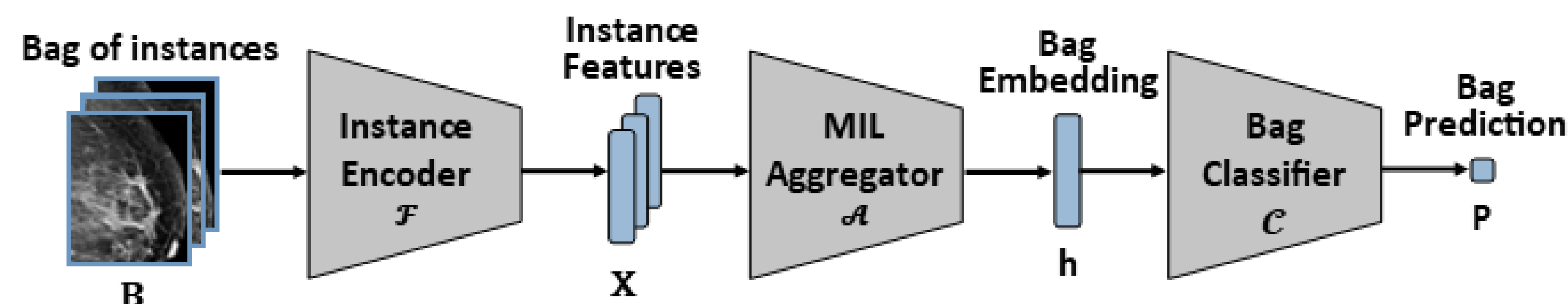


Introduction

- Mammography** is the gold standard for early breast cancer detection.
- Multiple Instance Learning (MIL)** enables weakly supervised learning from image-level labels, supporting image-level classification and instance-level (e.g., patches) detection on high-resolution images.



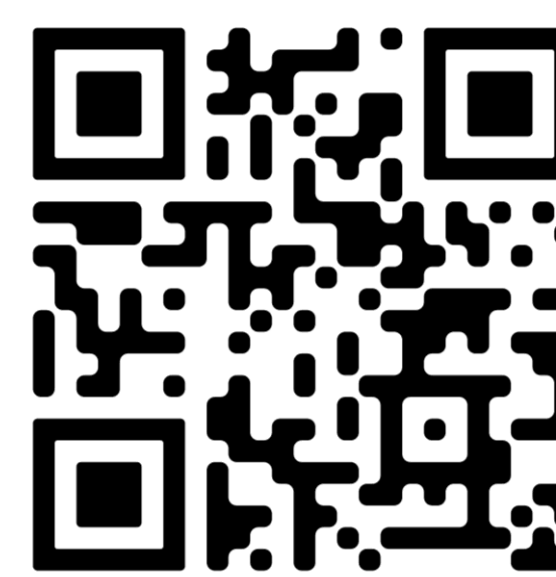
Challenge: MIL models in mammography overlook **instance interactions** & **multi-scale lesions**, limiting robustness across lesion types and sizes.

Contributions

Proposed a **Feature Pyramid Network (FPN)-based MIL** framework for weakly supervised classification and detection of breast lesions.

- Multi-scale analysis** across receptive-field granularities.
- Flexible & interpretable aggregation** using localized or context-aware attention.
- Adaptive scale fusion** to handle lesion size variability.
- Thorough evaluation** against baselines & SoTA models + ablation studies across different lesion types and sizes.

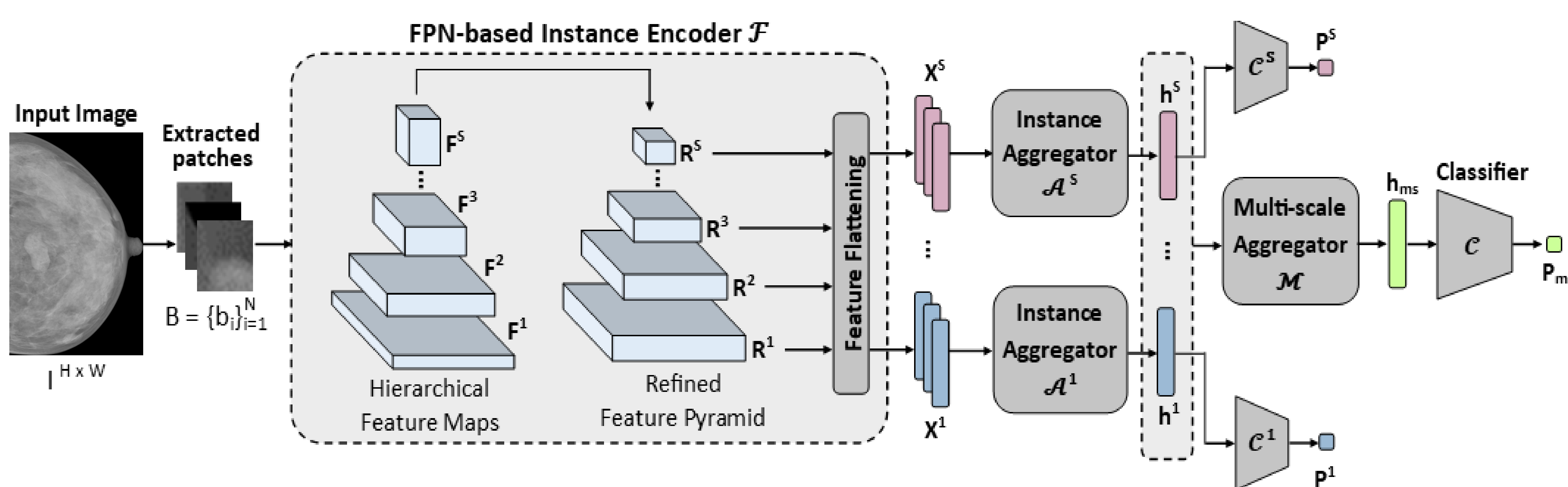
Code & Paper



Scan Me!

Methods

The proposed **FPN-MIL framework** has three main modules.



1. FPN-based Instance Encoder

Extracts fine-to-coarse pixel-level instances X^s at different scales s from a refined feature pyramid.

3. Multi-scale Aggregator

Adaptively combines the scales, producing:

- multi-scale image embedding h_{ms} for image classification
- multi-scale aggregated heatmap for lesion detection

2. Instance Aggregators

At each scale, aggregate the instance features X^s into an image embedding h^s , also producing interpretable scale-specific heatmaps.

Attention-based MIL (AbMIL)

Localized attention

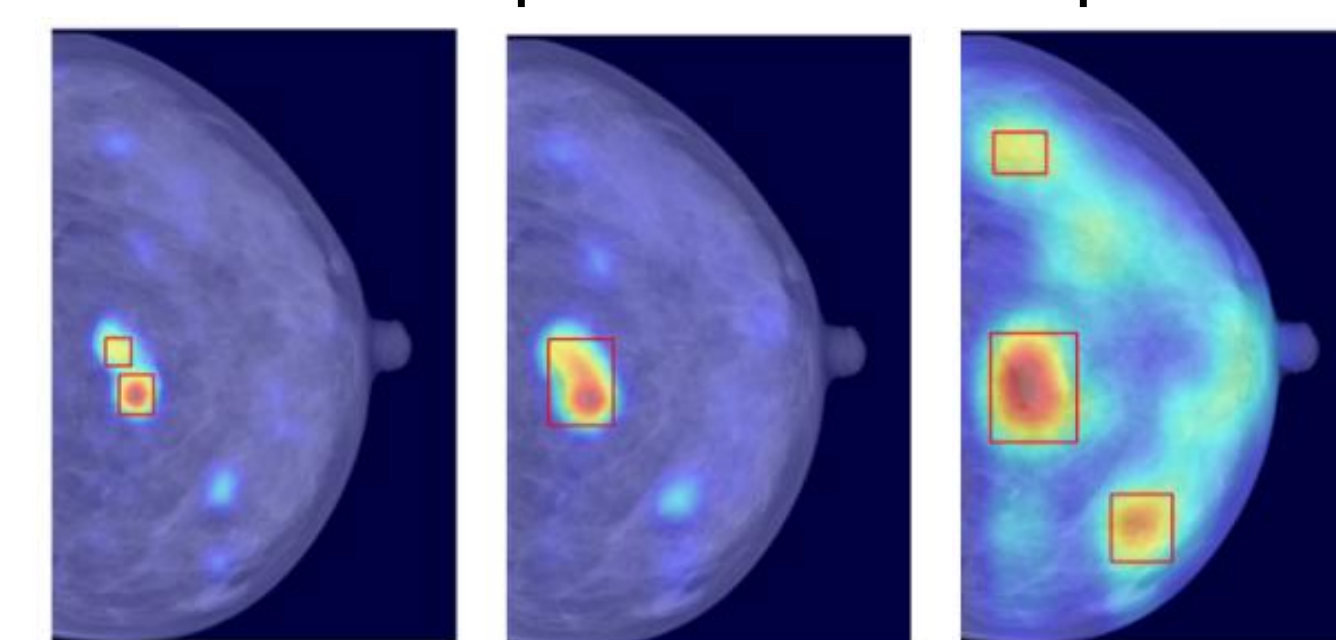
Set Transformer (SetTrans)

Efficient context-aware attention

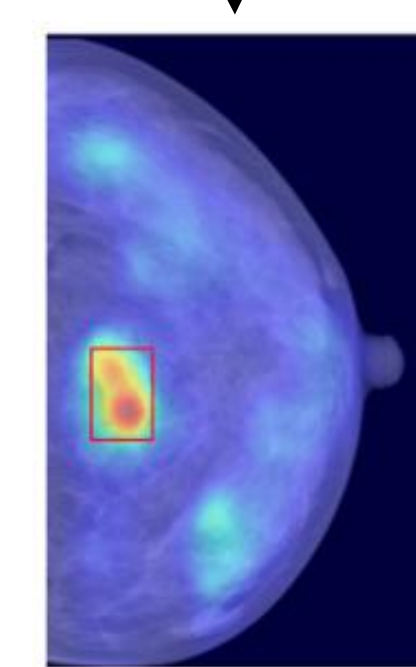
Model Outputs

- Image Classification**
Prediction P_{ms} of lesion presence
- Lesion Detection**

Scale-specific Heatmaps



Small scale Medium scale Large scale



Multi-scale Aggregated Heatmap

Experimental Results

Experiments were performed on the **Vindr-Mammo** dataset, assessing performance on **image classification (AUC)** and **lesion detection (mAP)**.

→ **Comparison with baselines & SoTA models**

- FPN-MIL outperforms Single-scale Patch-based (SSP)-MIL baselines**
- Our best models are lesion-dependent**
FPN-SetTrans better for calcifications (distributed point-like lesions)
FPN-AbMIL better for masses (isolated volume-like lesions)

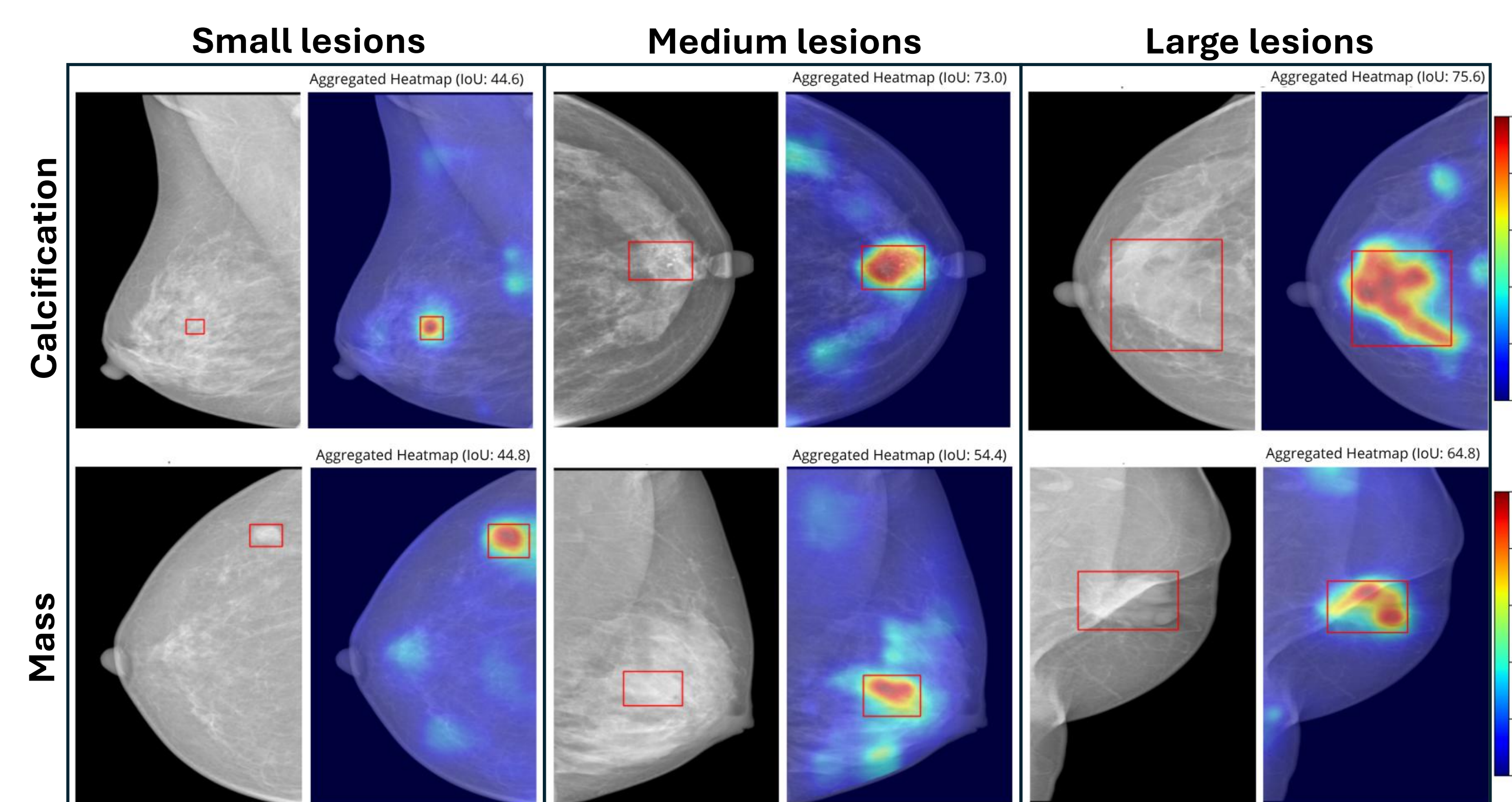
- Outperform or competitive against FSC, FSOD & WSOD SoTA models**

Type	Model	Calcification					Mass				
		AUC	mAP	mAP _s	mAP _m	mAP _l	AUC	mAP	mAP _s	mAP _m	mAP _l
FSC	EN-B2	92.0	-	-	-	-	73.0	-	-	-	-
FSOD	RetinaNet	-	17.0	-	-	-	-	37.0	-	-	-
WSOD	Mammo-FActOR	-	20.0	-	-	-	-	38.0	-	-	-
SSP-MIL	AbMIL	90.5	15.9	0.0	26.6	52.1	75.8	14.7	0.0	18.8	61.0
	SetTrans	88.9	18.4	0.1	29.4	57.6	73.2	5.8	0.0	9.1	22.0
FPN-MIL	(Our) FPN-AbMIL	93.5	32.0	9.1	34.8	57.5	79.2	28.2	4.7	32.1	66.2
	(Our) FPN-SetTrans	94.2	37.4	18.8	39.5	62.2	77.4	24.3	3.0	28.0	73.2

→ **Ablation Studies**

- ✓ **FPN > Multi-Scale Patches (MSP)** given its finer receptive-field granularity.
- ✓ **Multi-scale attention aggregator** improves robustness to lesion size variability.

Inst-Enc	MS-Aggr	Calcification					Mass				
		AUC	mAP	mAP _s	mAP _m	mAP _l	AUC	mAP	mAP _s	mAP _m	mAP _l
MSP	Attention	91.3↓	18.5↓	0.3↓	22.8↓	54.9↓	77.1↓	9.5↓	0.0↓	9.5↓	46.6↓
FPN	w/o	93.8↓	33.0↓	8.5↓	35.7↓	61.6↓	78.8↓	25.2↓	5.0↑	30.7↓	56.0↓
FPN	Concat	92.2↓	28.8↓	12.6↓	17.2↓	59.4↓	76.9↓	19.4↓	7.0↑	32.6↑	26.4↓
FPN	Attention	94.2	37.4	18.8	39.5	62.2	79.2	28.2	4.7	32.1	66.2



Interpretability: Our multi-scale aggregated heatmaps highlight clinically relevant breast lesions across different types and sizes.

Conclusions

- The proposed FPN-MIL framework has a modular and adaptable design, robust across different lesion types and sizes.
- Our best models outperform or are competitive against SoTA in breast lesion classification & detection while more label-efficient.
- Future work:** Explore more MIL aggregators and jointly analyze multi-view mammograms.