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Obscuration to Clarity: Bone Suppression for Enhanced Localization in Pneumothorax Segmentation of Chest Radiographs

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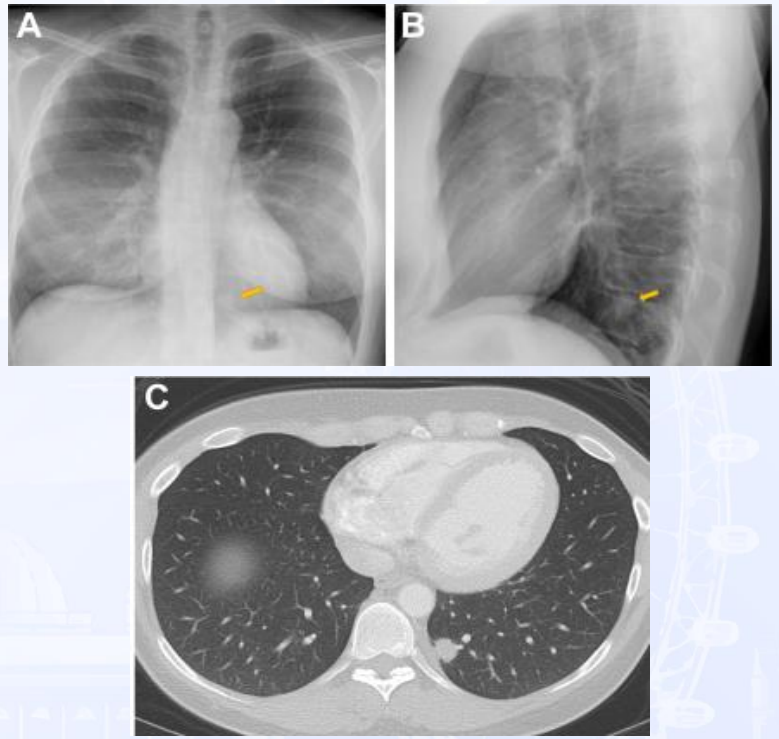
Clinical Motivation

Chest Radiography (CXR)

- **Widely Used First-Line Imaging:** Primary modality for cardiopulmonary disease due to low radiation does, and cost-effectiveness.

Challenges

- **The 2D Projection Problem:** Inherent anatomical superimposition of 3D thoracic structures onto a 2D plane.
- **Anatomical Overlap and Occlusion:** Ribs and clavicles overlap lung parenchyma, obscuring subtle soft-tissue abnormalities.
- **Diagnostic Risk:** lead to missed or delayed diagnoses in anatomically regions (e.g., apical and retrocardiac areas).



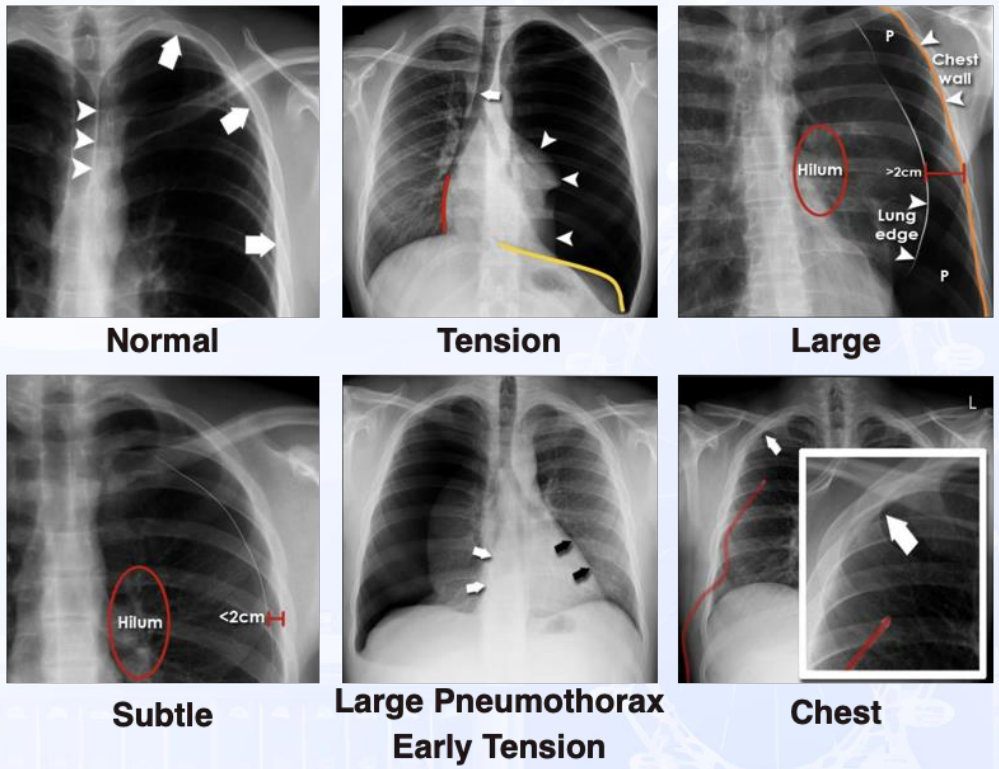
Diagnostic Blind Spot in CXR: Nodule obscured by cardiac-diaphragmatic overlap (PA) and spinal superimposition (lateral), confirmed on CT.

P. M. de Groot et al., "Pitfalls in Chest Radiographic Interpretation: Blind Spots," Semin. Roentgenol., 2015.

Clinical Motivation

Pneumothorax - A Critical Case for Precise Localization

- **Clinical Severity Spectrum**
  From asymptomatic air accumulation → to life-threatening *tension pneumothorax*.
- **Why It Is Hard to See (Imaging Challenge)**
  Diagnosis depends on detecting a thin, low-contrast visceral pleural line, which is easily overlooked.
- **Why It Gets Hidden (Anatomical Interference)**
  Overlying bony structures (ribs, clavicle) can obscure regions of lung collapse.
- **Clinical Consequence (Diagnostic Risk)**
  These factors lead to a high miss rate, with up to 50% of cases undetected on standard radiographs in certain settings.

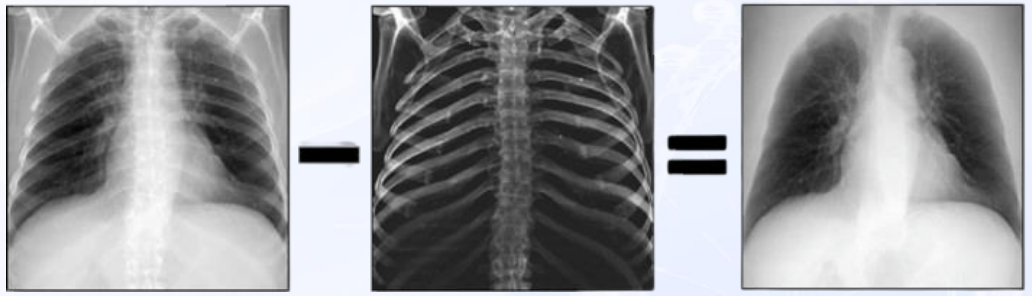


Steven A. Sahn et al., "Spontaneous Pneumothorax," New England Journal of Medicine, 2000.

Clinical Motivation

Bone Suppression as a Clinical Imperative

- **Computational Enhancement:** Removes bony structures to enhance underlying soft-tissue visibility.
- **Scalable & Non-Invasive:** Modern deep learning methods work on standard CXRs without additional radiation exposure.
- **Reducing Anatomical Noise:** Improves the conspicuity of clinically relevant structures for reliable detection.
- **Pathway to Precise Localization:** Enables a shift toward improved boundary delineation and clinical severity estimation.

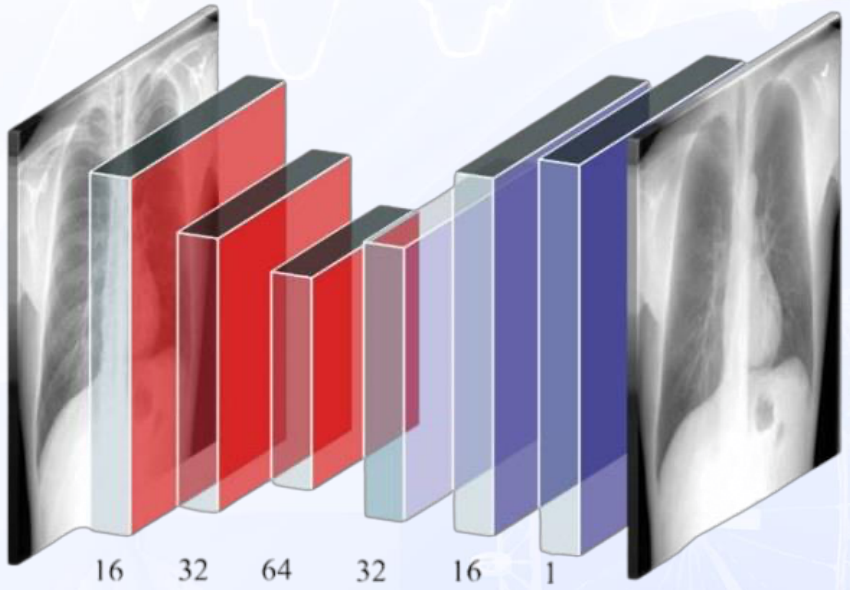


Schalekamp, Steven, et al. "Bone suppressed images improve radiologists' detection performance for pulmonary nodules in chest radiographs." European Journal of Radiology 82.12 (2013): 2399-2405.

Related Works

Evolution of Bone Suppression Technology

- **Traditional Approach:** Dual-Energy Subtraction (DES) is effective but limited by specialized hardware and higher radiation.
- **Deep Learning Era:** Significant gains in downstream classification tasks for TB, COVID-19, and Lung Nodules.
- **The Research Gap:** Existing literature is predominantly classification-centric (image-level predictions).



Deep learning-based Bone Suppression Pipeline

Does removing structured anatomical occlusions improve feature learning for precise spatial localization and segmentation, or only global classification performance?

Z. Szucs-Farkas et al., "Single-Exposure Dual-Energy Subtraction Chest Radiography: Detection of Pulmonary Nodules and Masses in Clinical Practice," European Radiology, 2008.
S. Rajaraman, G. Zamzmi, et al., "Chest X- ray Bone Suppression for Improving Classification of Tuberculosis-Consistent Findings," Diagnostics, 2021.

Related Works

Study	Task Focus	Architecture	Segmentation
Rajaraman et al.	Tuberculosis (CXR)	VGG-16	✗
Rajaraman et al.	COVID-19 (CXR)	U-Net, FPN	✗
Bae et al.	Lung Nodules	GANs	✗
Xu et al.	Lung Diseases	Mask R-CNN	✗
Han Li et al.	Lung Diseases	U-Net, CycleGAN	✗
This Work	**Pneumothorax**	**UNet++, MANet, SegFormer, TransUNet**	✓

Table 1. Comparison of Bone Suppression Downstream Applications

S. Rajaraman, G. Cohen, et al., "DeBoNet: A Deep Bone Suppression Model Ensemble to Improve Disease Detection in Chest Radiographs," PLoS ONE, 2022.
S. Rajaraman, G. Zamzmi, et al., "Chest X- ray Bone Suppression for Improving Classification of Tuberculosis-Consistent Findings," Diagnostics, 2021.
Bae et al., "Bone Suppression for Nodule Detection," Korean J Radiol, 2022
Di Xu, Qifan Xu, et al., "An Efficient and Robust Method for Chest X-ray Rib Suppression That Improves Pulmonary Abnormality Diagnosis," Diagnostics, 2023.
Han Li, Hu Han, et al., "High-Resolution Chest X-Ray Bone Suppression Using Unpaired CT Structural Pri- ors," IEEE Transactions on Medical Imaging, 2020.

Contributions

Reframing Bone Suppression for Segmentation

→ Evaluate bone suppression as a pre-processing strategy for pixel-wise and boundary-level pneumothorax localization

Comprehensive, Multi-Dimensional Benchmarking

→ Systematic evaluation across **2 datasets** (SIIM-ACR, PTX-498), **4 architectures** (CNNs & Transformers), and **3 boundary-aware metrics** (DSC, MASD, NSD)

Boundary-Aware Localization Analysis

→ Move beyond overlap to quantify precise boundary delineation and localization fidelity

Architecture-Agnostic & Cross-Task Validation

→ Demonstrate consistent gains across models and show improvements extend to both segmentation and classification performance

Methodology

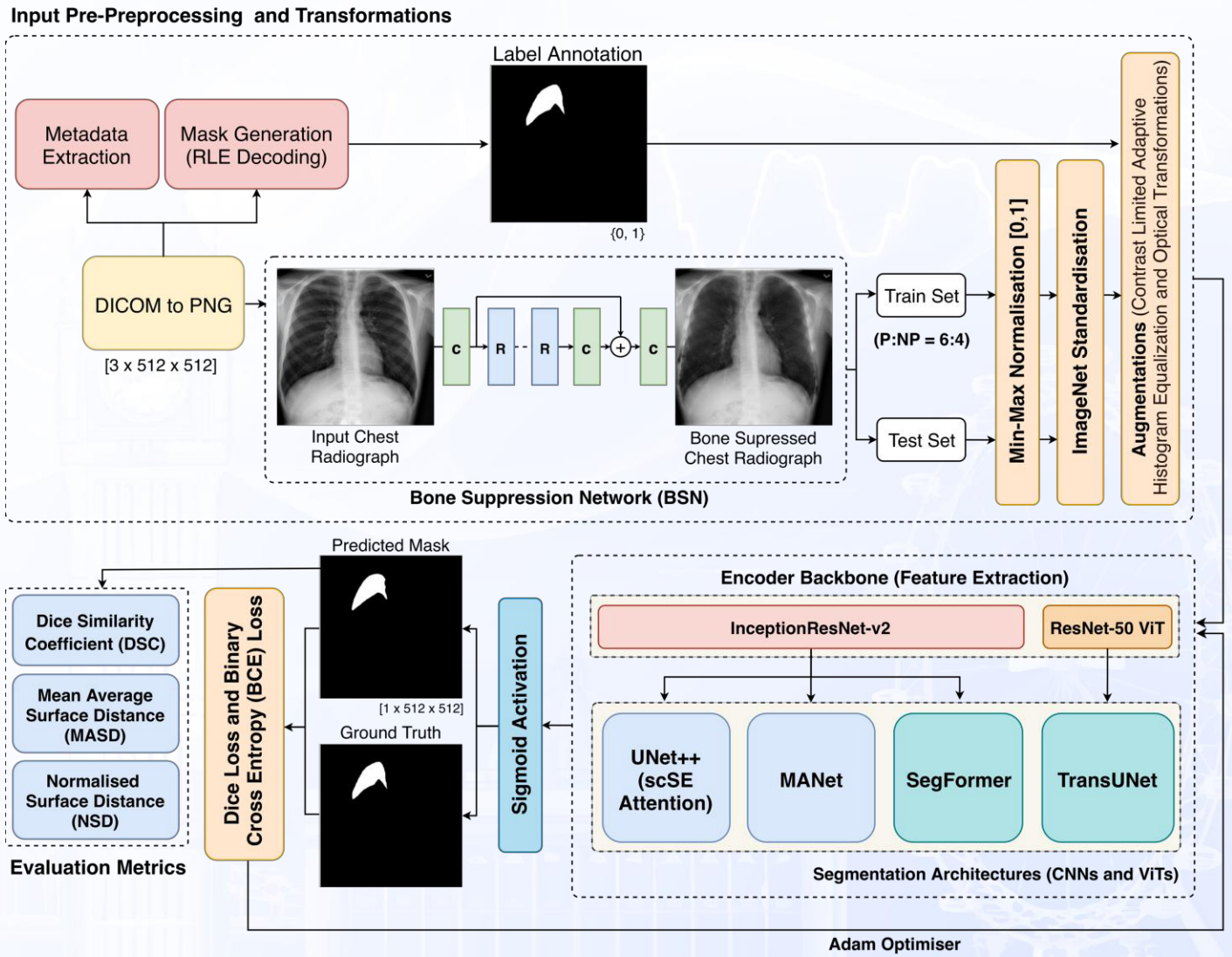
Two-Stage Segmentation Pipeline

Stage 1: Bone Suppression Network (Pre-processing)

A ResNet-based residual model trained to suppress dense skeletal structures while preserving fine-grained soft-tissue detail.

Stage 2: Benchmarking Segmentation

- **CNN-based:**
  UNet++ (with scSE attention) and MANet
- **ViT-based:**
  SegFormer and TransUNet



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Methodology

Dataset

Bone Suppression Training

- **Source:** Bone Suppressed JSRT Dataset
- **Composition:** 4,500 paired CXRs augmented from 247 bone-suppressed images
- **Optimization Strategy:** Multi-objective MS-SSIM and MAE loss to minimize structural distortion while preserving critical soft-tissue cues.

Pneumothorax Segmentation & Evaluation

- **SIIM-ACR (Multi-center):** 12,047 CXR DICOM files with pixel-level annotations.
- **PTX-498 (External Validation):** 498 positive cases from three hospitals to ensure robust cross-dataset evaluation.

Table 2. Bone Suppression Performance

BSN Performance Metric	Value
MS-SSIM (Reconstruction Error)	0.017
MSE (Reconstruction Error)	0.014
Inference Efficiency	~0.42s/b

Table 3. Class Distribution (SIIM-ACR)

Phase	Dataset	+ve (%)	-ve (%)
Train	SIIM-ACR	22%	78%
	Upsampled	**57%**	**43%**
Test	SIIM-ACR	22%	78%
	PTX-498	100%	0%

Pneumothorax Kaggle Challenge - Society for Imaging Informatics in Medicine. (n.d.). Society for Imaging Informatics in Medicine.
Yunpeng Wang, Kang Wang, et al., "DeepSDM: Boundary-aware Pneumothorax Segmentation in Chest X-Ray Images," Neurocomputing, 2021.

Methodology

Training Regime

Component	Details
Loss Function	Dice + BCE (α_D = 1, α_B = 2)
Optimizer	Adam
Learning Rate	1e-4 (ReduceLROnPlateau)
Epochs	75-100
Batch Size	16
Initialization	ImageNet pre-trained
Activation	Sigmoid (threshold = 0.5)
Hardware	NVIDIA RTX A6000 (48GB)

Evaluation Metrics

- **DSC (Dice) -** Dice Similarity Coefficient ↑ (global overlap for segmentation quality)
- **MASD -** Mean Average Surface Distance ↓ (average boundary deviation)
- **NSD –** Normalized Surface Distance ↑ (tolerance-based boundary dice score)
- **MCC -** Matthews Correlation Coefficient ↑ (balanced classification performance)

Results

Quantitative: Superior Performance with BS-CXRs

Architecture	Encoder	BS-CXR	Segmentation			Classification	
			DSC (↑)	MASD (↓)	NSD (↑)	F1 (↑)	MCC (↑)
UNet++	Inception-ResNetV2	-	0.8064	5.4757	0.7673	0.7695	0.7004
		✓	**0.8317**	**4.5423**	**0.7903**	**0.7933**	**0.734**
MANet	Inception-ResNetV2	-	0.783	5.4116	0.7397	0.7355	0.6569
		✓	**0.8213**	**4.8838**	**0.7832**	**0.7788**	**0.7141**
SegFormer	Inception-ResNetV2	-	0.8088	5.3425	0.7665	0.7577	0.6866
		✓	**0.8288**	**5.0721**	**0.7882**	**0.8065**	**0.7496**
TransUNet	ResNet50-ViT	-	0.7987	5.6073	0.7594	0.7496	0.6744
		✓	**0.8342**	**5.0335**	**0.789**	**0.7973**	**0.7382**

- **Bone suppression delivers consistent, statistically significant ($p < 0.05$) gains across all models (↑DSC, ↑NSD, ↓MASD)**

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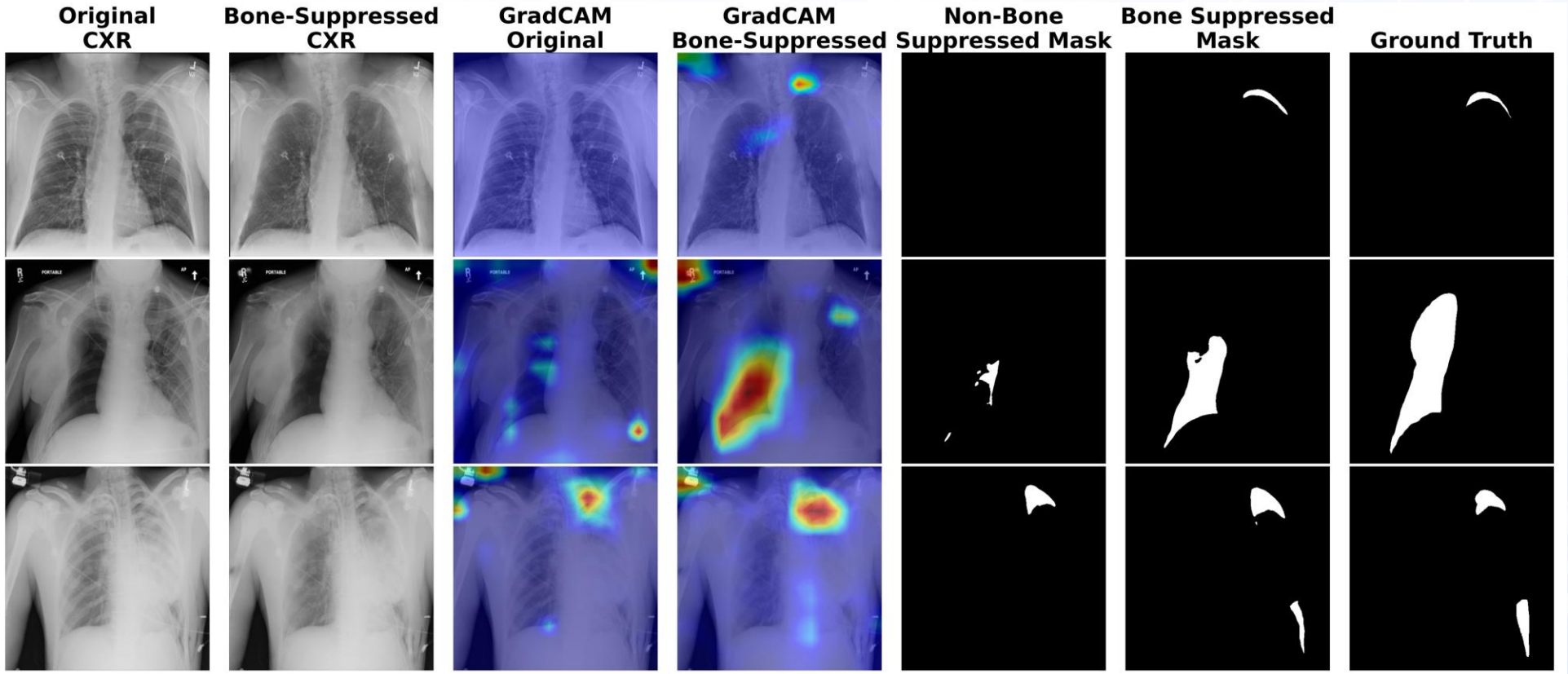
Results

Qualitative: Grad-CAM Maps Depicting Sharpened Focus with BS-CXRs



- Bone suppression sharpens model attention to pneumothorax regions, reducing rib-induced noise and improving localization

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Results

Consistent Gains and Improved Localization

- On an average, bone suppression boosted segmentation results by:

↑ DSC (+3.7%)	↓ MASD (-10.6%)	↑ NSD (+3.9%)

- **Architecture-Agnostic Gains:** Bone suppression (BS-CXR) consistently boosts both segmentation and classification performance across all tested CNN and ViT architectures.
- **Improved pneumothorax localization** with fewer boundary contour errors (↓ MASD) and reduced pixel-level misclassifications at lung edges (↑ NSD), leading to better overall overlap with ground truth (↑ DSC)
- **Robust Classification:** The improvements carry over to downstream classification, showing marked increases in F1 and MCC scores.

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Conclusion

Obscuration to Clarity

- We show that removing structured anatomical occlusions at the input level fundamentally improves feature representations for boundary-sensitive pneumothorax segmentation, addressing a key limitation of 2D CXR imaging.
- **Clinical Relevance:** Improved pixel-level localization translates to more reliable detection and triaging, supporting accurate severity assessment of pneumothorax in automated clinical workflows
- **Future Work: End-to-end joint optimization**, scaling to **larger multi-center datasets**, and validation across **broader thoracic pathologies** to strengthen generalizability and clinical deployment

Thank you

I’m happy to take questions!

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Ethical Compliance

This study utilizes publicly available, de-identified datasets (SIIM-ACR and PTX-498) and does not involve any direct patient interaction; therefore, ethical approval was not required.

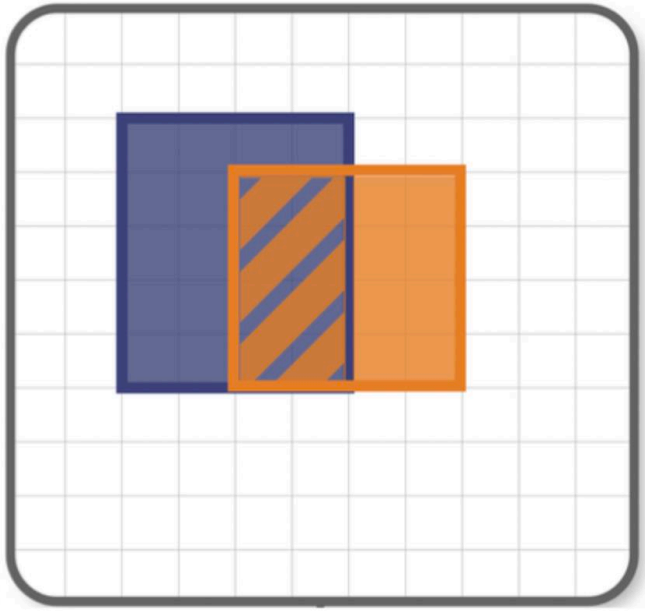
Appendix

Methodology

Evaluation Metrics – Mean Dice Similarity Coefficient

DSC (F1 score)

$$DSC(A,B) = \frac{2}{\square + \square} = \frac{2\,|A \cap B|}{|A| + |B|} = \frac{2\,PPV \cdot Sensitivity}{PPV + Sensitvity}$$



A

B

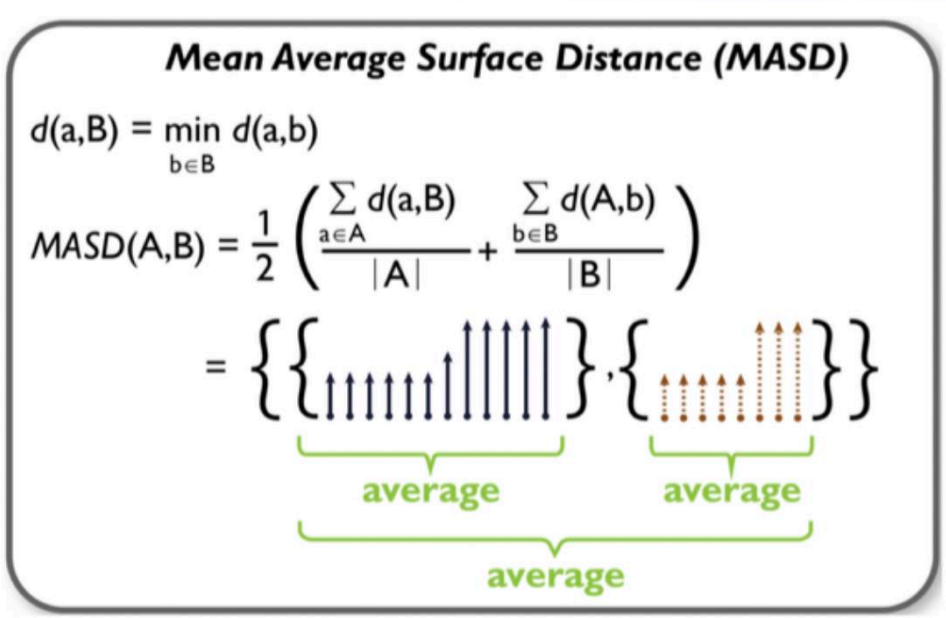
A ∩ B

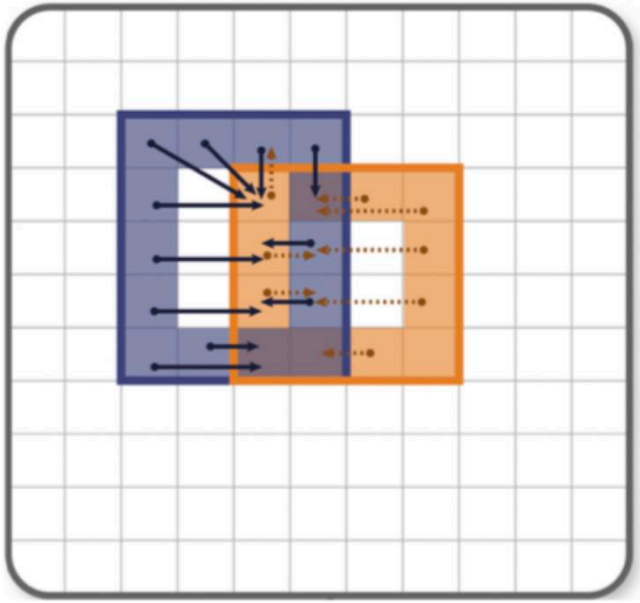
- Quantifies the global overlap between the predicted and ground truth masks to evaluate overall alignment

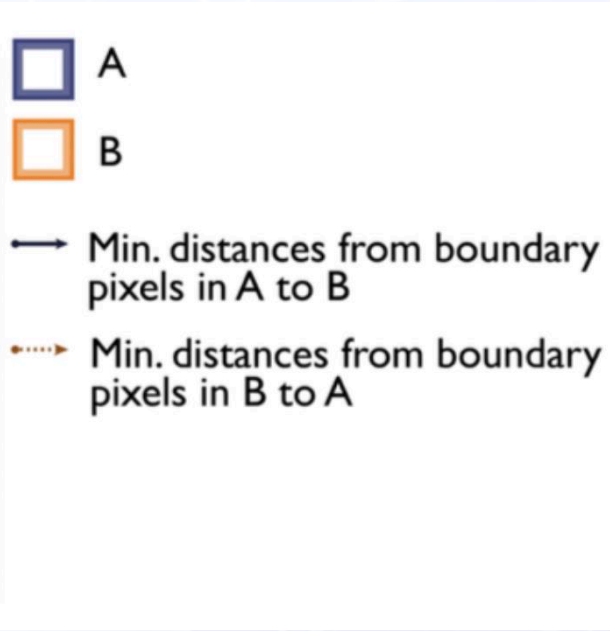
Annika Reinke, Minu D Tizabi, et al., "Common Limitations of Image Processing Metrics: A Picture Story," arXiv:2104.05642, 2021.

Methodology

Evaluation Metrics – Mean Average Surface Distance





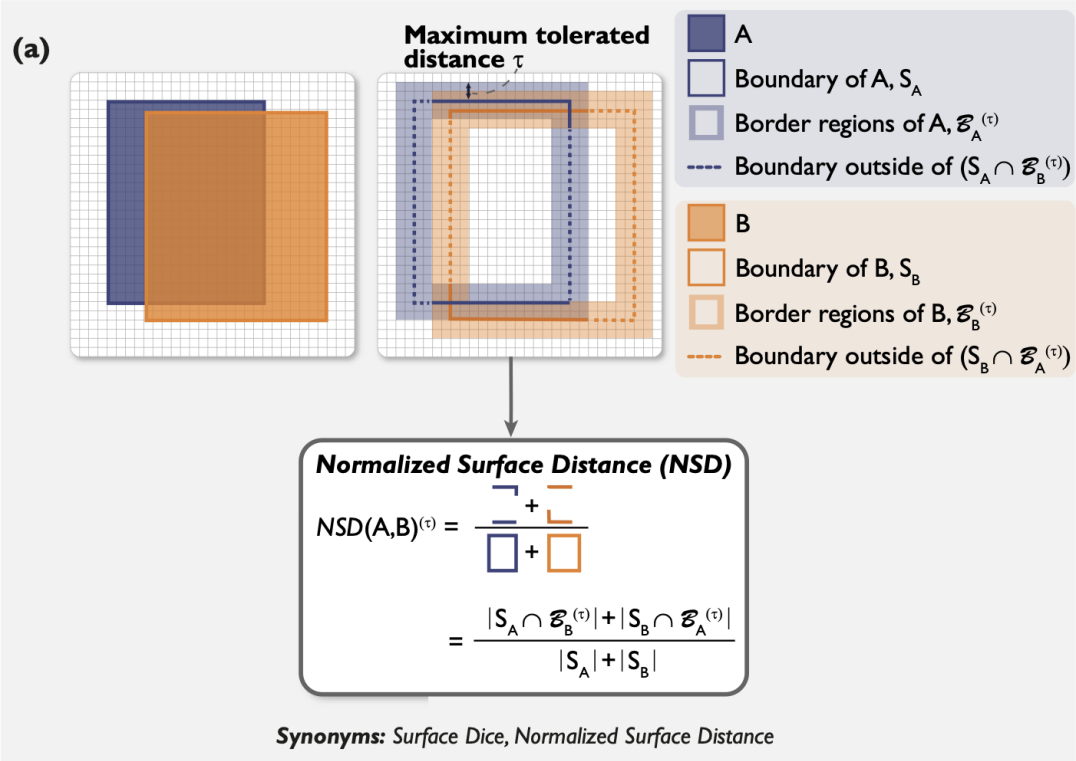


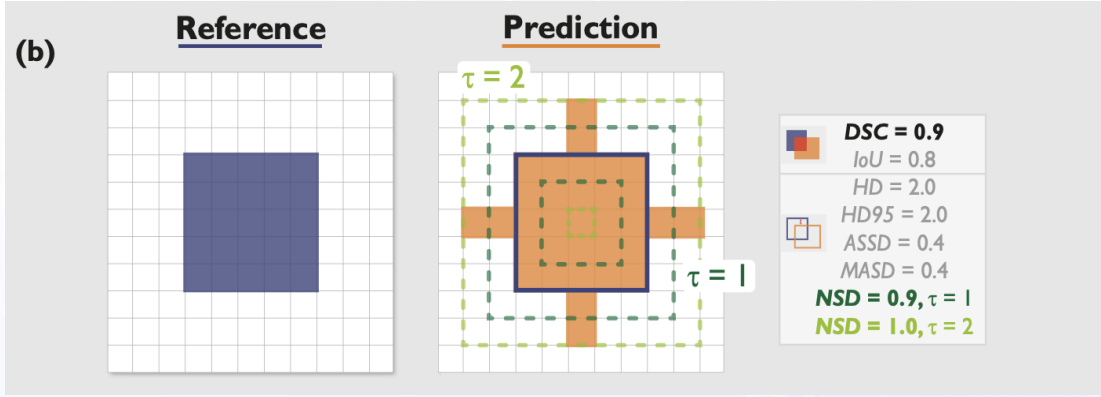
- Computes the average distance between the predicted and ground truth boundaries to measure boundary deviation

Annika Reinke, Minu D Tizabi, et al., "Common Limitations of Image Processing Metrics: A Picture Story," arXiv:2104.05642, 2021.

Methodology

Evaluation Metrics – Normalized Surface Distance





- **Measures pixel-level misclassifications near boundaries within a specific tolerance to assess boundary localization**

Annika Reinke, Minu D Tizabi, et al., "Common Limitations of Image Processing Metrics: A Picture Story," arXiv:2104.05642, 2021.

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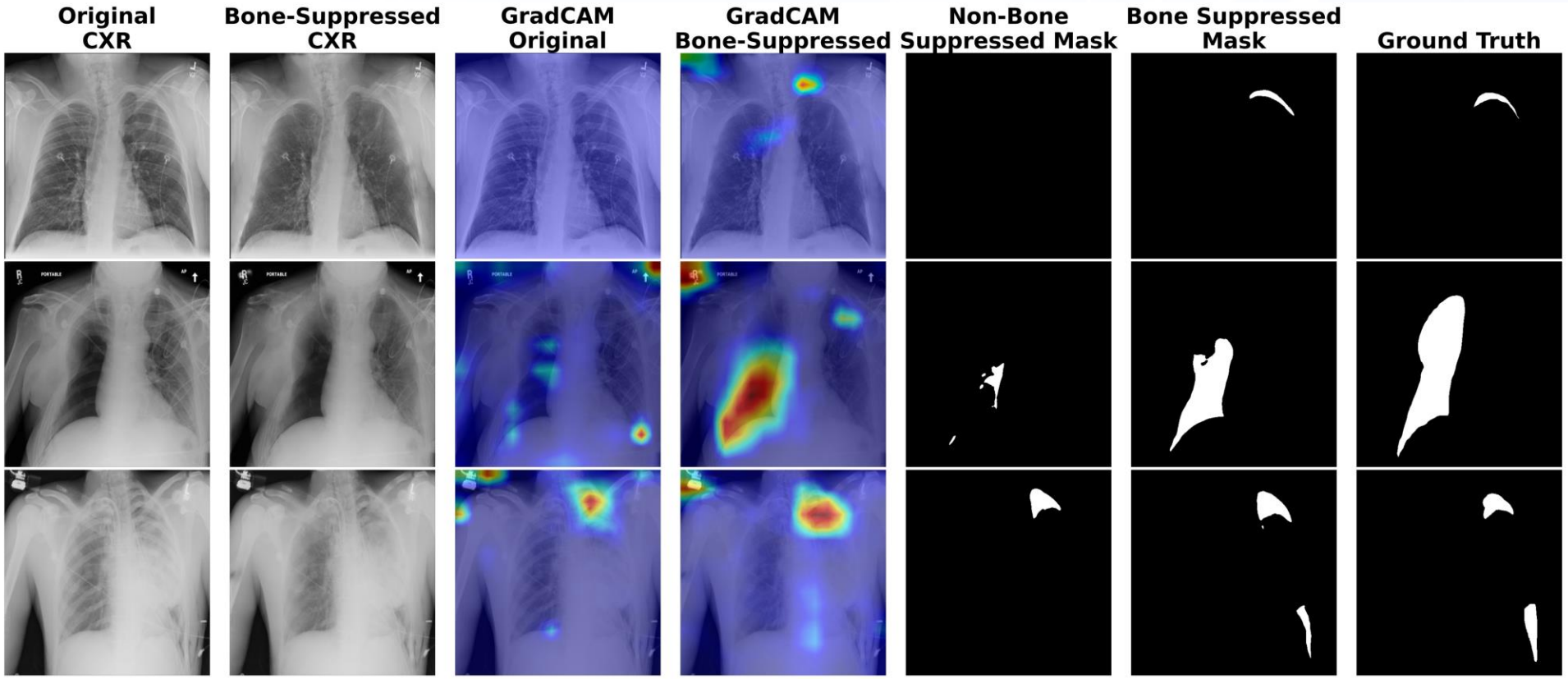
Grad-CAM Maps Depicting Sharpened Focus with Bone Suppression



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