

#### UNIVERSITY OF HAWAI'I

### CANCER CENTER

#### Learning a Clinically-Relevant Concept Bottleneck for Lesion Detection in Breast Ultrasound

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### Detect and classify lesions in breast ultrasound imaging in an explainable way.





## We can predict existing, clinically-relevant reporting guidelines as concepts.





CBMs align intermediate model representations with these human-defined concepts.





#### CBMs allow for steerable, physician-in-the-loop Al to be used in the clinic.



### Clinical Concepts for Breast US

Concepts defined with lexicon of Breast Imaging-Reporting and Data System Masses (BI-RADS)

Indicative of malignancy Indicative of benignity C. D'Orsi, L. Bassett, and S. Feig, "Breast imaging reporting and data system (BI-RADS)," *Breast imaging Atlas, 4th edn. American College of Radiology, Reston,* 2018.

Attribute	Categories		
	Oval		
Shape	Round		
	<u>Irregular</u>		
Orientation	Parallel		
	Not parallel		
Margin	Circumscribed		
	Not circumscribed		
Echo Pattern	Anechoic		
	<u>Hyperechoic</u>		
	Complex cystic and solid		
	<u>Hypoechoic</u>		
	Isoechoic		
	<u>Heterogeneous</u>		
Posterior Features	No posterior features		
	Enhancement		
	<u>Shadowing</u>		
	Combined pattern		

#### Oval Parallel Circumscribed No features Anechoic





2. K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," p. arXiv:1703.06870. [Online].



### Stage 2: Concept classification





### Stage 3: Cancer classification







- Data from Hawai'i and Pacific Islands Mammography Registry<sup>3</sup>
- 994 women with 8,854 images
- Matched by birth year and ultrasound machine type
- Split 70% train, 10% valid, 20% test











Model	Average Precision		Average Precision <sub>75</sub>	
INICUEI	Segm	BBox	Segm	BBox
<b>BI-RADS CBM</b>	0.49	0.47	0.55	0.53
STNet (Qin et. al 2023)	N/A	0.40	N/A	0.43
CVA-Net (Lin et. al 2022)	N/A	0.36	N/A	0.39

CBM = Concept Bottleneck Model

C. Qin, J. Cao, H. Fu, R. M. Anwer, and F. S. Khan, "A Spatial-Temporal Deformable Attention Based Framework for Breast Lesion Detection in Videos," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 2023: Springer, pp. 479-488.

Z. Lin, J. Lin, L. Zhu, H. Fu, J. Qin, and L. Wang, "A New Dataset and a Baseline Model for Breast Lesion Detection in Ultrasound Videos," in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2022: Springer, pp. 614-623.

## Concept bottleneck does not degrade performance and aids interpretability.

Model	Side channel?	Nonlinear?	AUROC @ IoU = 0.75
Baseline	N/A	N/A	0.88 (0.85, 0.91)
<b>BI-RADS CBM</b>	No	No	0.86 (0.82, 0.90)
<b>BI-RADS CBM</b>	No	Yes	0.86 (0.83, 0.90)
<b>BI-RADS CBM</b>	Yes	Yes	0.87 (0.84, 0.91)

CBM = Concept Bottleneck Model

# Experiment 2: We can intervene on concepts and improve model performance.



Linear Post-Bottleneck Design

## **Experiment 1: The effect of the intervention differs based on model complexity.**



**Decreasing interpretability** 



https://github.com/hawaii-ai/bus-cbm

BI-RADS CBM presents an explainable AI solution for lesion detection, description, and classification from breast US.







Shepherd Research Lab



