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Multi-scale Attention-based Multiple Instance Learning for Breast Cancer Diagnosis

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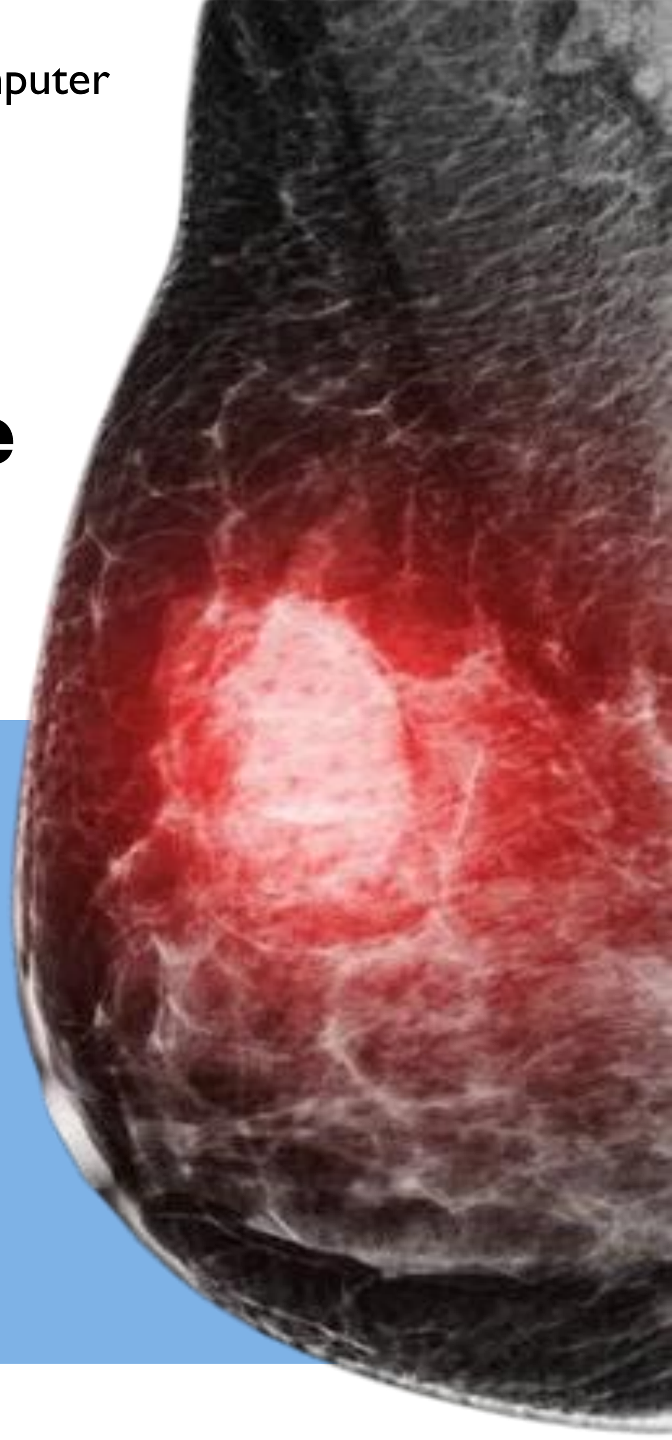
LARSyS Laboratory of Robotics and Engineering Systems



Mammographic Breast Cancer Diagnosis

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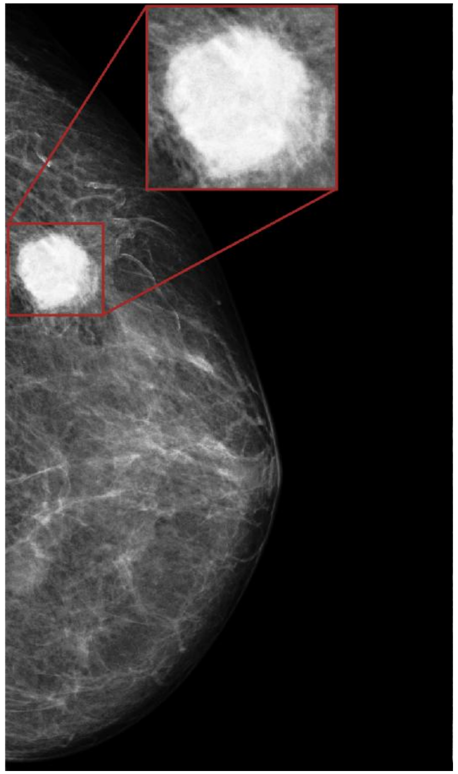
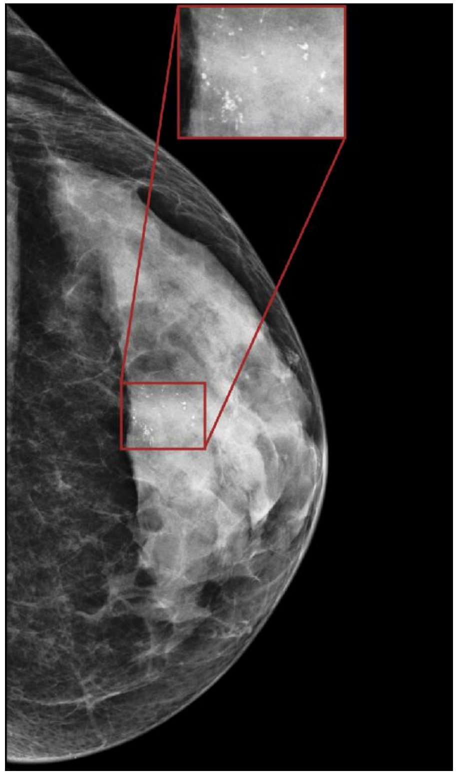
Mass



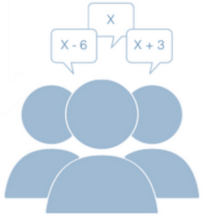
Calcifications



Challenges

High workload

Complex & diverse lesion features

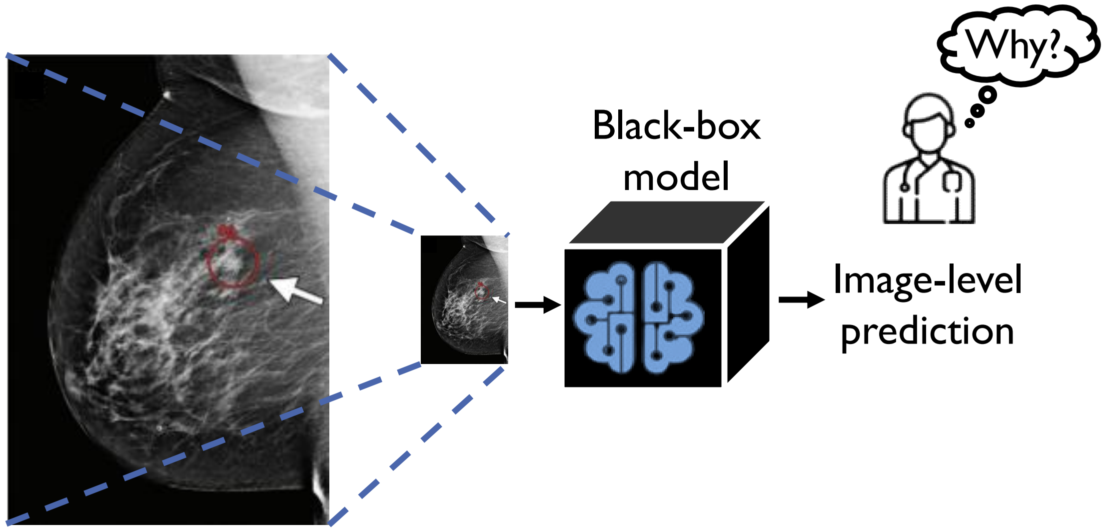


Intra- & inter-reader variability

Deep Learning (DL)-based Models

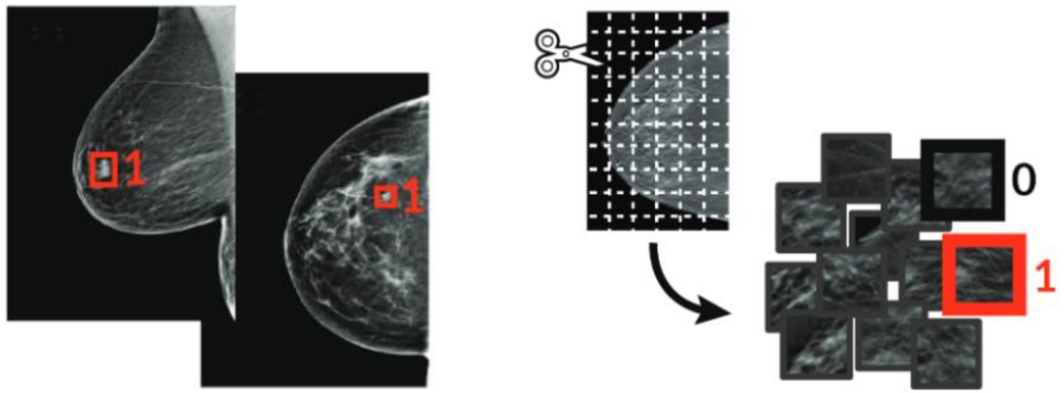
Full image-based DL models

- × Loss of detail from harsh downsampling
- × Lack interpretability



Region of Interest (ROI)-based DL models

- ✓ Improved performances & interpretability
- × Costly annotations under fully supervised learning

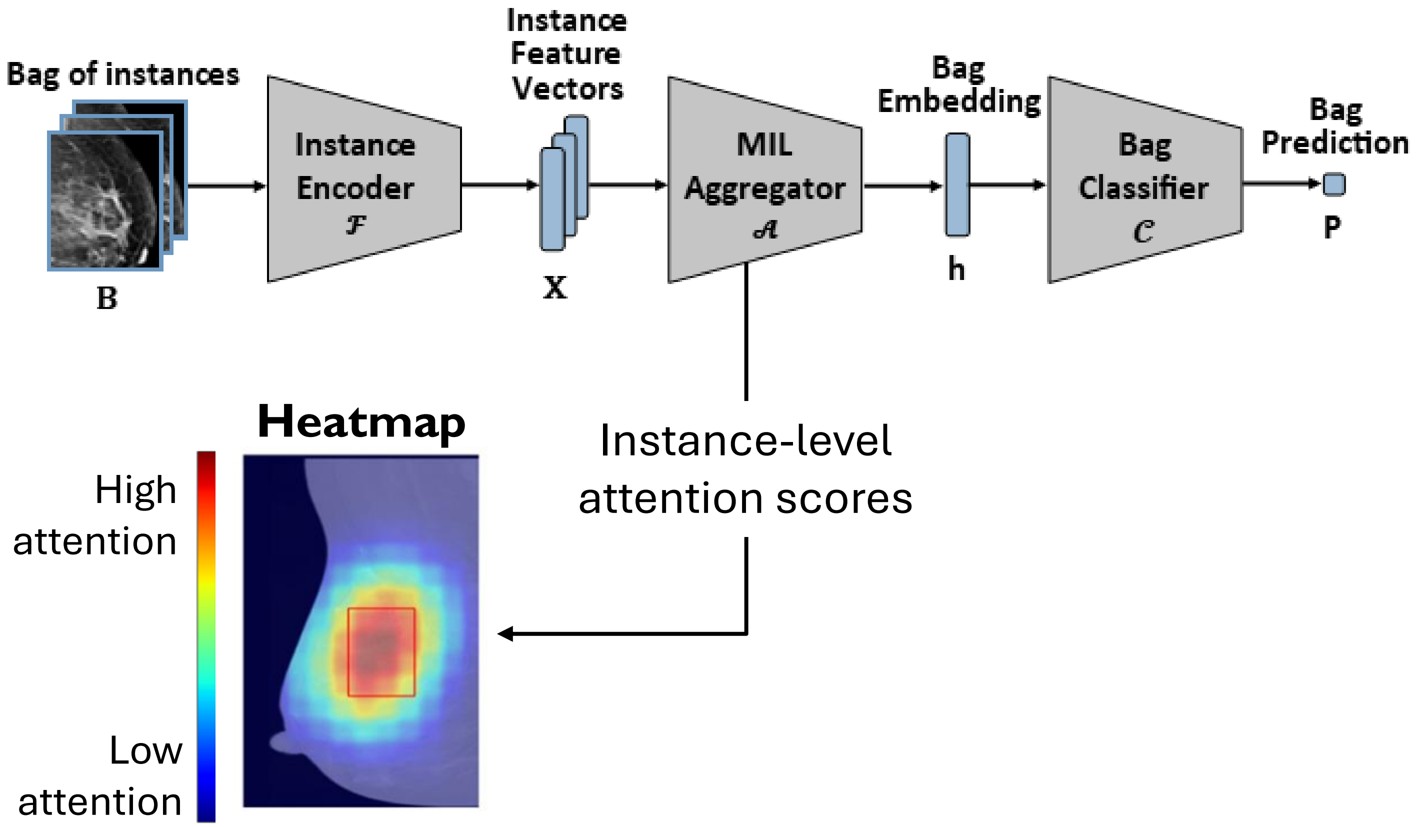


Bounding-box annotations

Patch-wise annotations

Multiple Instance Learning (MIL)

Typical MIL Framework in Mammography



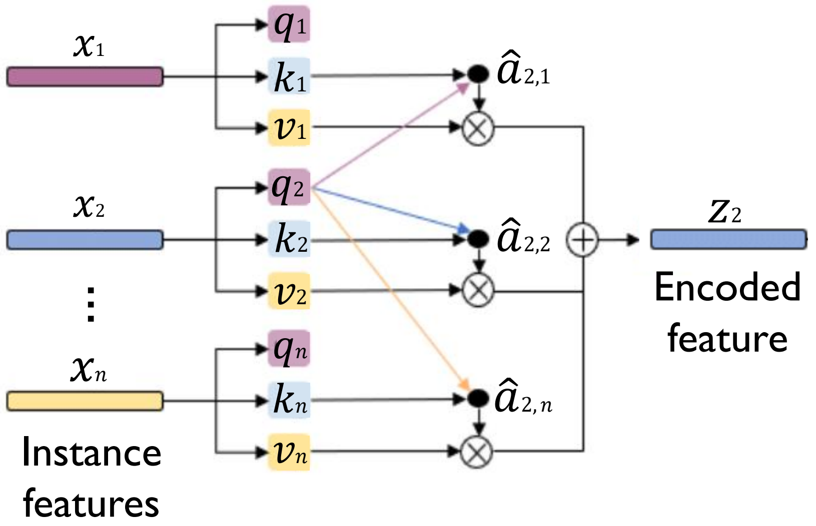
- ✓ Handles high-resolution images
- ✓ Attention-based aggregators enable image classification and instance detection
- ✓ Supervision with weak image-level labels

Limitations

- ✗ Neglects contextual information between instances
- ✗ Non-adaptive to multi-scale lesions

Related Works

Transformer Architectures



✓ Accounts for instance interactions

✗ $\mathcal{O}(n^2)$ computational complexity

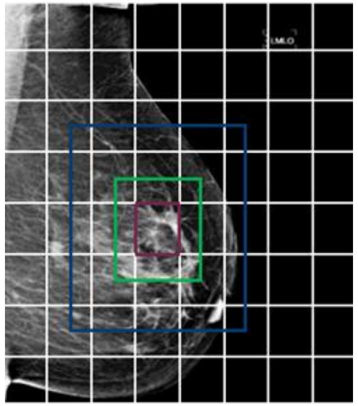
⇓

Efficient Transformers !

Multi-scale MIL models

Based on Multi-scale Patches (MSP)

MuSTMIL[1]; MSAA-Net[2]



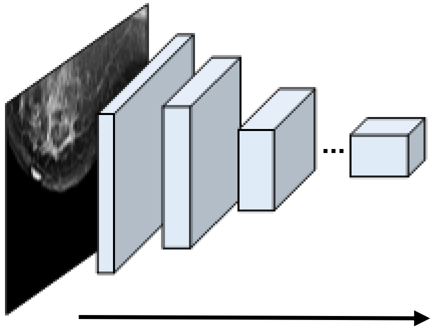
✓ High representational power across scales

✗ Increases computational burden

✗ Coarse patch-level detection granularity

Based on Feature Pyramids

Swin-MIL[3]



✓ Enhanced pixel-level detection granularity

✗ Operates on downsampled images

✗ Large semantic gap across scales

Contributions

Proposed a novel **multi-scale attention-based MIL framework** for weakly supervised classification and detection of breast lesions in high-resolution mammograms.

Multi-scale Instance Encoder

Builds a refined feature pyramid from single-scale patches

Flexible Instance Aggregators

Investigated localized and context-aware attention mechanisms

Multi-scale Aggregator

Adaptive scale fusion for robustness to lesion size variability

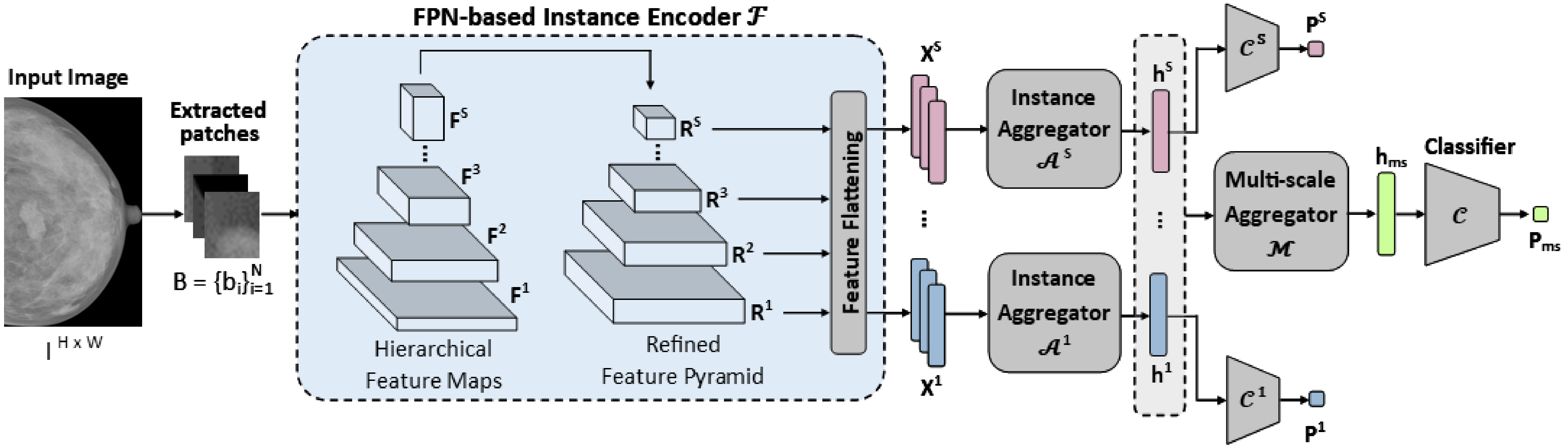
Comparison with Baselines & SoTA

Benchmark against baselines and SoTA models

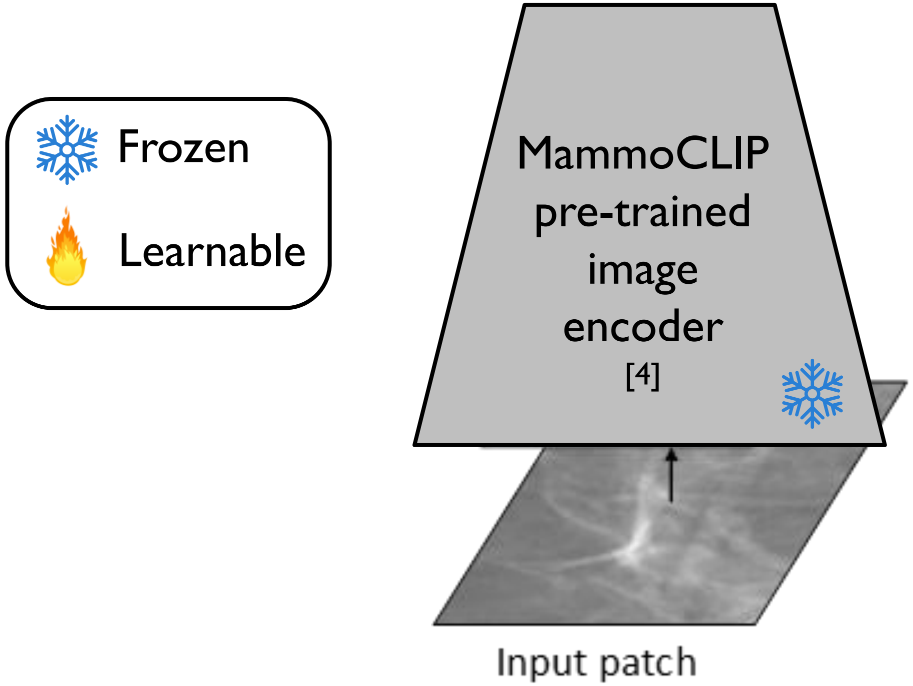
Ablation Studies

Evaluate the effectiveness of the main modules

Multi-scale Attention-based MIL Framework



Multi-scale Instance Encoder



Multi-scale Instance Encoder

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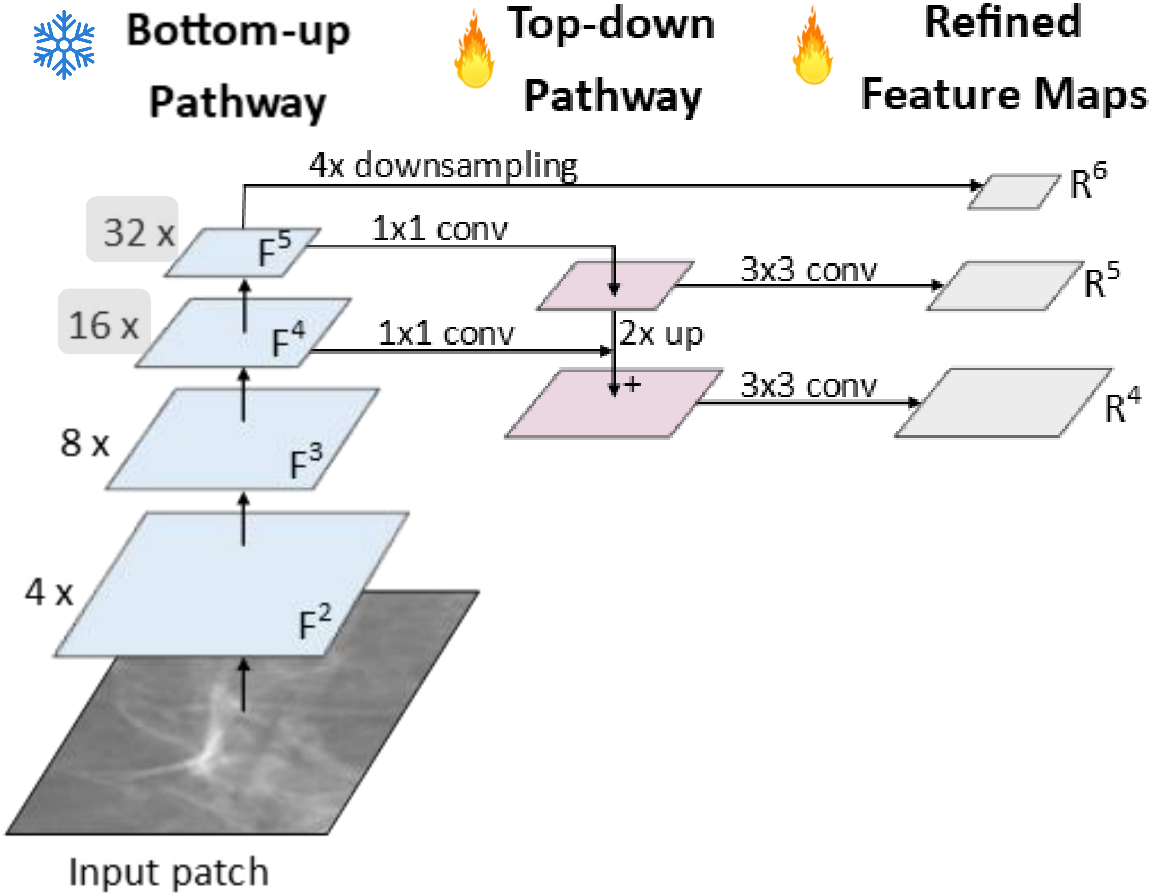
Feature Pyramid Network (FPN) [5]

Frozen

Learnable

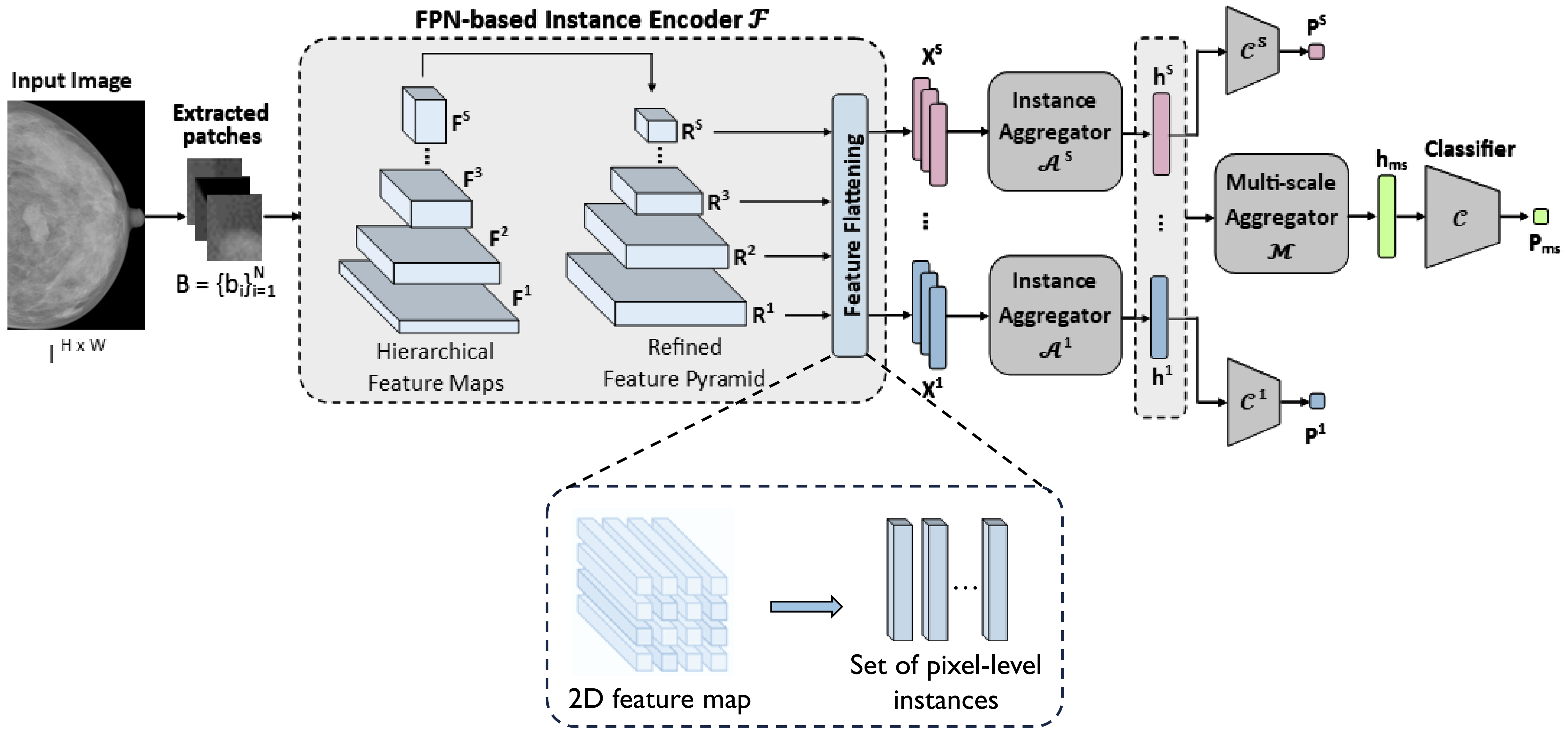


Large receptive-field

Medium receptive-field

Small receptive-field

Multi-scale Attention-based MIL Framework



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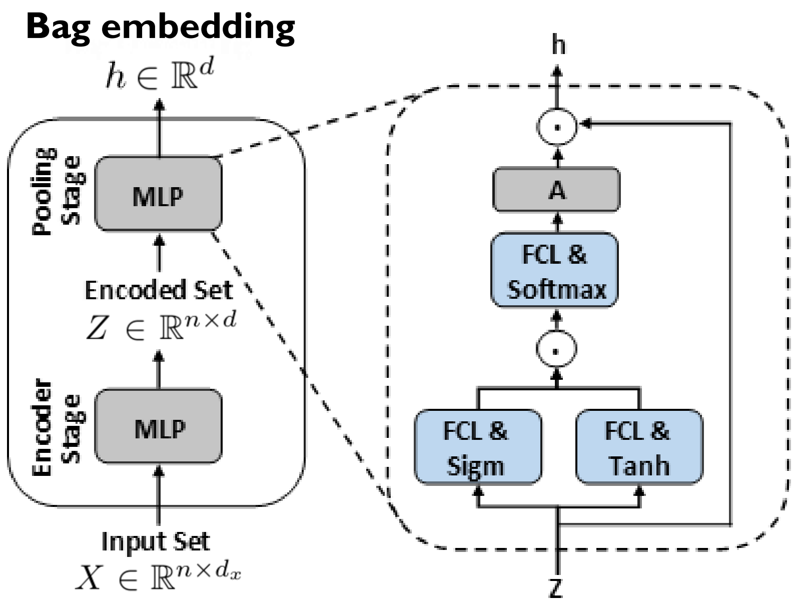
Attention-based MIL (AbMIL) [6]

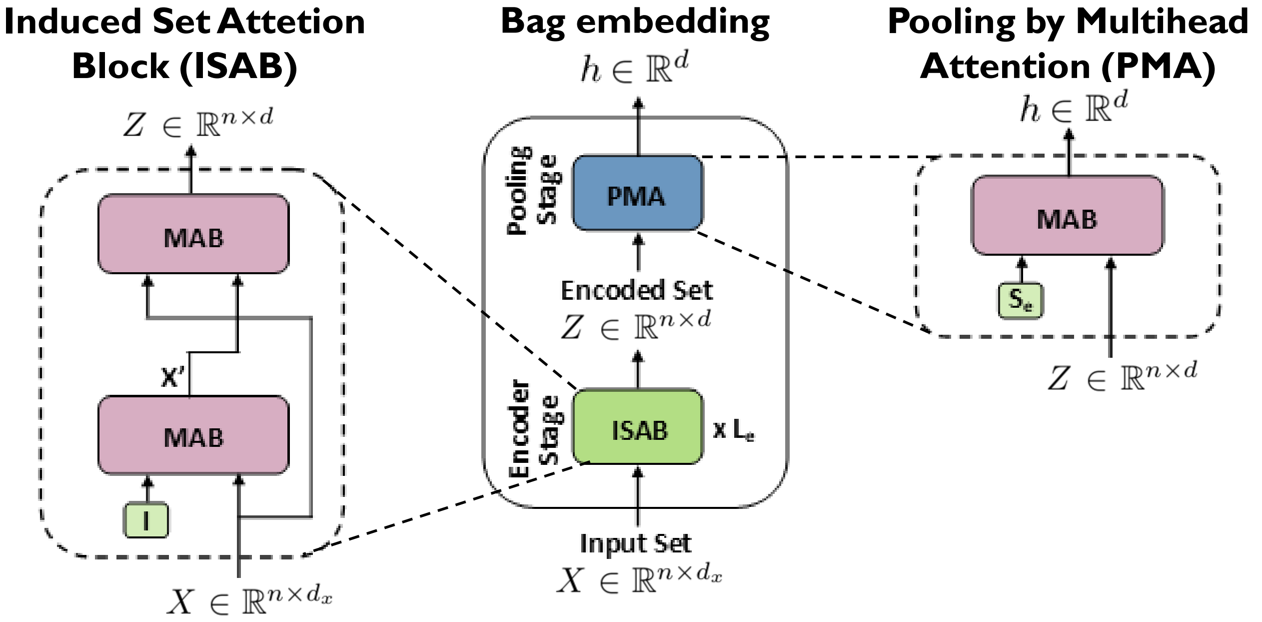
Localized attention instance aggregation, computing instance-level attention weights independently.



$$h = \sum_{i=1}^{n} a_i z_i$$

Set Transformer (SetTrans) [7]

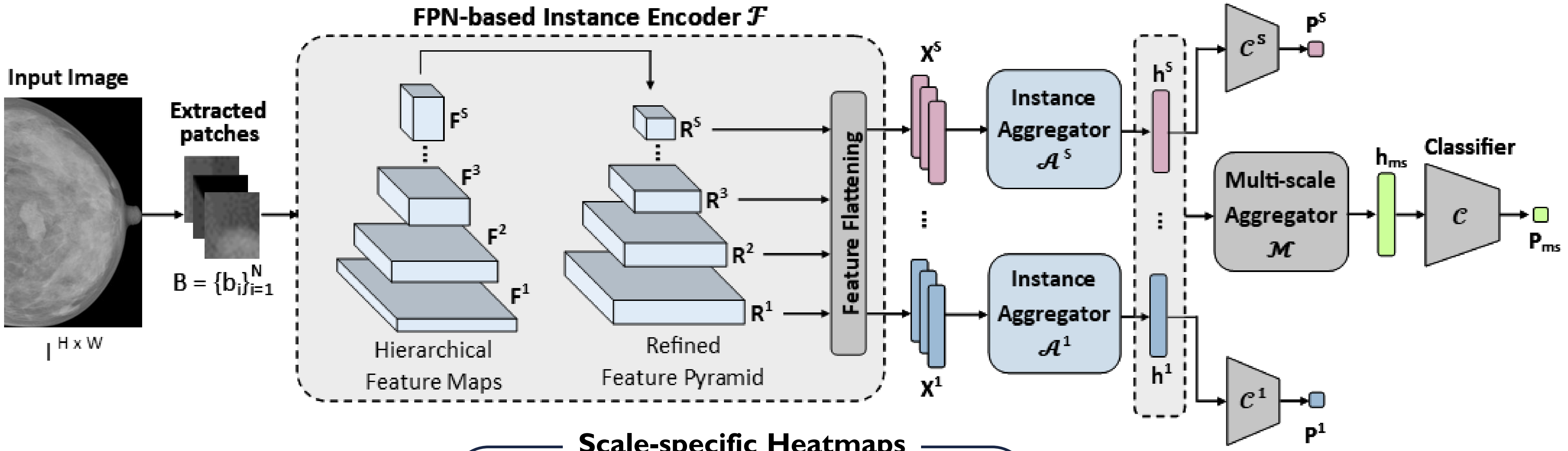
Efficient context-aware aggregation, with its basic operation – Multihead Attention Block (MAB) – being the vanilla transformer encoder.

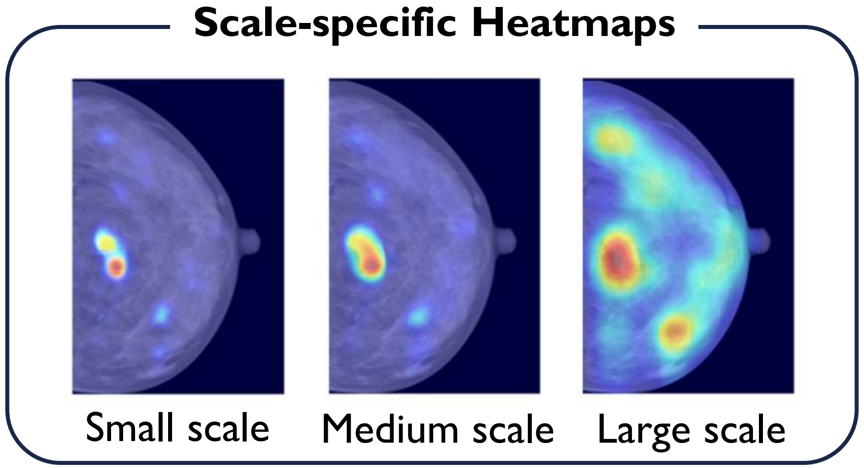


Number of inducing points : $m = 10 \times \log(n)$

Computational Complexity : $\mathcal{O}(m.n)$

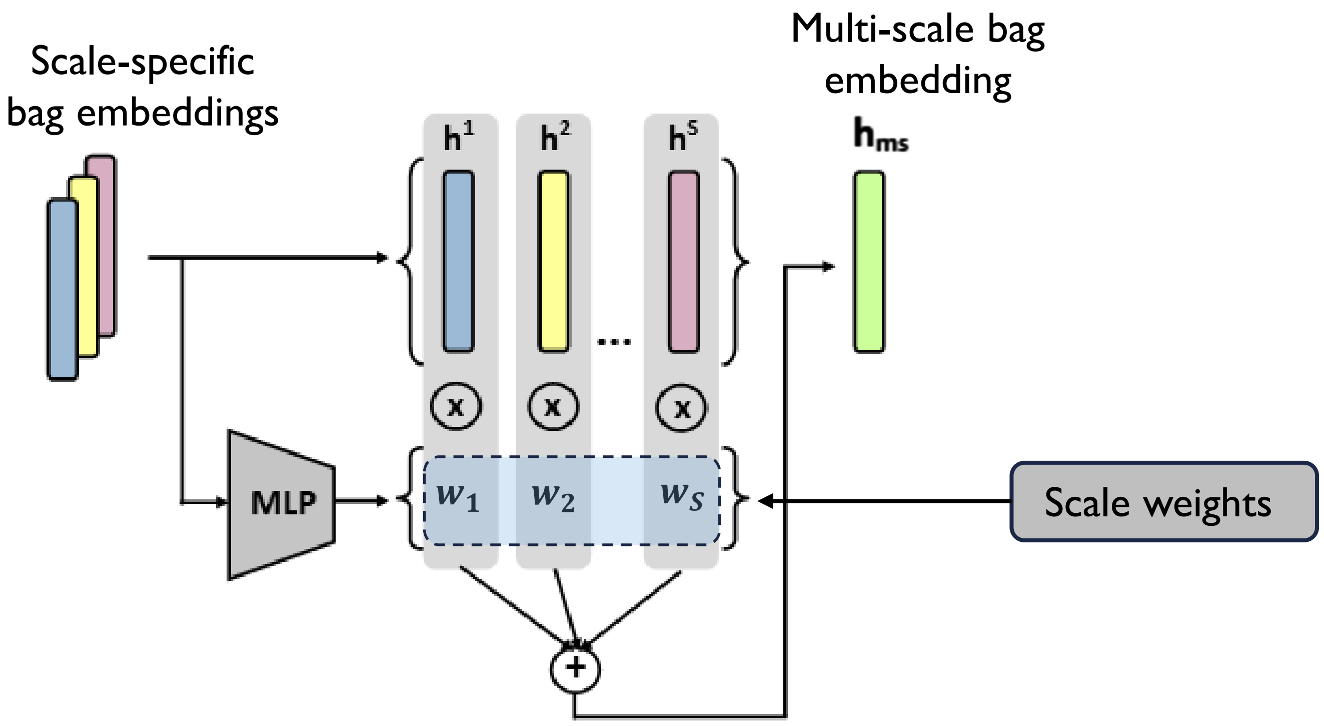
Multi-scale Attention-based MIL Framework

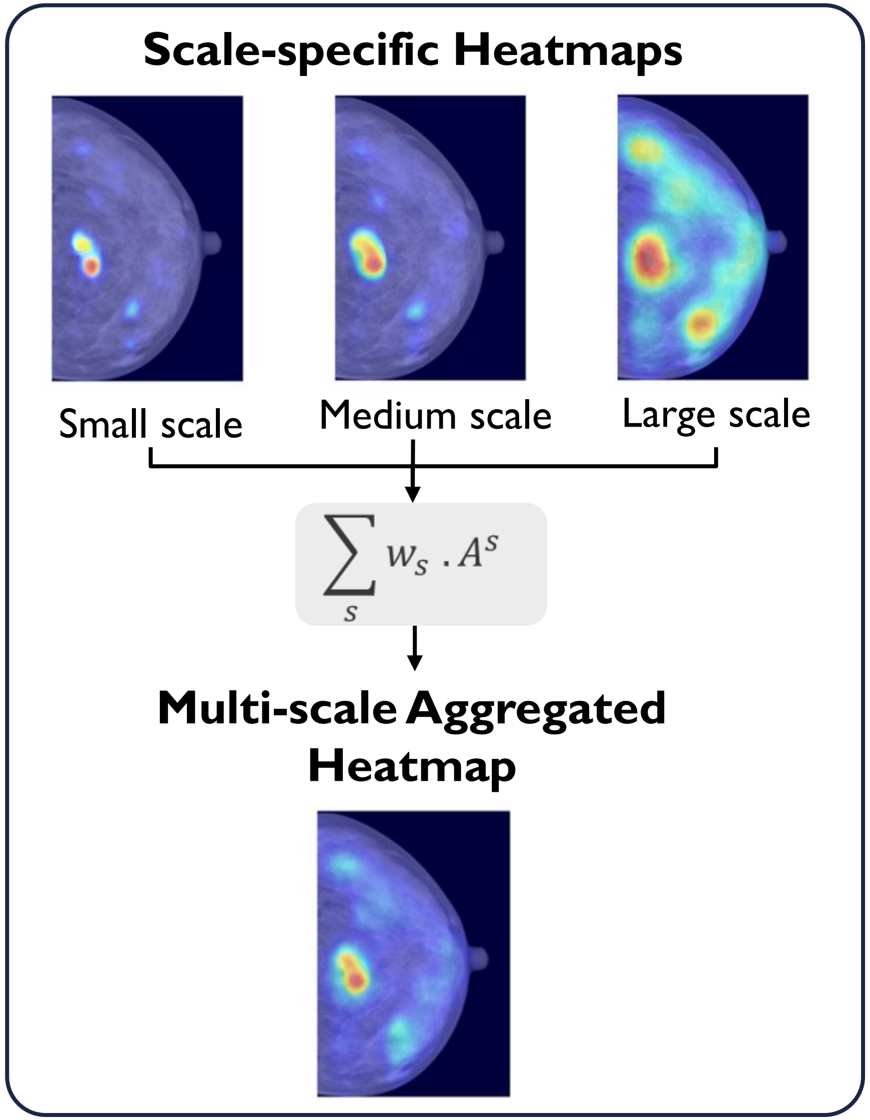




Multi-scale Aggregator

Attention-based MIL (AbMIL) [6]





Multi-scale Attention-based MIL Framework

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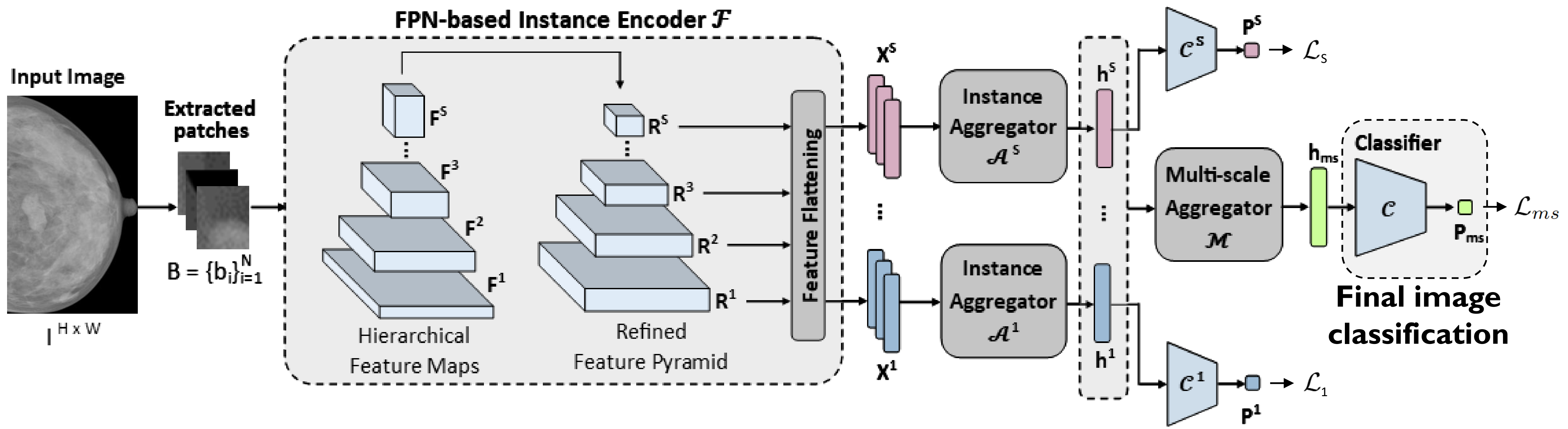


Loss function : $\mathcal{L}_{mil} = \mathcal{L}_{ms} + \sum_{s=1}^{S} \mathcal{L}_s$

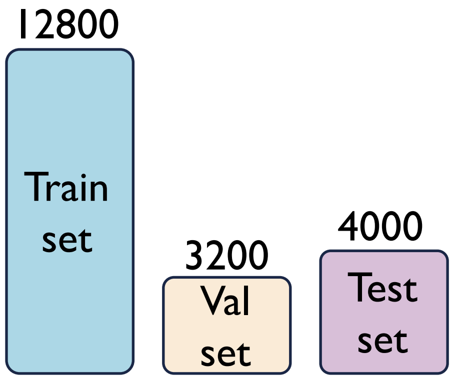
Multi-scale loss term

Deep-supervised scale-specific loss terms

Experimental Setup

VinDr-Mammo Dataset

- Used original train-test slipt
- 80%–20% class-stratified patient-wise train-validation split



Available annotations

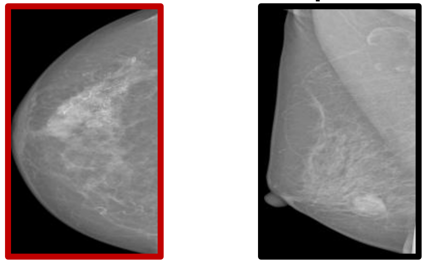
Image-level labels for training & classification evaluation

Bounding-boxes for detection evaluation

Image Classification

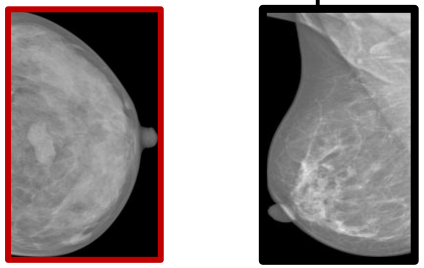
Calcifications

Present · Not present



Mass

Present · Not present

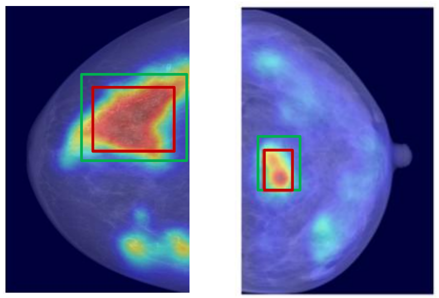


Evaluation metric

AUC-ROC

Lesion Detection

Multi-scale Aggregated Heatmaps



Calcifications · Mass

Predicted Bounding-box

Ground-truth Bounding-box

Evaluation metric

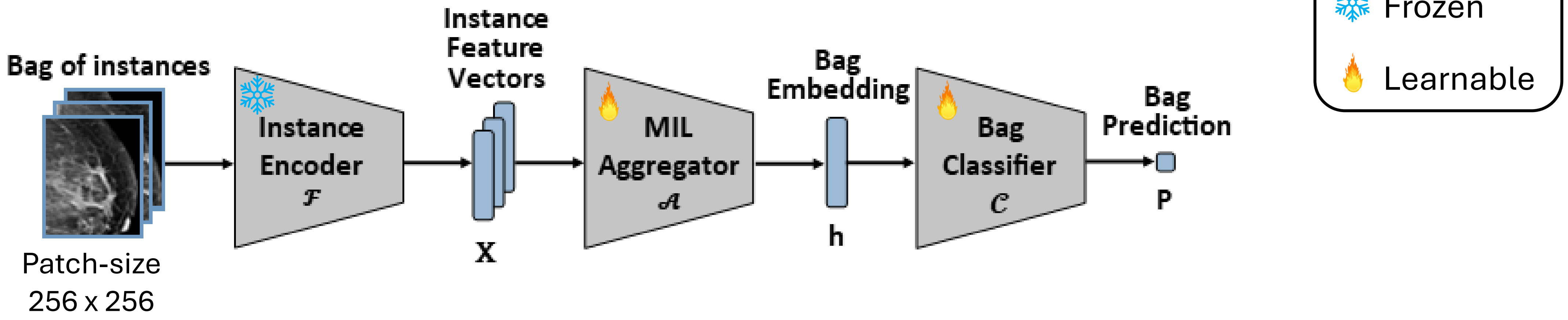
Mean Average Precision (mAP)

Lesion size categories

- Small Lesions: area $\leq 128^2$
- Medium Lesions: $128^2 <$ area $\leq 256^2$
- Large Lesions: area $> 256^2$

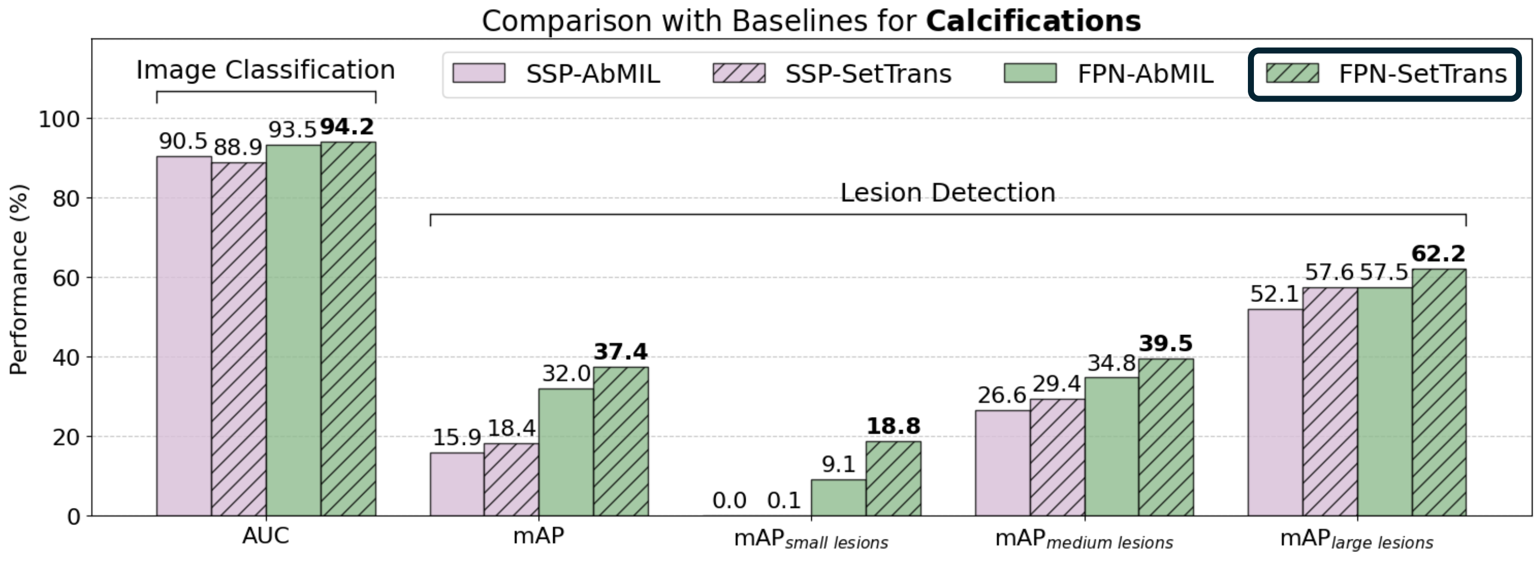
Comparison with Baselines

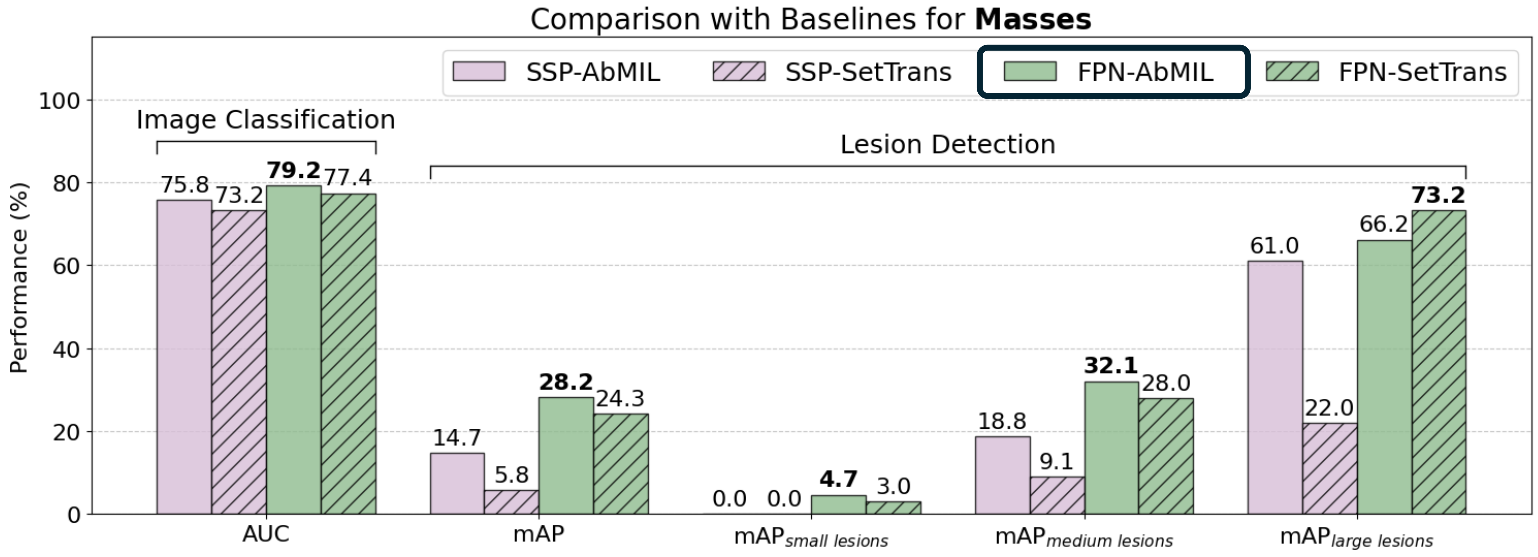
Single-Scale Patch-based (SSP)-MIL Baselines



- **Instance Encoder**: Frozen MammoCLIP [4] backbone
- **MIL Aggregator**: AbMIL[6] or SetTrans [7]

Comparison with Baselines

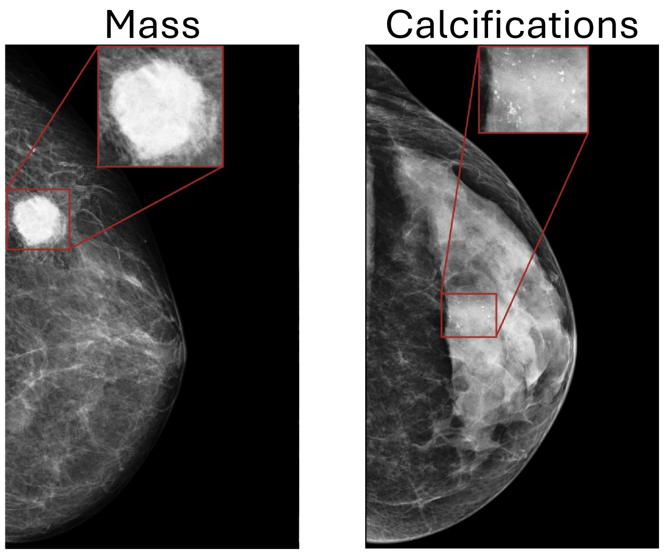




Best instance aggregator is lesion-dependent

→ SetTrans for calcifications

→ AbMIL for masses



Our FPN-MIL models significantly outperform the **SSP-MIL baselines**

Comparison with State-of-the-Art Models

Learning Paradigms	Model	Calcifications		Mass	
		AUC	mAP	AUC	mAP
Fully Supervised Classification (FSC)	EfficientNet-B2 **[4]**	92.0	---	73.0	---
Fully Supervised Object Detection (FSOD)	RetinaNet **[4]**	---	17.0	---	37.0
Weakly Supervised Object Detection (WSOD)	Mammo-FActOR **[4]**	---	20.0	---	**38.0**
Multipe Instance Learning (MIL)	**FPN-MIL (Ours)**	**94.2**	**37.4**	**79.2**	28.2

Our best-performing models...

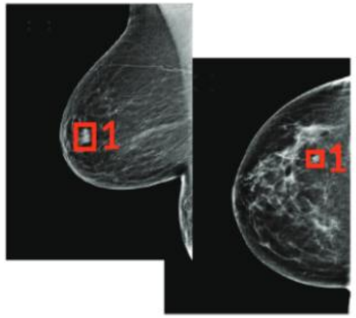
- ✓ Outperformed FSC baseline in image-level classification
- ✓ Outperformed FSOD & WSOD baselines in calcification detection
- ! Underperformed FSOD & WSOD baselines in mass detection

Weakly Supervised Object Detection

Radiology Reports
Suspicious mass in upper left...

Sentence-level annotations

Fully Supervised Object Detection



Bounding-box annotations

Multiple Instance Learning

Image-level annotations

Heatmap Visualization: Our Best-Performing Models

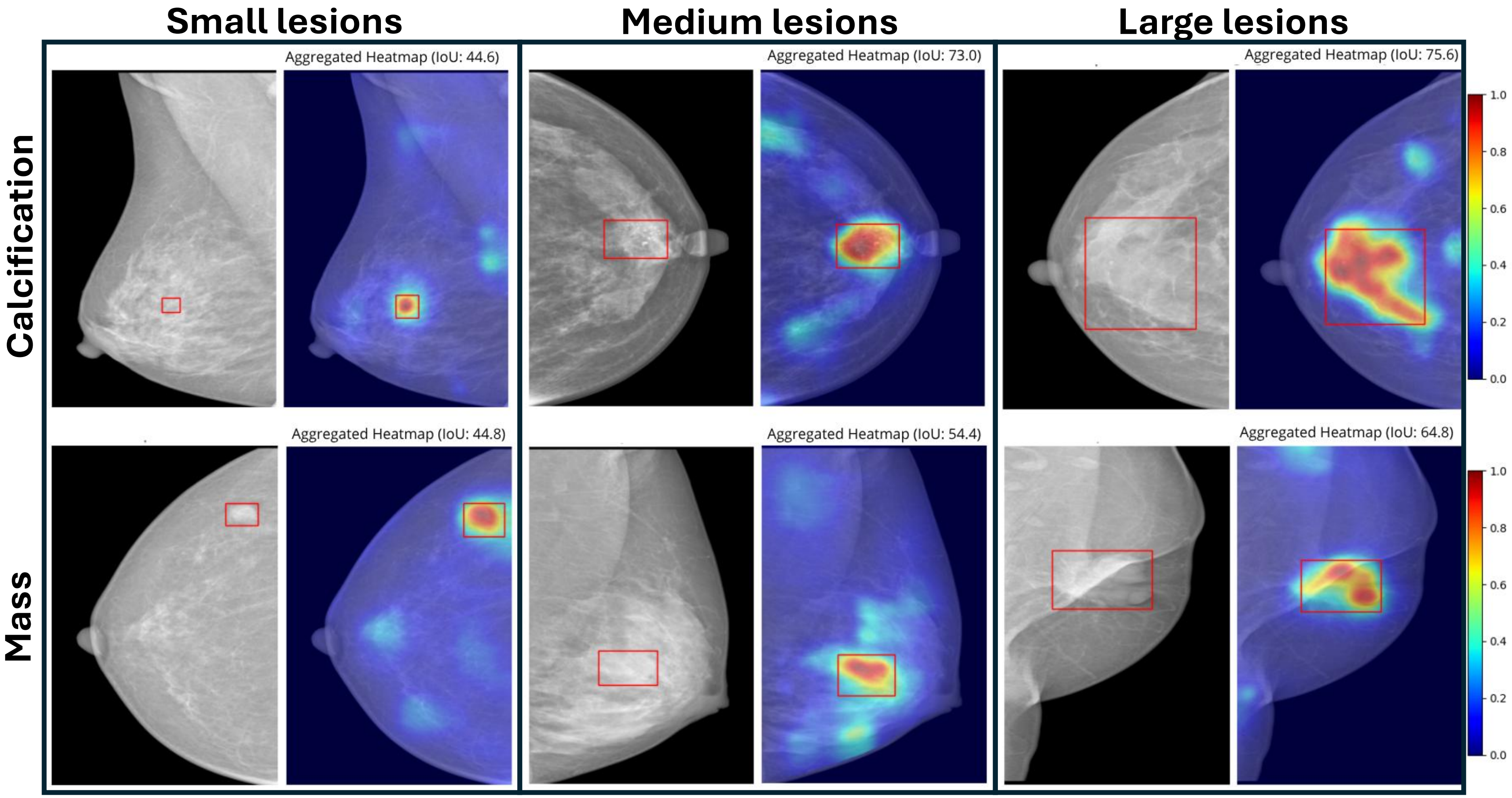
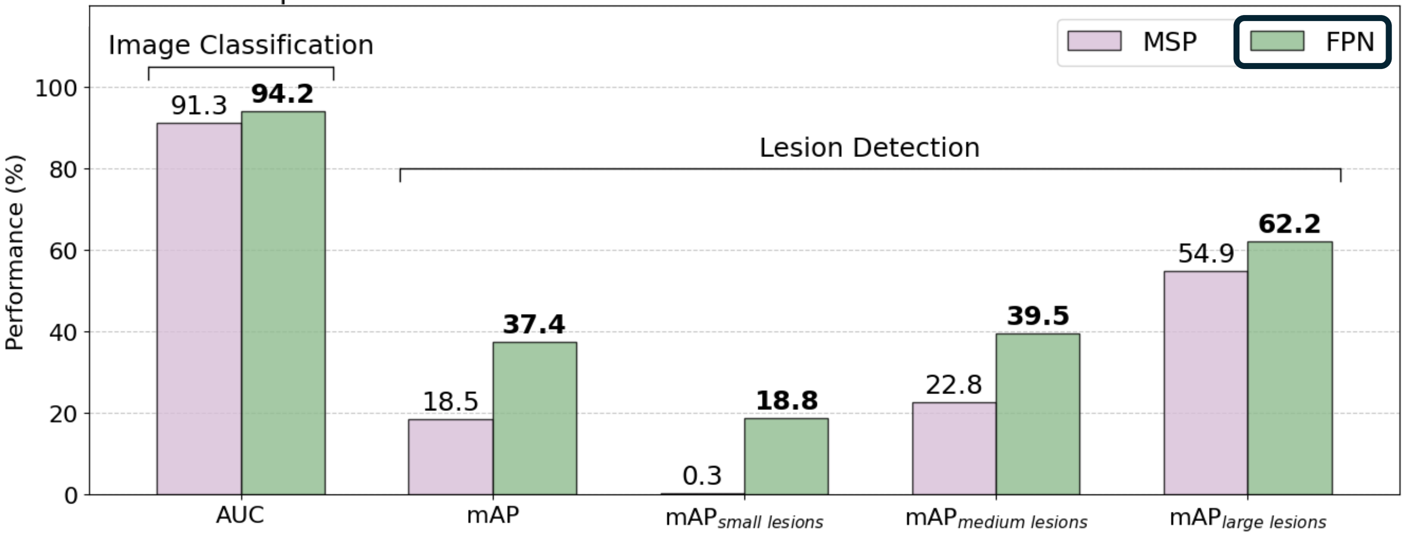


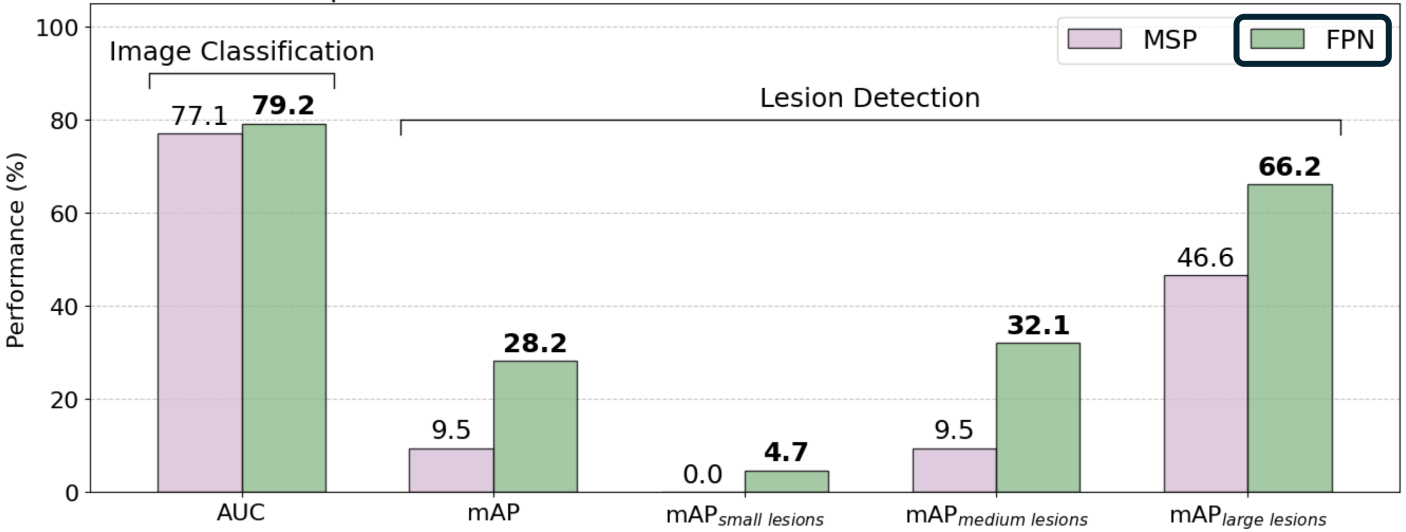
Fig. 1. Multi-scale aggregated heatmaps produced by the proposed framework, namely the FPN-SetTrans for calcifications and FPN-AbMIL for masses.

Ablation Studies

Impact of Different Multi-scale Instance Encoders for **Calcifications**



Impact of Different Multi-scale Instance Encoders for **Masses**



The proposed **FPN-based instance encoder achieves ...**

✓ Improved classification performance

⇩

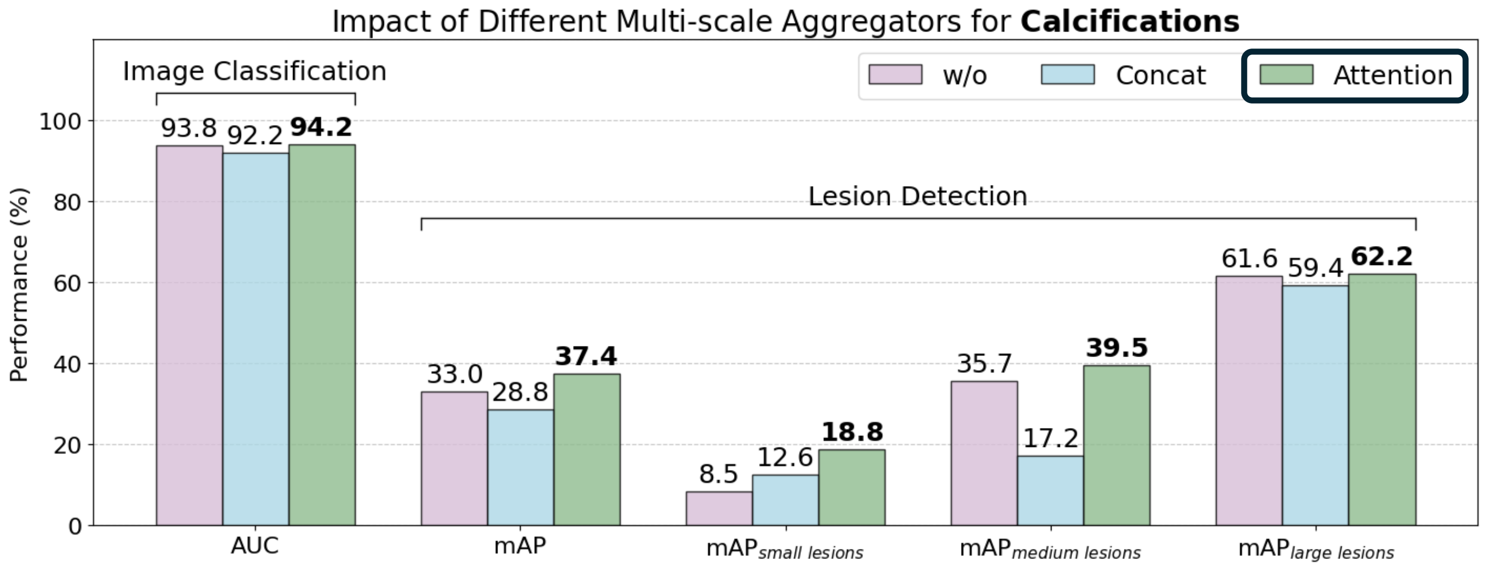
More discriminative instance features

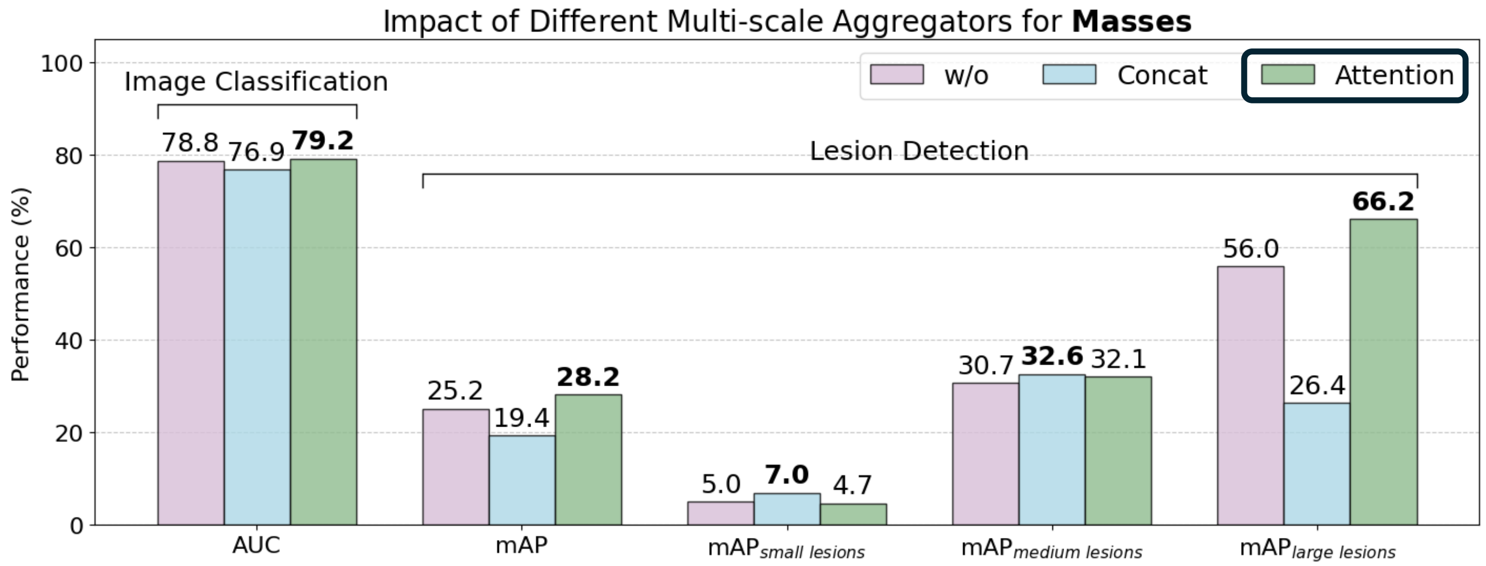
✓ Improved detection performance

⇩

Finer-grained instance features across different receptive-fields

Ablation Studies





Attention gives the best classification and detection trade-off.

- ✓ Better preserves relevant features across scales.
- ✓ Improves robustness to lesion size variability.

Conclusions & Future Work

- This work proposed a novel **multi-scale attention-based MIL framework** for weakly supervised classification and detection of breast lesions in high-resolution mammograms.
- It has a modular and adaptable design, robust across different lesion types and sizes.
- Outperformed or achieved competitive performance against baselines and SoTA models.
- Provides an extensible and strong framework for computationally and label-efficient mammographic lesion detection.

In the future:

- Investigate more instance aggregators (e.g., with positional encodings).
- Jointly analyze multi-view mammograms.

Multi-scale Attention-based Multiple Instance Learning For Breast Cancer Diagnosis

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Paper & Code

Thank you !

Join me on Poster Session 3: **Poster C183**

Acknowledgements

LARSyS
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fct Fundação para a Ciência e a Tecnologia

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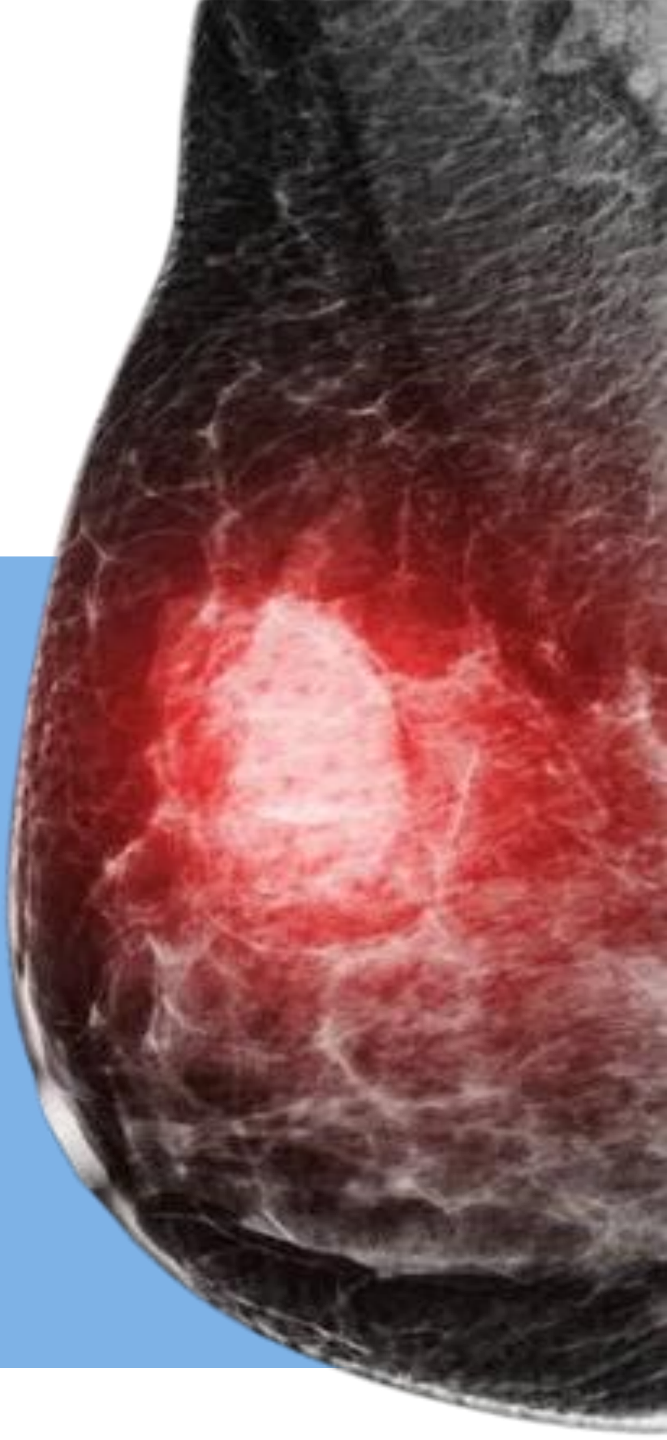
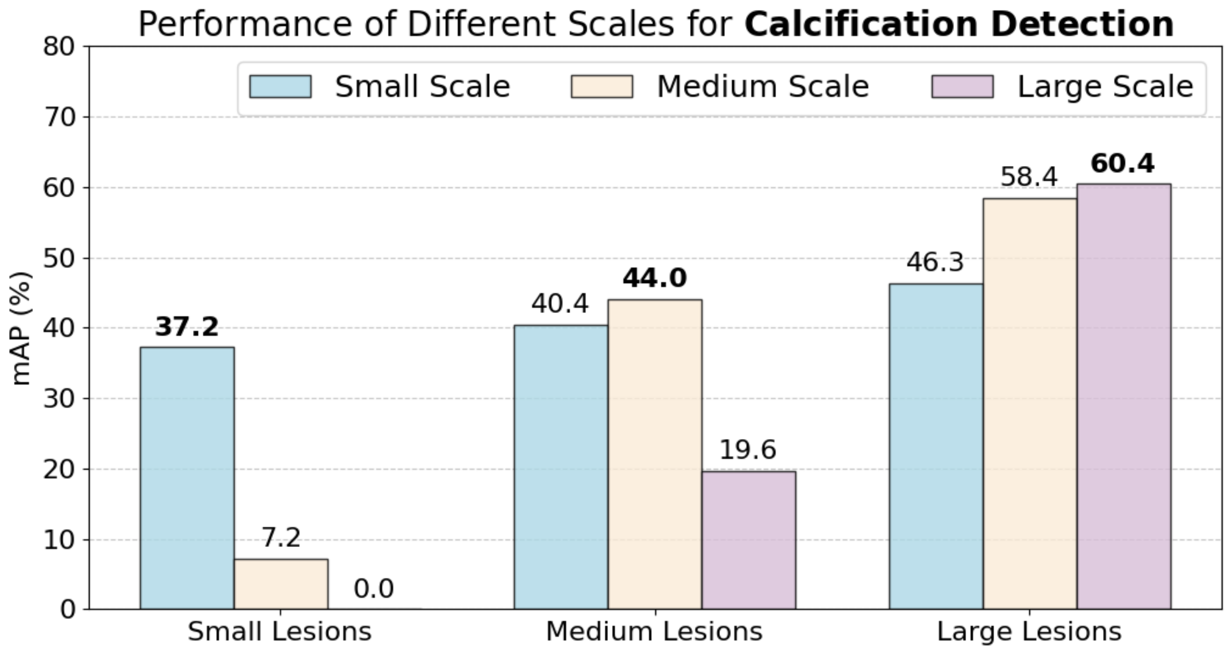
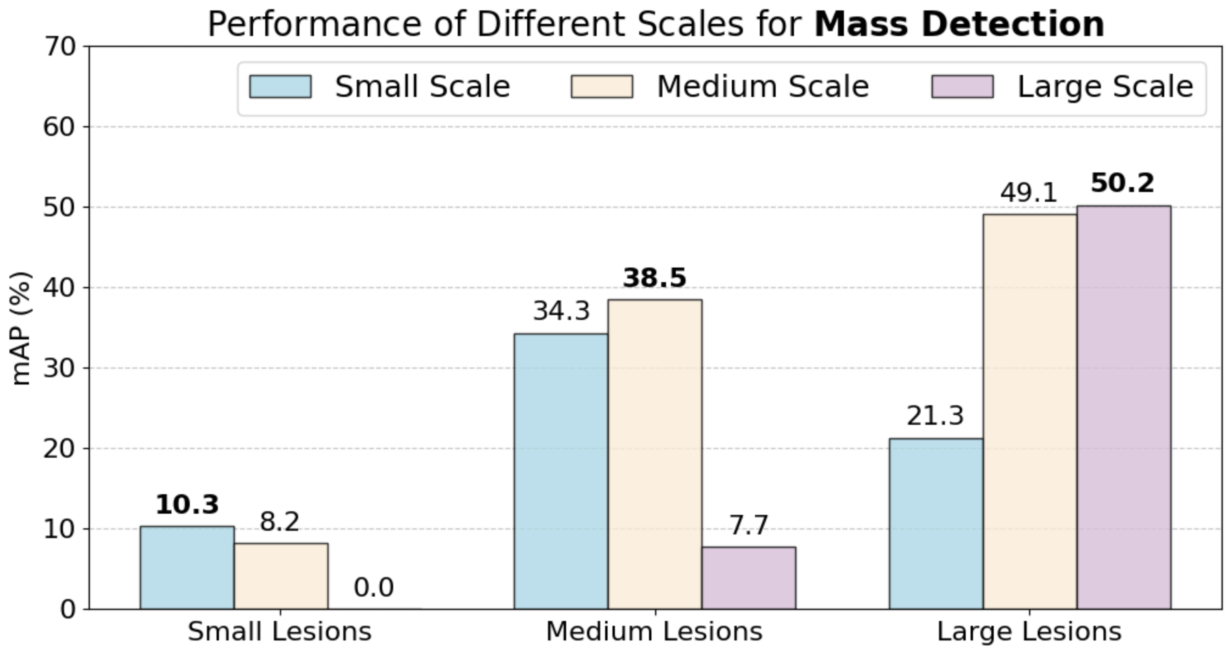
Appendix

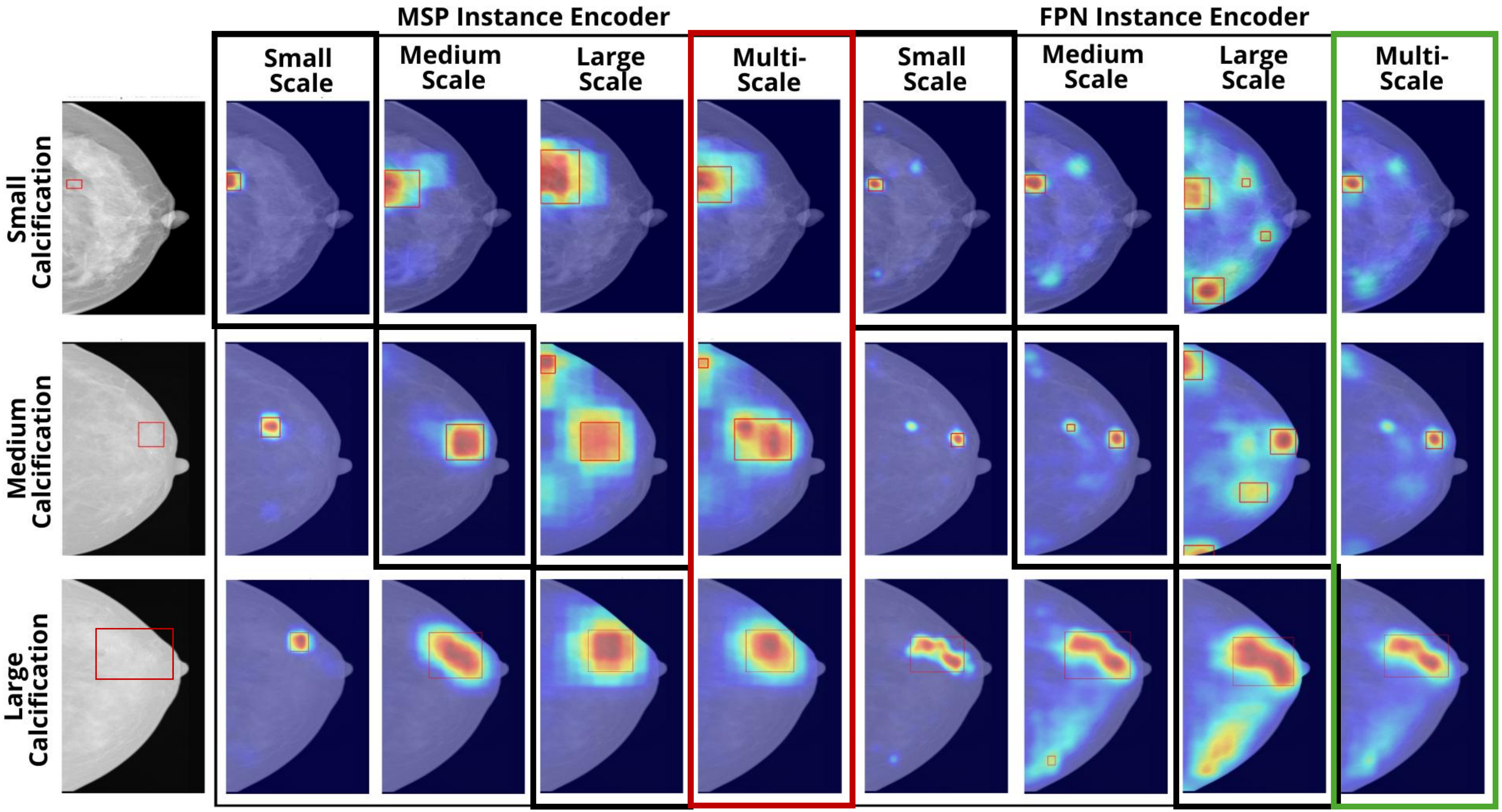


Detection Performance across Scales

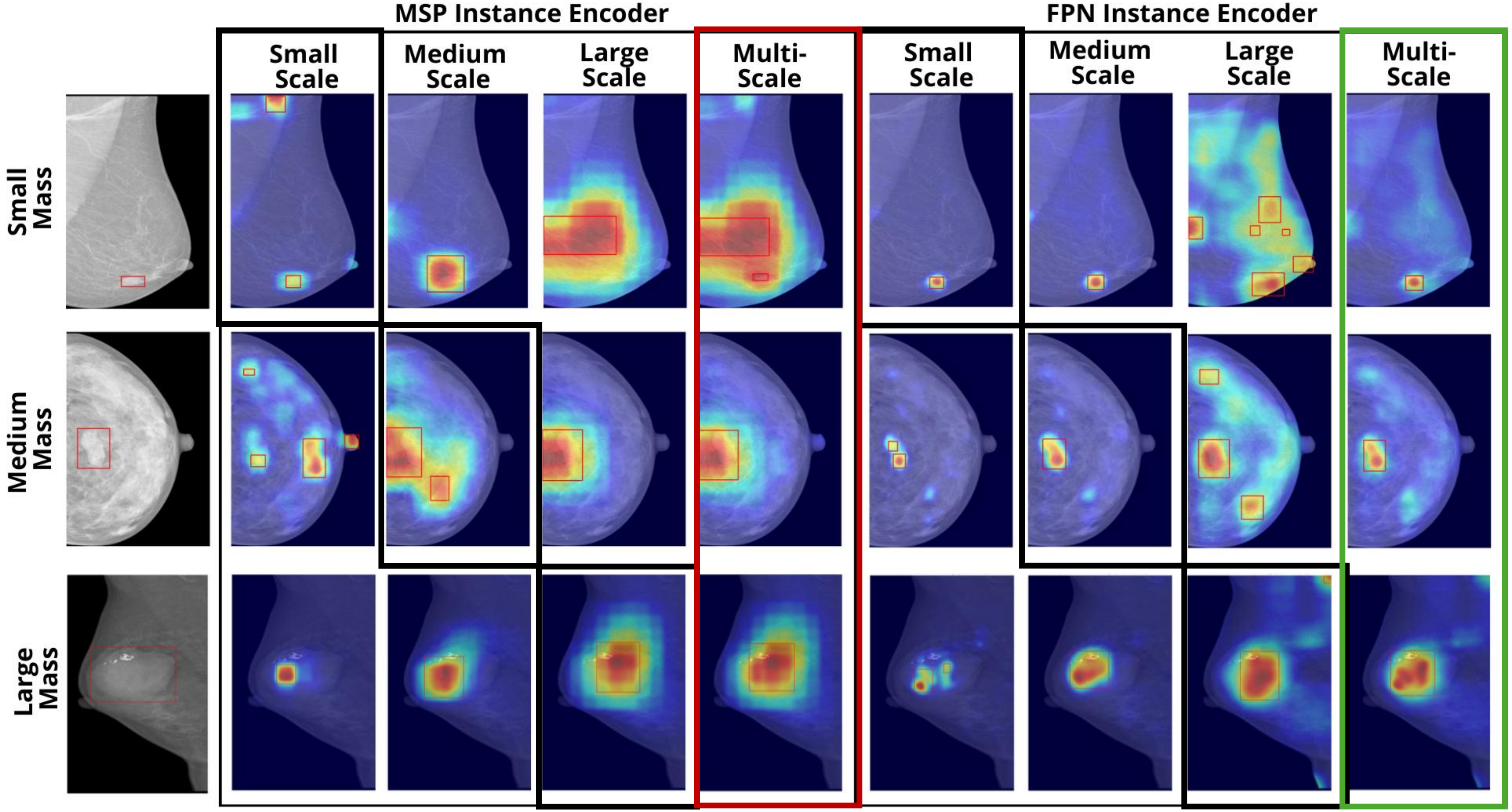




Impact of Different Multi-scale Instance Encoders



Impact of Different Multi-scale Instance Encoders



Set Transformer: Permutation Invariance Property

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Encoder Stage: Permutation-equivariant function

$$f(\pi(X)) = \pi(f(X))$$

Pooling Stage: Permutation-invariant function

$$g(\pi(X)) = g(X)$$

Set Transformer → Composition of functions

$$\text{Model} = g(f(X))$$

$$\text{Model}(\pi(X)) = g(f(\pi(X))) = g(\pi(f(X))) = g(f(X)) \Rightarrow \boxed{\text{Final model is pemutation-invariant}}$$

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Set Transformer: Efficient Context-aware Aggregation

Number of instances n_s and corresponding number of inducing points m_s for all analyzed scales when using scale-specific instance aggregators modeled by SetTrans in the proposed framework. The number of patches $N = 6$ extracted from the input mammograms are analyzed across three different scales $s = \{small,\ medium,\ large\}$, each associated with a specific reduction factor r_s relative to the original patch size dimensions $H_p = W_p = 512$.

Scales s	**Reduction Factor** r_s	**Number of instances** $n_s = N \times \frac{H_p}{r_s} \times \frac{W_p}{r_s}$	**Number of Inducing Points** $m_s = 10 \times \log(n_s)$
Small	16	6144	38
Medium	32	1536	32
Large	128	96	20

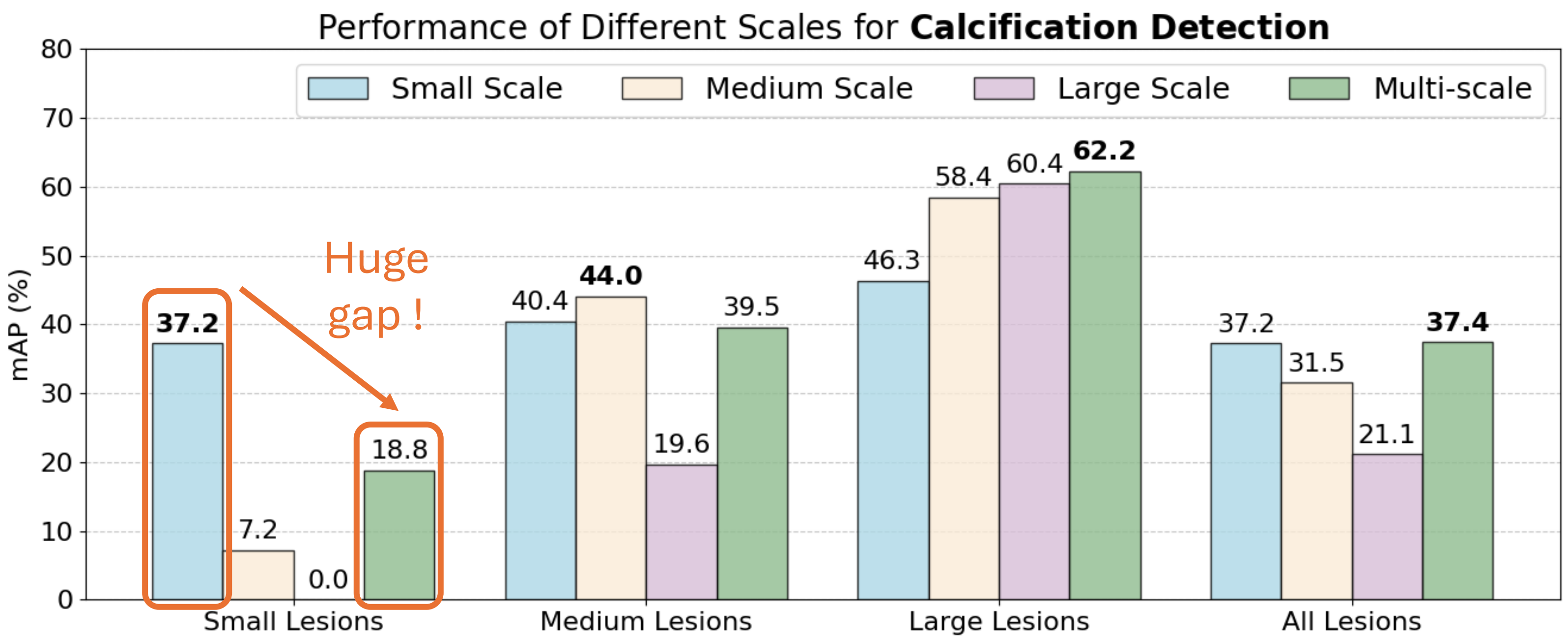
Future Work: Multi-level Instance Aggregators

Gif adapted from: https://research.google/blog/nested-hierarchical-transformer-towards-accurate-data-efficient-and-interpretable-visual-understanding/

Limitations: Multi-scale Aggregator

The **multi-scale aggregator** is optimized for MIL classification

Can learn non-optimal scale weights for the post-hoc detection analysis



Fine-grained details captured by the small-scale branch are **not fully preserved**

Limitations: Multi-scale Aggregator

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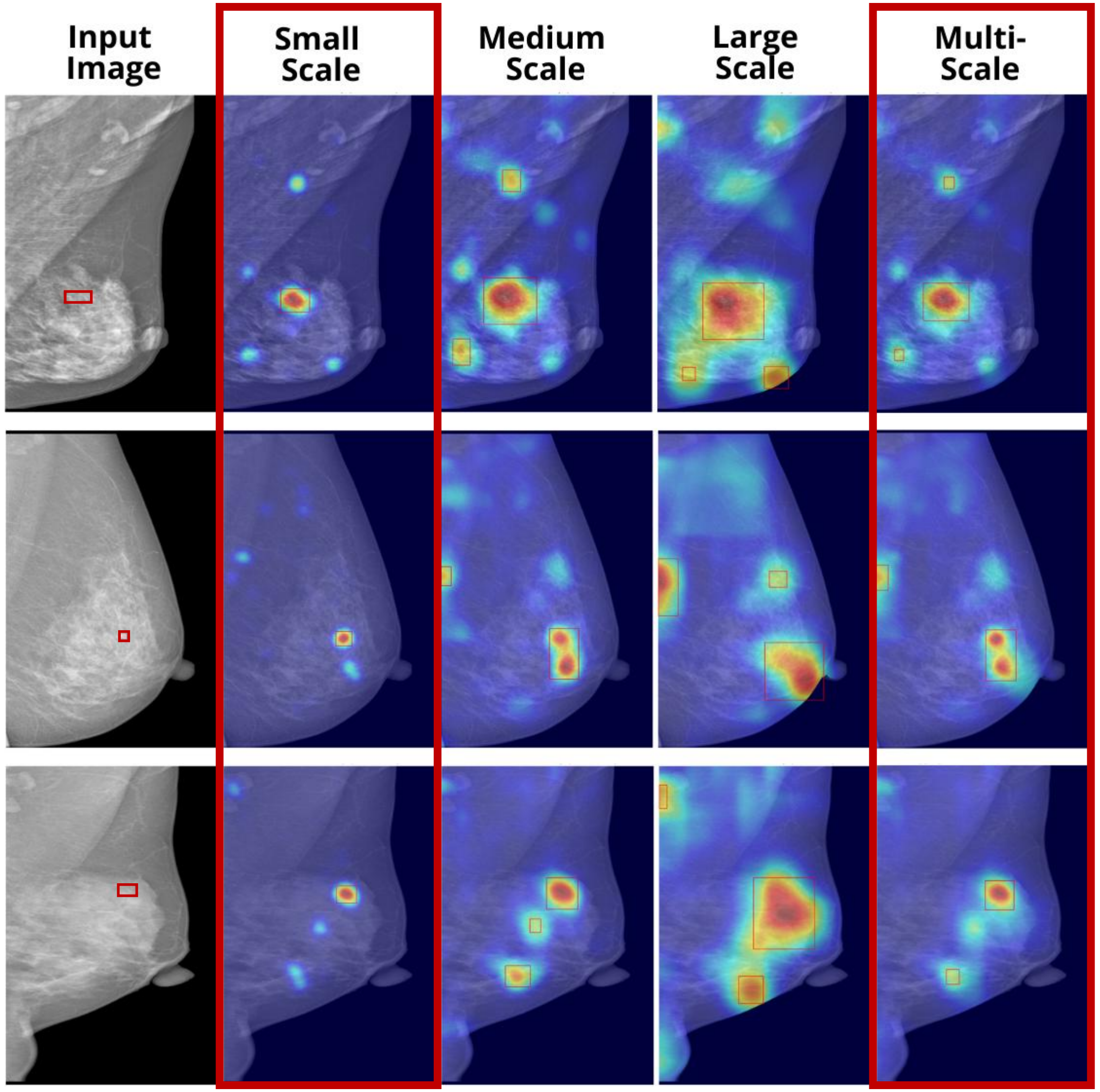

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