

# Computing and Healthcare

Presented by Joy Liu at JamCoders 2025

# University of California, Berkeley



# Yala Lab!



**Adam Yala**

Assistant Professor of  
Computational Precision Health  
Statistics  
Electrical Engineering and Computer Science  
UC Berkeley and UCSF



Long (Tony) Lian  
PhD Student



Kumar Krishna Agrawal  
PhD Student



Longchao (Joy) Liu  
Masters Student



Arya  
Principal Dog



Natalia Harguindeguy  
PhD Student



Michael Nercessian  
PhD Student



Xinyang Han  
PhD Student

# Cancer: Earlier Detection + Reduced Overtreatment

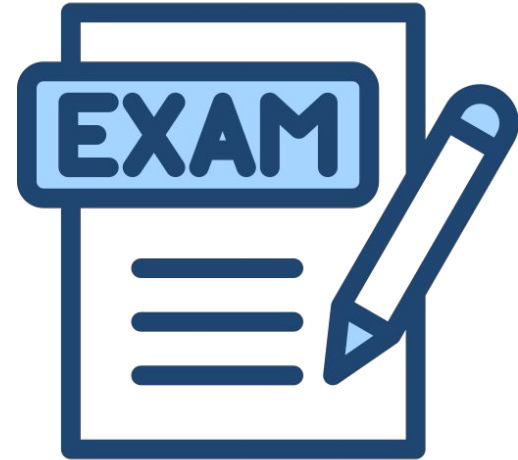
Who do we screen?



When do we screen?

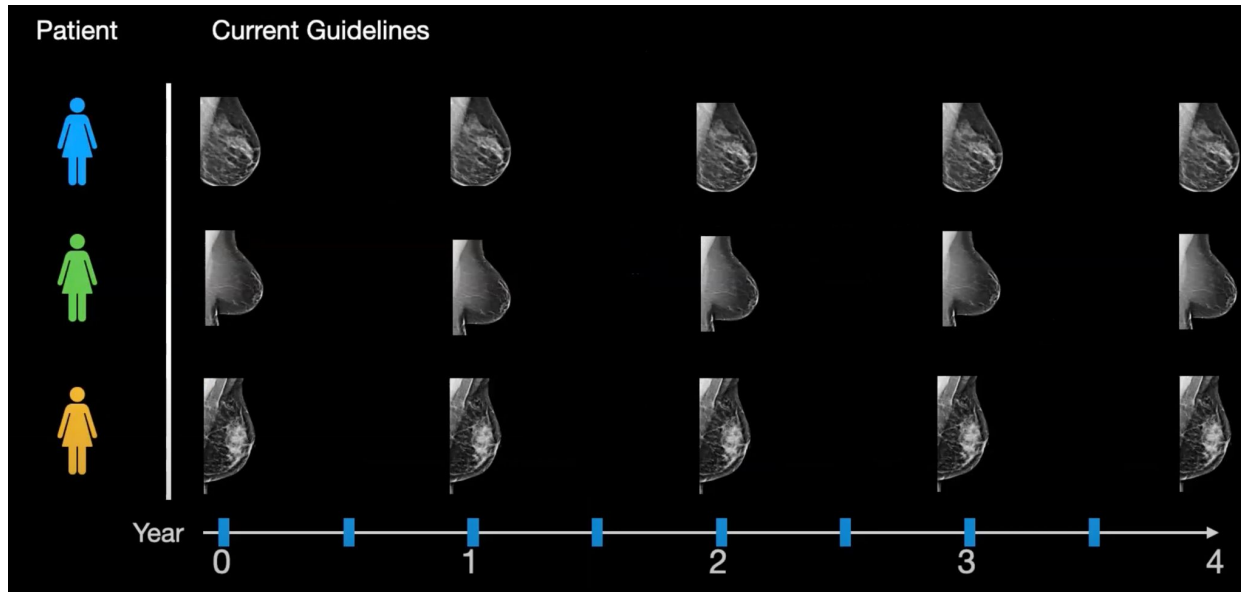


Does our algorithm work?







# Screening Guidelines

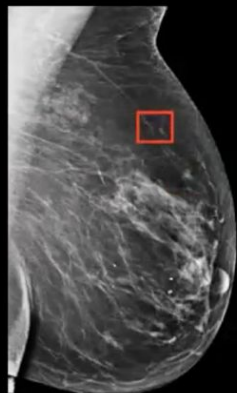
- Risk scores determine who gets supplemental screening or chemoprevention
- Risk is based on your personal factors and family medical history



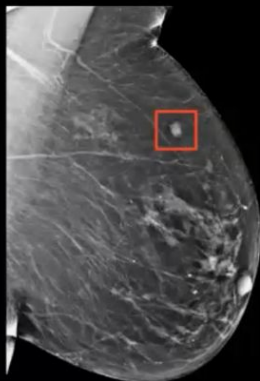
# Can we do better?

	Early Detection	Reduce Overtreatment
Screen constantly		
Never screen		

## Predict Cancer Risk

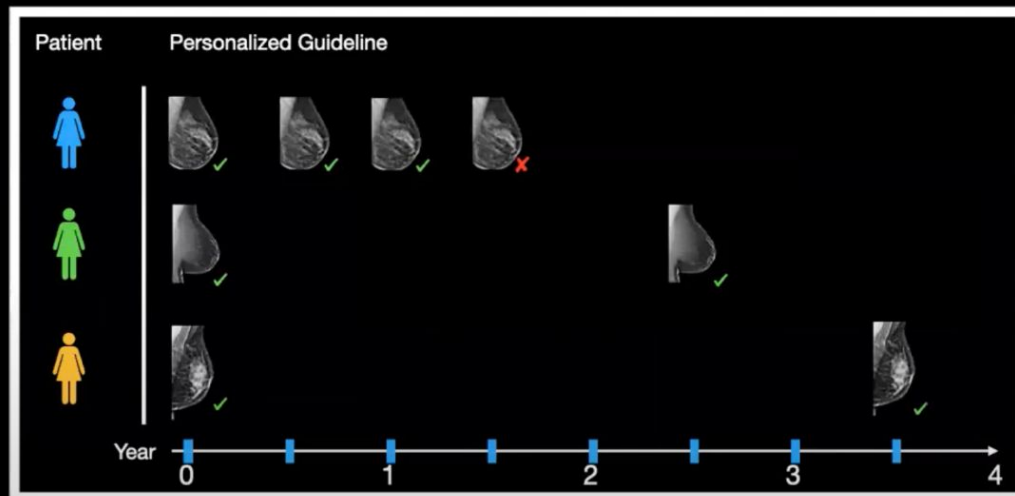


Year 0



Year 5

## Create personalized screening policy



# How do we do this?

1. Collaborate with doctors



# How do we do this?

1. Collaborate with doctors
2. Look at lots of past data

# How do we do this?

1. Collaborate with doctors
2. Look at lots of past data
3. Create a model

# How do we do this?

1. Collaborate with doctors
2. Look at lots of past data
3. Create a model
4. While model  $\neq$  good:

# How do we do this?

1. Collaborate with doctors
2. Look at lots of past data
3. Create a model
4. While model  $\neq$  good:  
improve(model, data, doctors, computer scientists, **lots** of time)

# How do we do this?

1. Collaborate with doctors
2. Look at lots of past data
3. Create a model
4. While model  $\neq$  good:  
    improve(model, data, doctors, computer scientists, **lots** of time)
5. Test on data the model has never seen

# How do we do this?

1. Collaborate with doctors
2. Look at lots of past data
3. Create a model
4. While model  $\neq$  good:  
    improve(model, data, doctors, computer scientists, **lots** of time)
5. Test on data the model has never seen
6. Deploy it in the clinic!

■ Tyrer-Cuzick (Prior State of Art)  
■ MIRAI (Ours - New Result)

AUC

0.62

0.76

MGH Test Set



0.76

0.75

0.76

0.75

0.78

0.79

0.82

MGH

Novant

Emory

Maccabi-Assuta

Karolinska

CGMH

Barretos

What else can you do?



# Make Screening Cheaper, Less Invasive for Patients

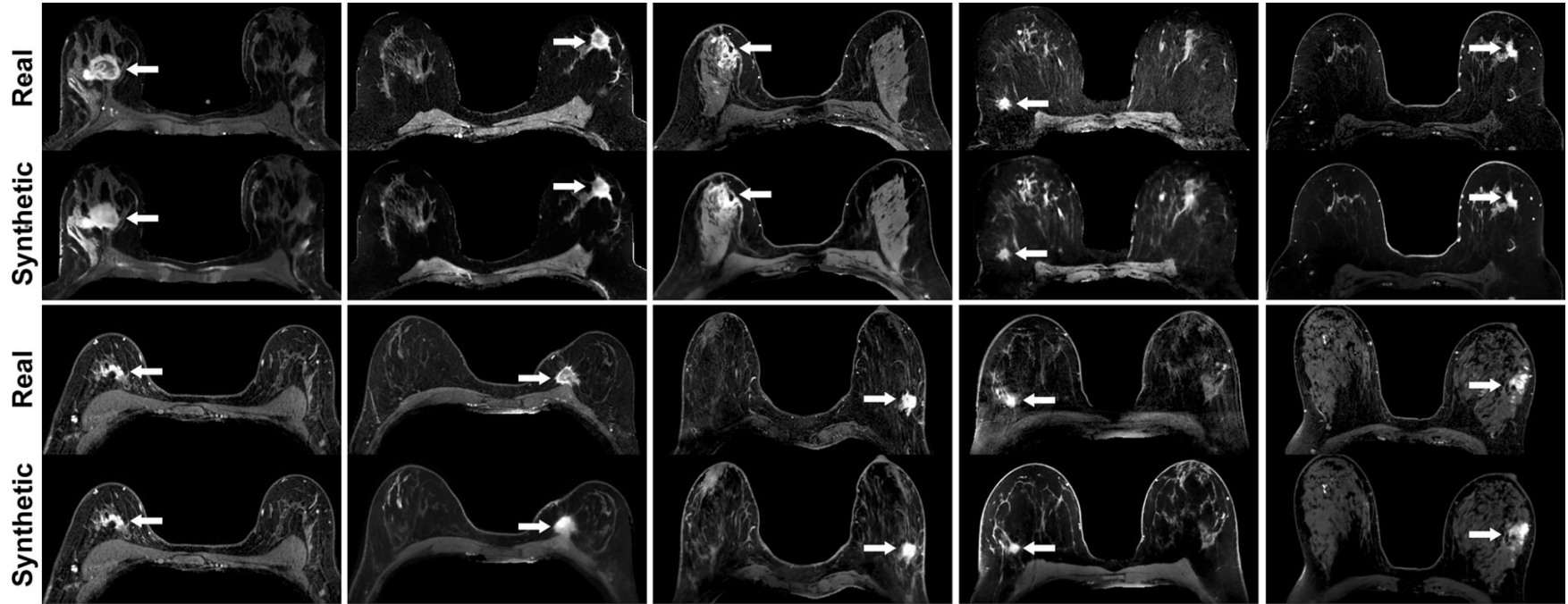
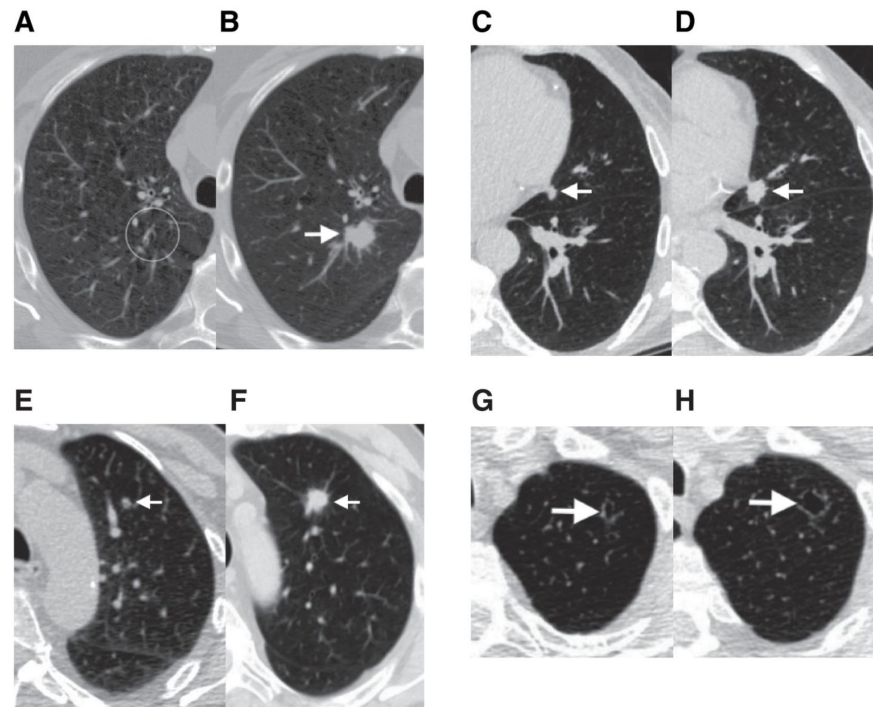
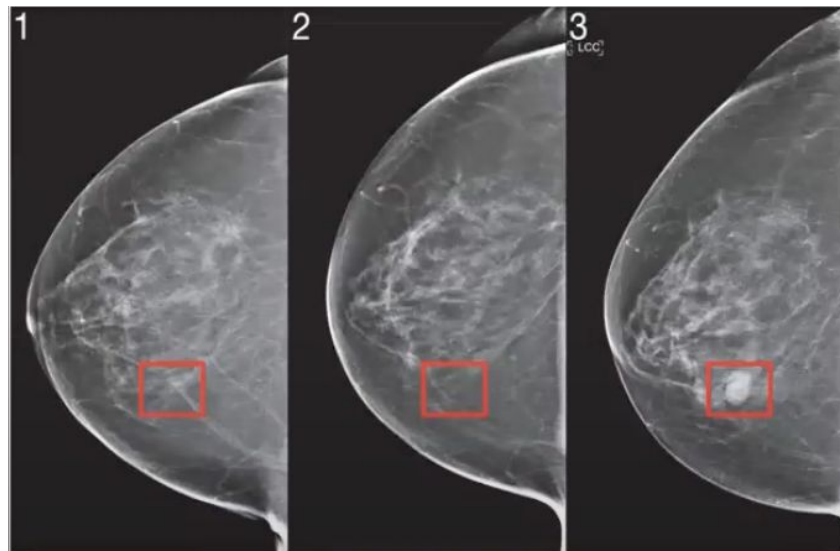
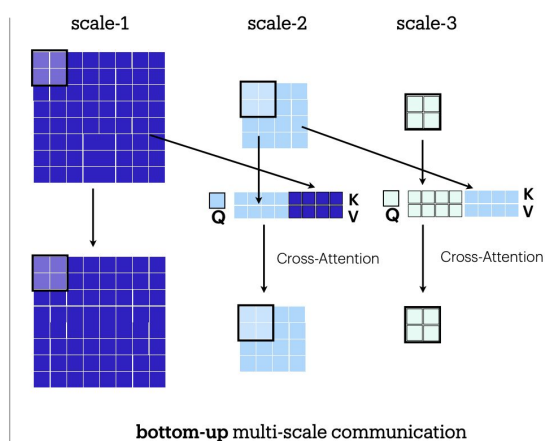
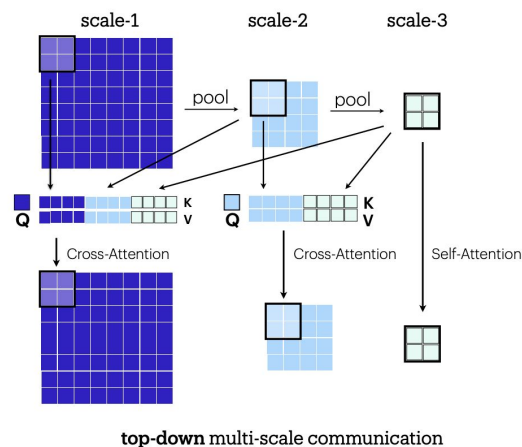
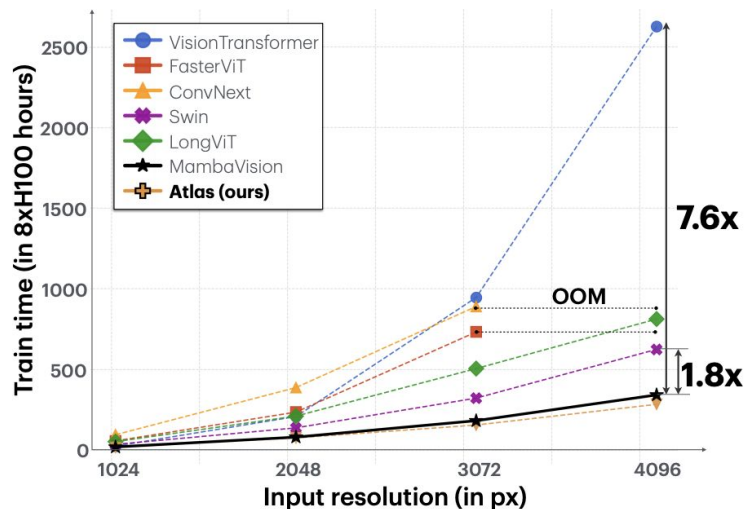


Image Credit: [Feasibility of Simulated Contrast-enhanced Breast MRI for Imaging Malignant Masses Using Deep Learning](#)

# Help Doctors Help Patients



# New Computational Methods



# Help Clinical Researchers Access Computational Tools

## 1. Problem definition



Label subset of reports and split into train, dev, test

### Create prompts

Are the following types of cancer included in the report? Possible diagnoses include: ductal carcinoma in situ, invasive ductal carcinoma, invasive lobular carcinoma, or adenocarcinoma.

DCIS	IDC	ILC	ADC
1	0	1	0

convert ground truth to the intended LLM response



parse the LLM response to the predicted labels in tabular form

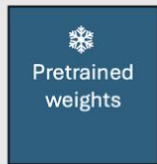
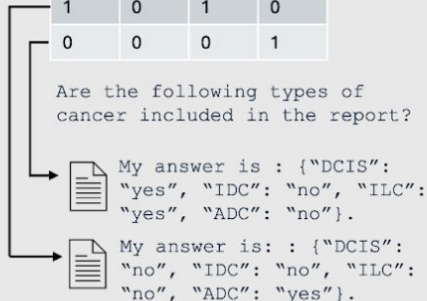
My answer is: {"DCIS": "yes", "IDC": "no", "ILC": "yes", "ADC": "no"}.

## 2. Experiments

### Training data

DCIS	IDC	ILC	ADC
1	0	1	0
0	0	0	1

Are the following types of cancer included in the report?



Pretrained weights



LoRA weights

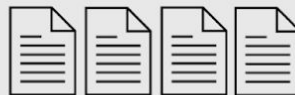


## 3. Deployment

Exact match scores on held-out test set

Outcome characteristic	Fine-tuned Llama 3.1 score
Anatomic site	99.5
Diagnosis	90.6
Laterality-specific subtyping (left)	97.8
Laterality-specific subtyping (right)	92.6

Inference on all unlabeled reports at the institution



60k+ automated extractions







Thanks for listening!

