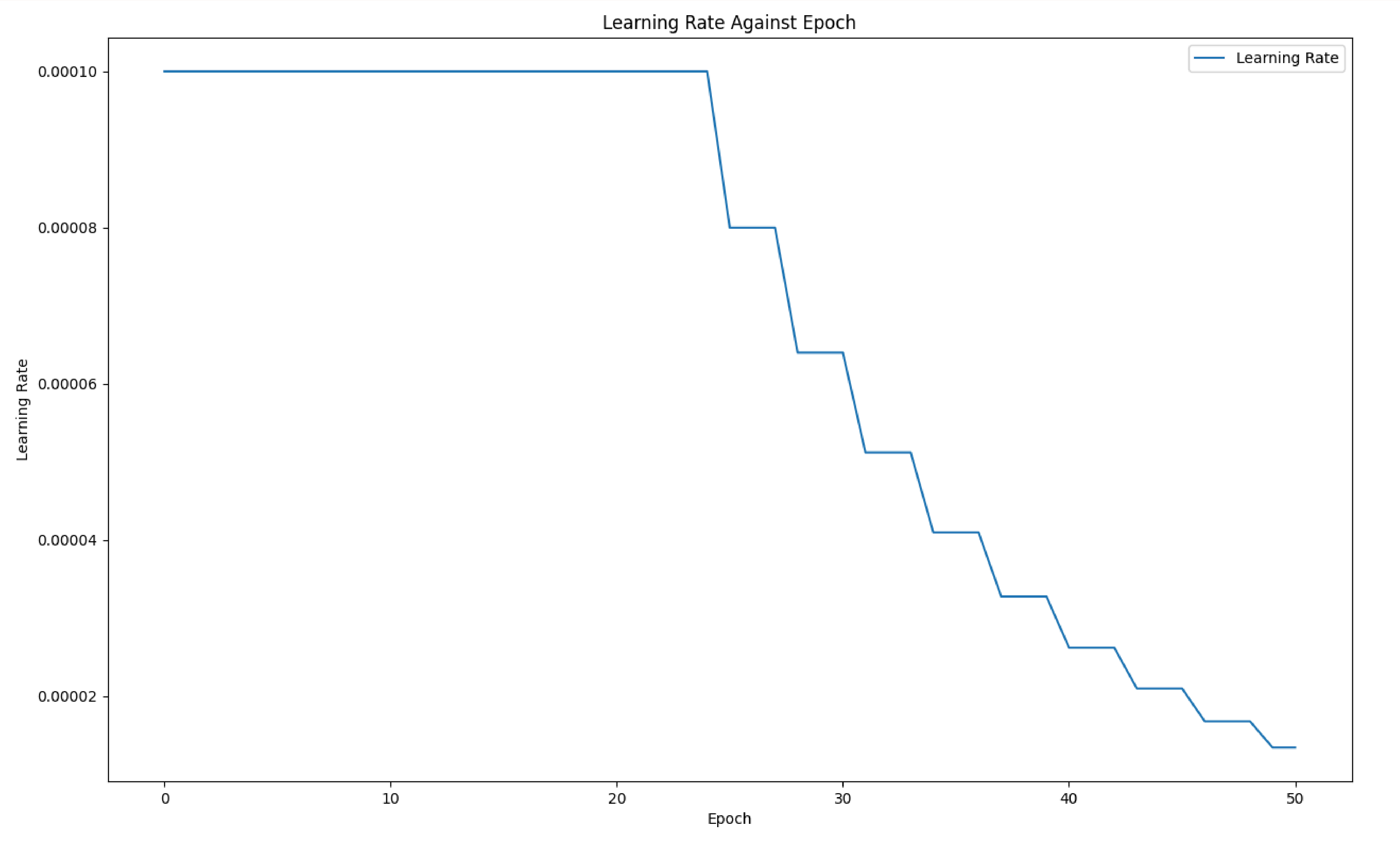
Submission and Description	Private Score
U-E-B4_22_final-rle.csv Complete (after deadline)	0.7600
U-SE-RXT_4_final-rle.csv Complete (after deadline)	0.7562





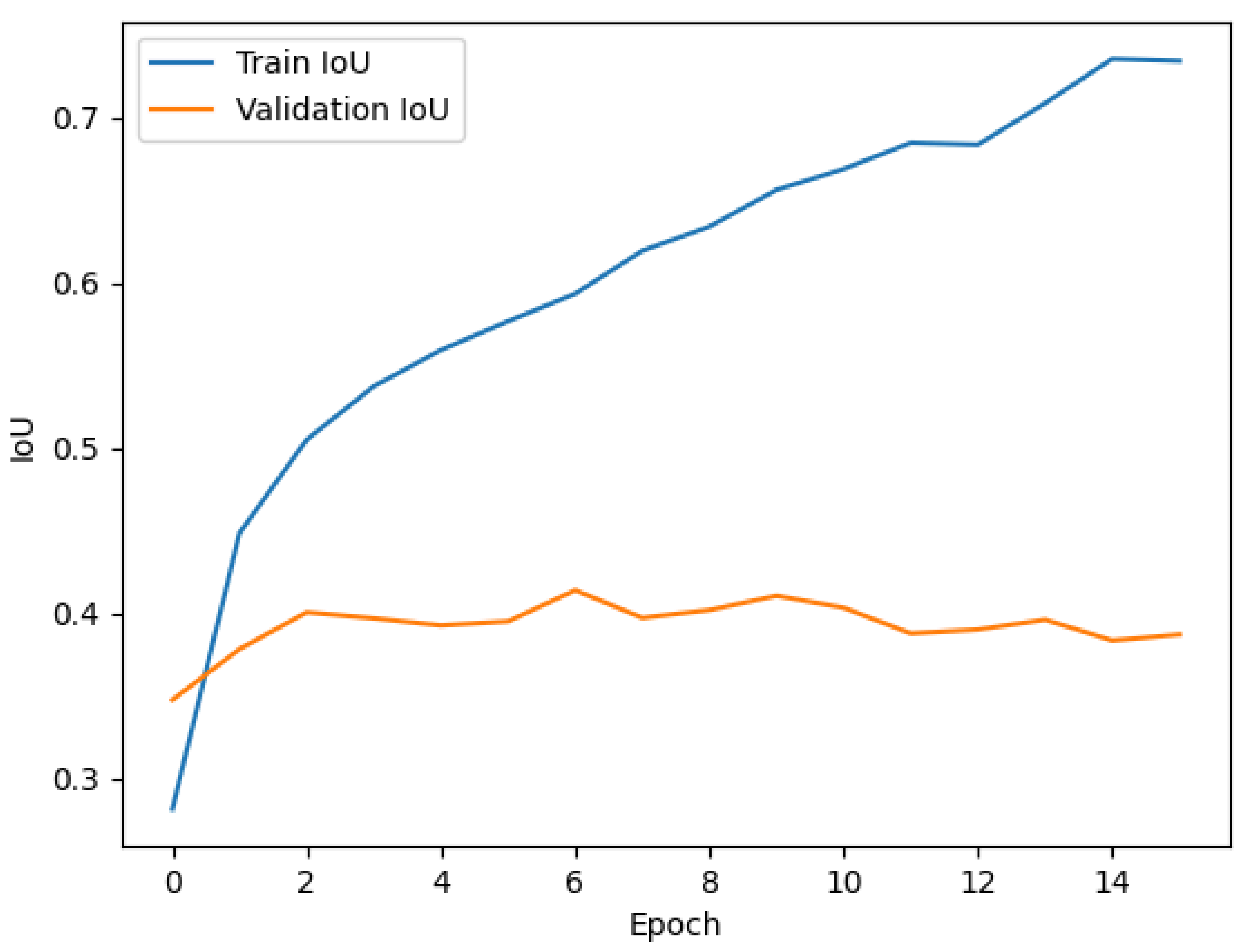
Results

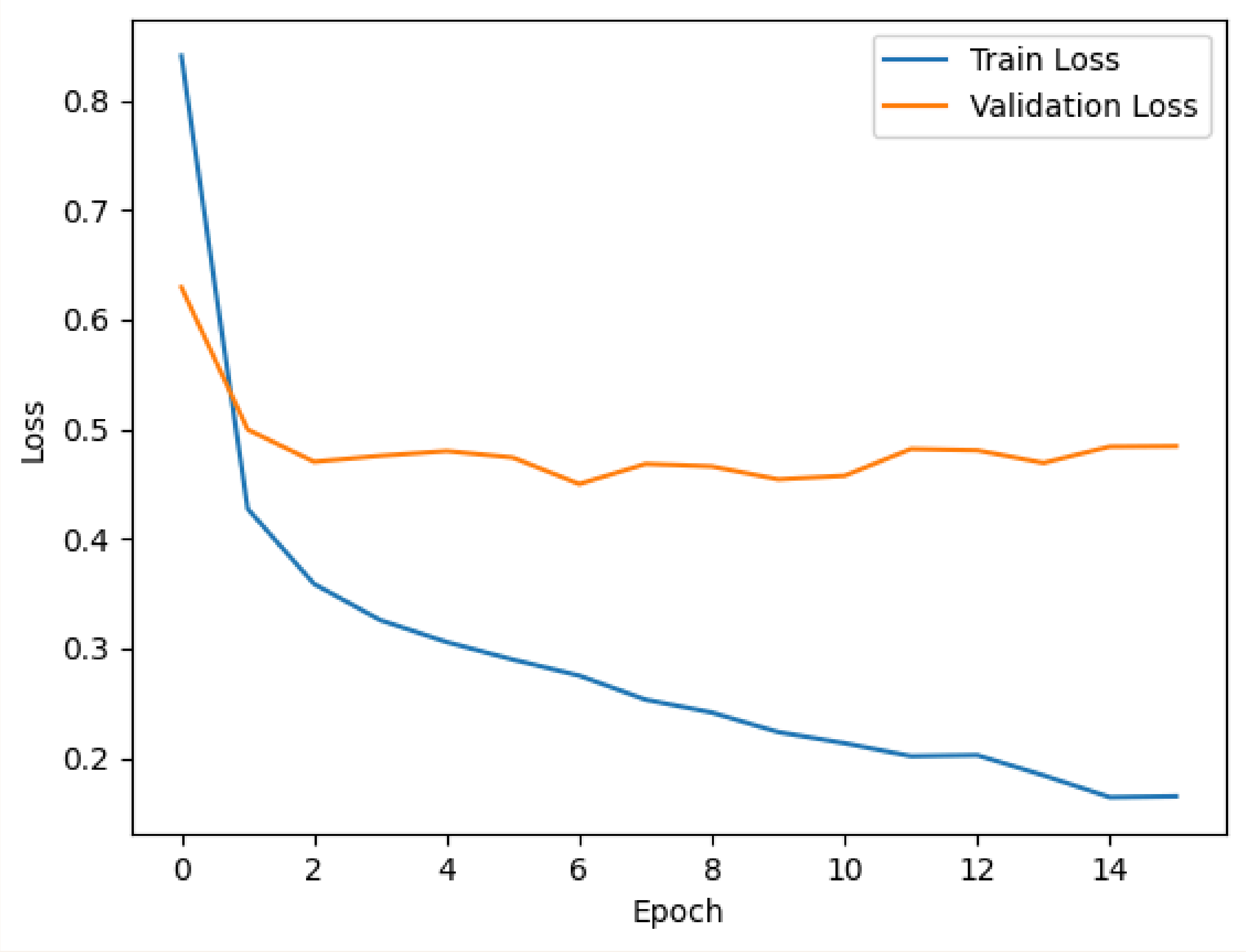
Core Architecture	Encoder	Scheduler	Optimizer	Initial LR	Test DSC
UNet	EfficientNet-B4	Reduce LR on Plateau	Adam	0.0001	0.7600



Results

Core Architecture	Encoder	Scheduler	Optimizer	Initial LR	Test DSC
UNet	SE-ResNeXt101	Reduce LR on Plateau	Adam	0.0001	0.7562





Results

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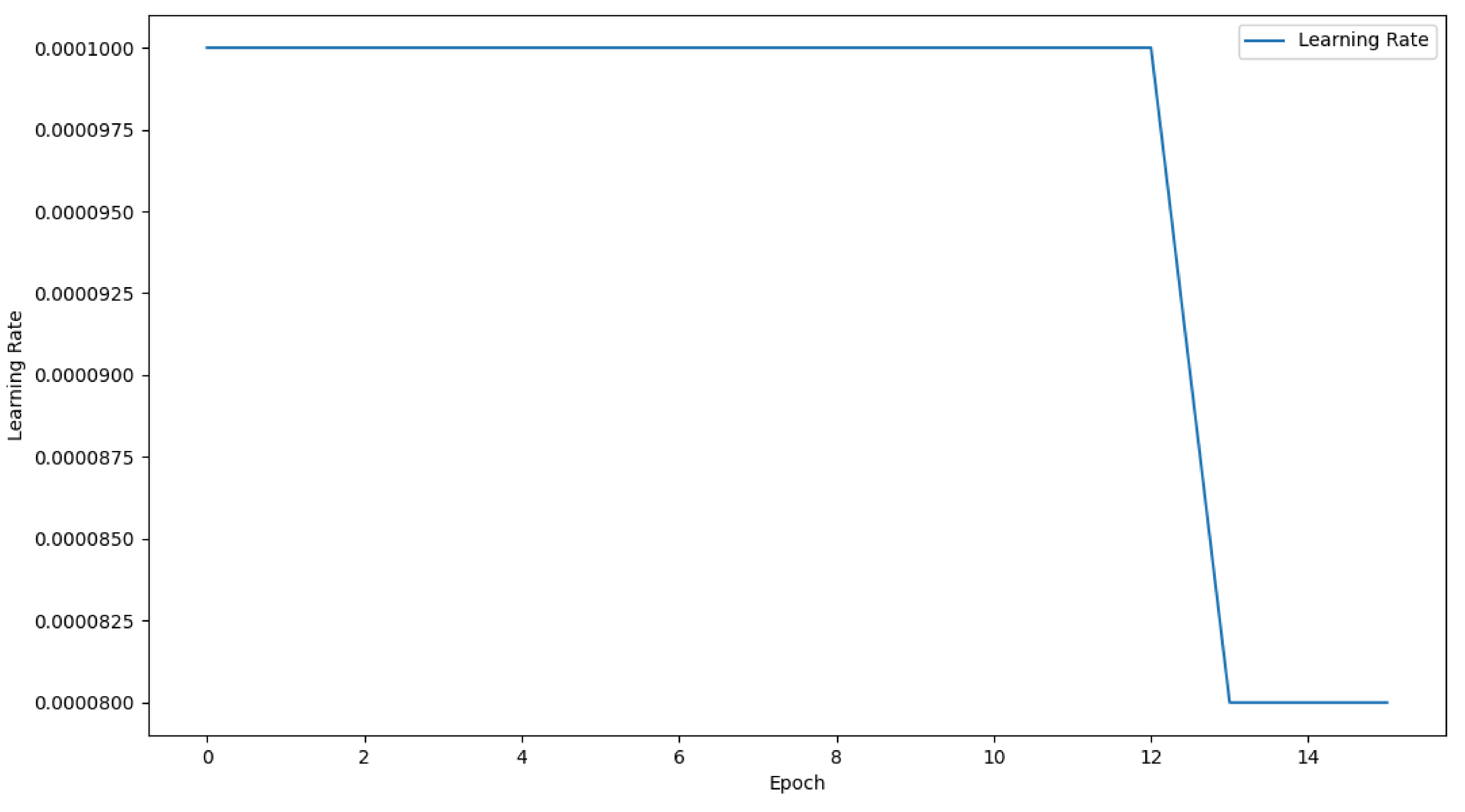
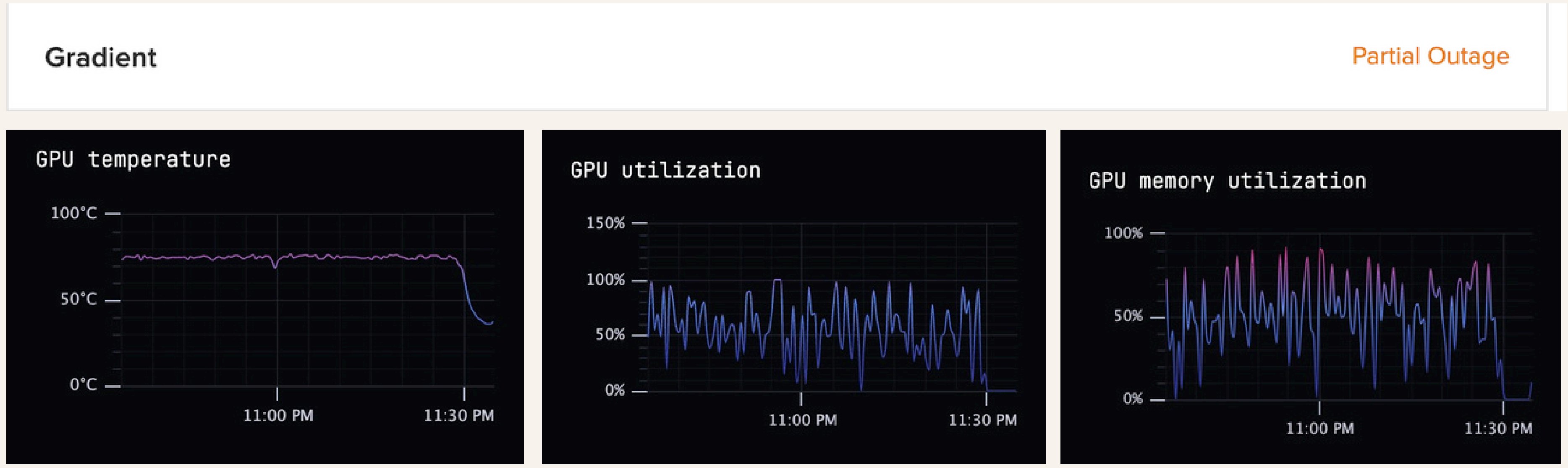
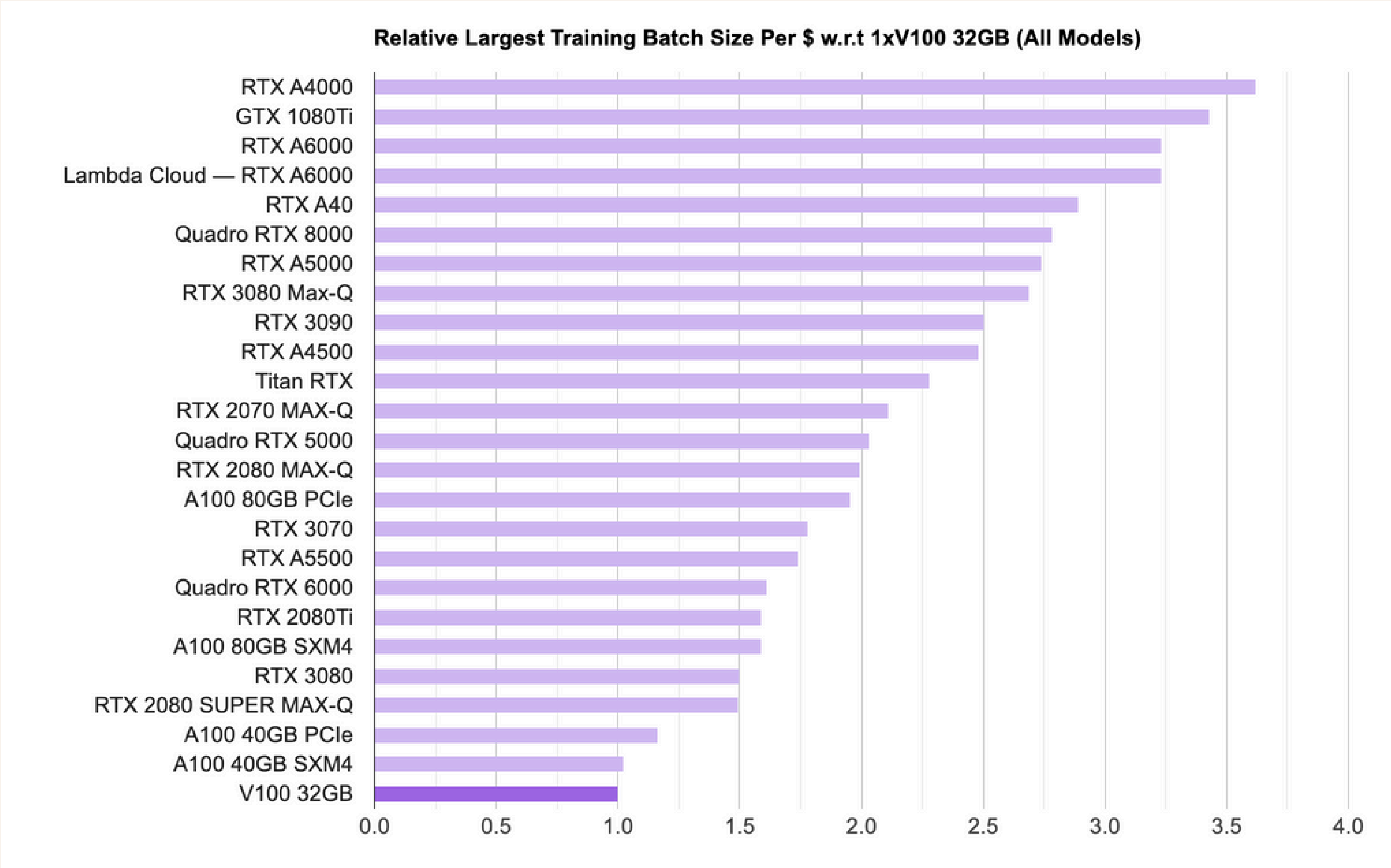


Computational Challenges

- Loading the entire UNet Model for training takes 12.67 GiB for a batch size of 8 images for **512x512 images**
- Need a CUDA compute score of over 8.6 to achieve 1.2s/it to complete the epoch within 30 minutes
- Choose to use the ampere architecture for its power efficiency and performance
- RTX A4000 for its batch size per dollar.
- Gradient Plan gives us a limited amount of 6 hours per GPU instance
- Limited pool of available GPUs with high wait times

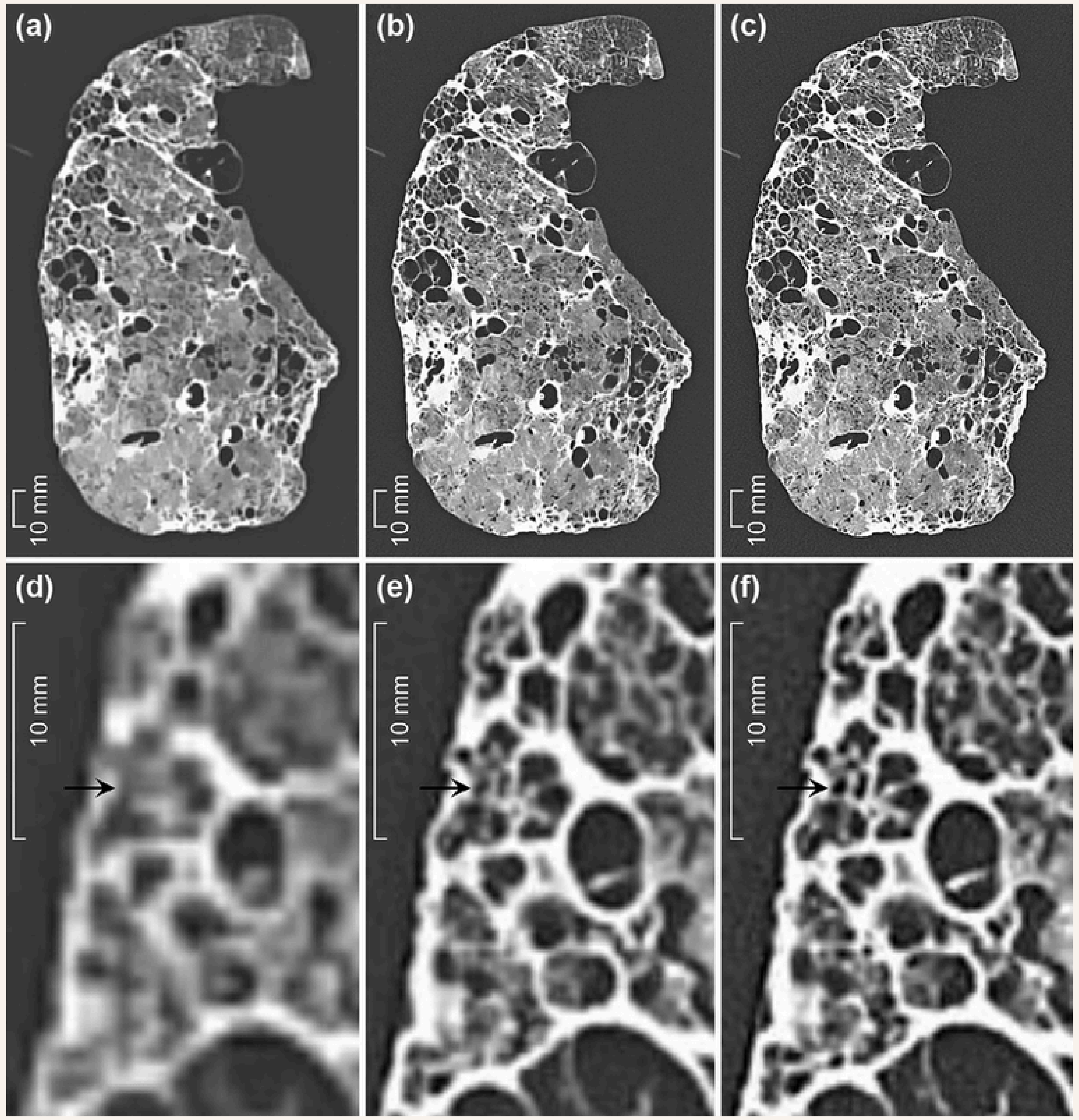




credits: Lamdba Labs 2023 Benchmark

Challenges

- Images were downsized from **1024 x 1024 to 512 x 512**, and hence the new images became **1/4th** of the original.
- This poses as a challenge in terms of **information loss** of the delicate thin lines that mark the boundaries of a collapsed lung.
- Predicted masks were then **upscaled** from 512 x 512 to 1024 x 1024, thereby **adding some form of new information**.
- Higher dice coefficient score could have been achieved if original images were used.



Deployment

ABCDE ASSESSMENT

STABLE

CHEST X-RAY

DETERMINE UNDERLYING CAUSE & TYPE of PNEUMOTHORAX

CHEST X-RAY

FINDINGS INCONSISTENT w/ PNEUMOTHORAX

ALTERNATIVE DIAGNOSIS

PNEUMOTHORAX

- PRIMARY SPONTANEOUS PNEUMOTHORAX
- SECONDARY SPONTANEOUS PNEUMOTHORAX
- NON-SPONTANEOUS PNEUMOTHORAX
  - OPEN PNEUMOTHORAX
  - CLOSED PNEUMOTHORAX

UNSTABLE

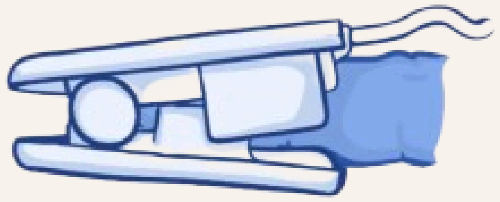
ACUTE MANAGEMENT

* STABILIZE AIRWAY, BREATHING, & CIRCULATION
* ASSESS NEED for VENTILATORY SUPPORT
  - might need to intubate
* OBTAIN IV ACCESS

UNSTABLE

ACUTE MANAGEMENT

* SUPPLEMENTAL O_2 maintain $SaO_2 > 92\%$
* CONTINUOUS VITAL SIGN MONITORING
  - ~ pulse oximetry
  - ~ blood pressure
  - ~ heart rate

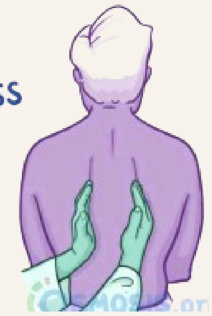


* FOCUSED H&P
* CHEST X-RAY

Hx
* SUDDEN CHEST PAIN

* SHORTNESS of BREATH

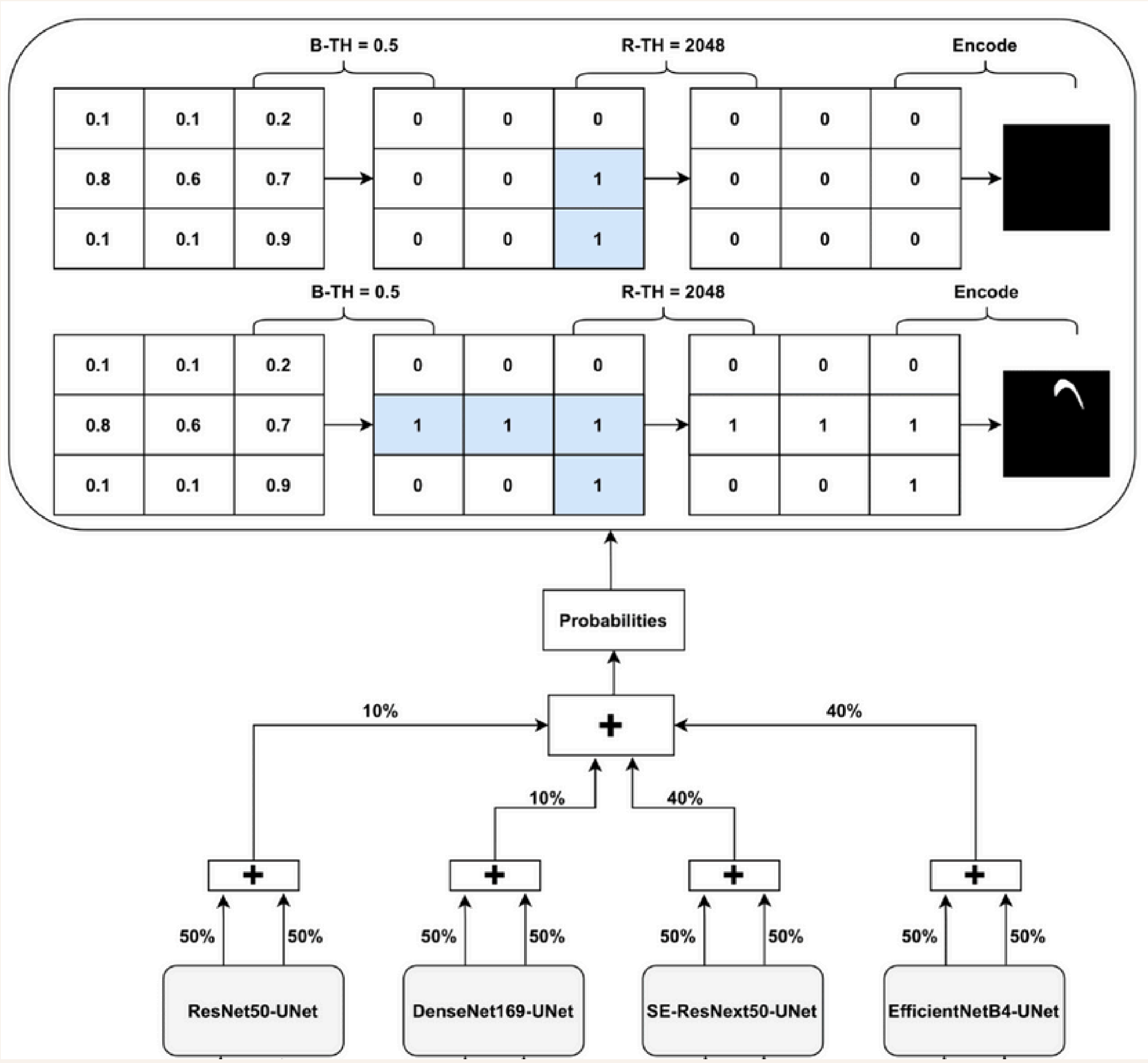
PE
* ASYMMETRIC CHEST
* TRACHEAL DEVIATION AWAY from AFFECTED SIDE
* HYPOTENSION
* RESPIRATORY DISTRESS
* ↓ or ABSENT BREATH SOUNDS on AFFECTED SIDE



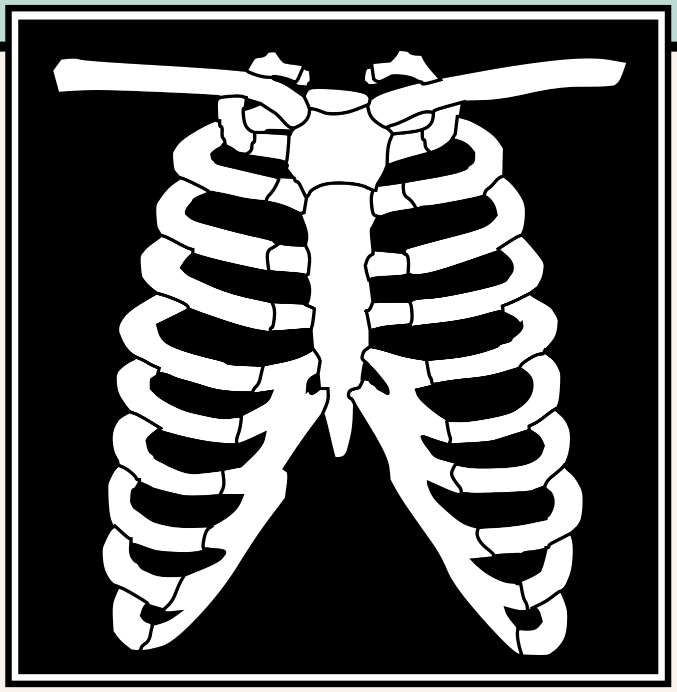
*Airway, Breathing, Circulation, Disability, and Exposure

Future Scope

- Apply a **Vision Transformer** approach for better **Global Feature Extraction** with access to better compute
- Increase data samples through integration with **CheXpert Dataset**
- Larger Batch Size
- **Semi-Supervision Model**
- Voting Classifiers (Ensemble Models)
- Cumulative Thresholding (2 or 3)



Abedalla, A., Abdullah, M., Al-Ayyoub, M., & Benkhelifa, E. (2021). Chest X-ray pneumothorax segmentation using U-Net with EfficientNet and ResNet architectures. PeerJ. Computer science, 7, e607. https://doi.org/10.7717/peerj-cs.607



THANK YOU

Amog Rao

Ananya Shukla

Nikhil Henry