

#### UNIVERSITY OF HAWAI'I

## CANCER CENTER

# Image-Based Models for Predicting Advanced Breast Cancer Risk

Lambert Leong<sup>1,2</sup>, Thomas Wolfgruber<sup>1</sup>, Brandon Quon<sup>1</sup>, **Arianna Bunnell**<sup>1,2</sup>, Dustin Valdez<sup>1</sup>, Jami Fukui<sup>1</sup>, Brenda Hernandez<sup>1</sup>, Yurii Shvetsov<sup>1</sup>, Karla Kerlikowske<sup>3</sup>, John Shepherd<sup>1,2</sup>

<sup>1</sup>University of Hawai'i Cancer Center, <sup>2</sup>University of Hawai'i at Mānoa, <sup>3</sup>University of California San Francisco





# Investigate imaging features associated with risk of advanced breast cancer

- Motivation
  - Advanced cancer is associated with poorer survival
  - Hawai'i has a high rate of advanced-stage breast cancer
  - Risk models for advanced breast cancer are limited and do not include imaging information.
- Hypothesis AI can fully interrogate images for any signals of advanced cancer risk



### Surveillance, Epidemiology, and End Results (SEER) Summary Staging

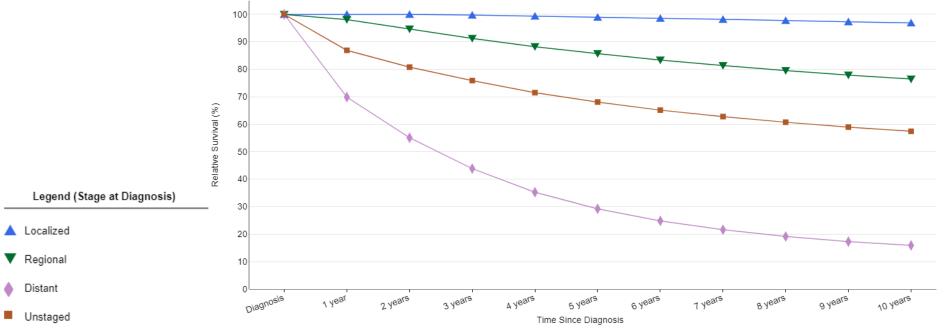
Code	Definition
0	In situ
1	Localized only
2	Regional by direct extension only
3	Regional lymph node involvement only
4	Regional by both direct extension and lymph node involvement
7	Distant site(s) involved

Stage	TNM
Stage 0	Tis, N0, M0
Stage IA	T1, N0, M0
Stage IB	T0, N1mi, M0
	T1, N1mi, M0
Stage IIA	T0, N1, M0
	T1, N1, M0
	T2, N0, M0
Stage IIB	T2, N1, M0
	T3, N0, M0
Stage IIIA	T0, N2, M0
	T1, N2, M0
	T2, N2, M0
	T3, N1, M0
	T3, N2, M0
Stage IIIB	T4, N0, M0
	T4, N1, M0
	T4, N2, M0
Stage IIIC	Any T, N3, M0
Stage IV	Any T, Any N, M1

Kalli, Sirishma, et al. "American joint committee on cancer's staging system for breast cancer: what the radiologist needs to know." Radiographics 38.7 (2018): 1921-1933.



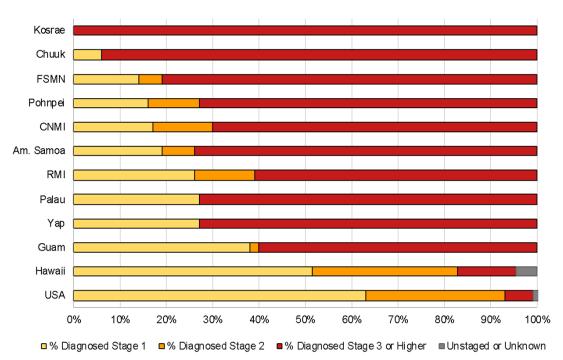
# Cancer diagnosed at later stages has significantly lower percent survival



SEER\*Explorer: An interactive website for SEER cancer statistics [Internet]. Surveillance Research Program, National Cancer Institute; 2023 Apr 19. [cited 2023 Jun 4]. Available from: <u>https://seer.cancer.gov/statistics-network/explorer/</u>.

# High Rate of Advanced-Stage Cancer in the Pacific

- Rates of advanced-stage cancer are high throughout the Pacific
- Despite a comprehensive screening program, Hawai'i has higher rates of advanced-stage compared the to the continental US



SEER\*Stat Database: Hawaii 1975-2017 and SEER Cancer Statistics Review 1975-2017)

## Associations of Standard Risk Factors to Advanced Stage Risk factors Technologies Risk factors Content of Standard Risk Factors to Advanced prognostic stage Advanced prognostic stage Advanced Prognostic stage Annual Progno

- Risk factors with strong associations to advanced cancer:
  - Disease with atypia
  - Dense breasts
  - Obesity

	Advanced prognostic stage II+ <sup>a</sup>				
Risk factors	An	nual	Biennial		
RISKTACTOIS	Premenopausal	Postmenopausal	Premenopausal	Postmenopausal	
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	
Age (in years) – linear term	0.98 (0.91, 1.06)	1.03 (1.00, 1.05)	1.01 (0.93, 1.11)	1.05 (1.02, 1.08)	
Age (in years), quadratic term	0.99 (0.99, 1.00)	1.00 (1.00, 1.00)	1.00 (0.99, 1.00)	1.00 (1.00, 1.00)	
Race and ethnicity					
Asian//Pacific Islander	0.79 (0.51, 1.24)	0.82 (0.60, 1.10)	0.66 (0.41, 1.09)	1.03 (0.79, 1.35)	
Black, non-Hispanic	1.65 (1.16, 2.36)	1.94 (1.61, 2.35)	1.17 (0.75, 1.82)	1.53 (1.17, 1.99)	
Hispanic	0.75 (0.41, 1.39)	1.33 (0.95, 1.87)	0.98 (0.59, 1.63)	0.84 (0.55, 1.28)	
White, non-Hispanic	ref	ref	ref	ref	
Other/Mixed	1.39 (0.65, 2.97)	1.28 (0.76, 2.14)	0.87 (0.36, 2.11)	1.11 (0.65, 1.91)	
1st degree family history of breast					
cancer <sup>b</sup>					
Yes	1.61 (1.21, 2.13)	1.37 (1.16, 1.60)	1.44 (1.00, 2.07)	1.20 (0.95, 1.51)	
No	ref	ref	ref	ref	
History of breast biopsy					
No prior biopsy	ref	ref	ref	ref	
Prior biopsy, benign diagnosis unknown	1.73 (1.25, 2.40)	1.58 (1.34, 1.87)	1.79 (1.23, 2.61)	1.60 (1.29, 1.97)	
Non-proliferative	1.36 (0.85, 2.17)	1.64 (1.27, 2.11)	1.30 (0.66, 2.54)	1.24 (0.79, 1.95)	
Proliferative without atypia	1.08 (0.48, 2.43)	1.65 (1.10, 2.47)	1.34 (0.43, 4.19)	1.24 (0.57, 2.67)	
Proliferative with atypia	2.43 (0.60, 9.82)	2.18 (1.03, 4.60)	0.00 (0.00, Inf)	2.37 (0.59, 9.52)	
BI-RADS breast density					
Almost entirely fat	0.41 (0.15, 1.14)	0.44 (0.31, 0.62)	0.40 (0.13, 1.25)	0.38 (0.24, 0.59)	
Scattered fibroglandular					
densities	ref	ref	ref	ref	
Heterogeneously dense		1.82 (1.55, 2.13)		1.61 (1.32, 1.97)	
Extremely dense	2.64 (1.71, 4.06)	2.41 (1.78, 3.25)	2.44 (1.49, 3.99)	2.11 (1.45, 3.06)	
Body mass index, kg/m <sup>2</sup>					
Underweight (<18.5)	0.64 (0.19, 2.10)	1.32 (0.74, 2.36)	0.79 (0.25, 2.49)	1.20 (0.61, 2.38)	
Normal (18.5-24.9)	ref	ref	ref	ref	
Overweight (25.0-29.9)	1.31 (0.93, 1.85)	1.42 (1.14, 1.76)	1.72 (1.19, 2.49)	1.61 (1.22, 2.11)	
Obese, grade I (30.0-34.9)	1.38 (0.88, 2.18)	1.72 (1.35, 2.20)	1.54 (0.97, 2.42)	2.07 (1.58, 2.71)	
Obese, grade II/III (≥35.0)	1.83 (1.17, 2.86)	2.30 (1.80, 2.95)	1.40 (0.79, 2.48)	1.85 (1.30, 2.65)	

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Kerlikowske K et al. Cumulative Advanced Breast Cancer Risk Prediction Model Developed in a Screening Mammography Population. JNCI : Journal of the National Cancer Institute. 2022;114(5):676-85.



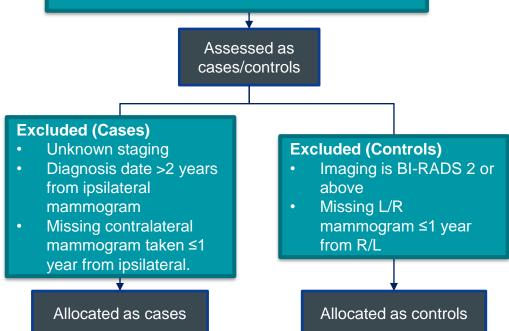
The data used in this study are sourced from the Hawai'i and Pacific Islands Mammography Registry (HIPIMR)

#### Inclusion

- In the registry before 8/31/22
- All 4 standard mammographic views or images
- Known staging, diagnosis, and outcome

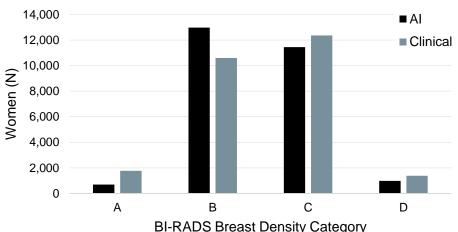
#### Excluded

- Missing MLO/CC view for L and R breast
- Has a prior tumor record
- Mammogram not acquired on Hologic System
- Unknown diagnosis or outcome





- Data exported as of 08/31/22
  - o 240,000 images
  - 26,000 women
    - 195 diagnosed with advanced-stage breast cancer



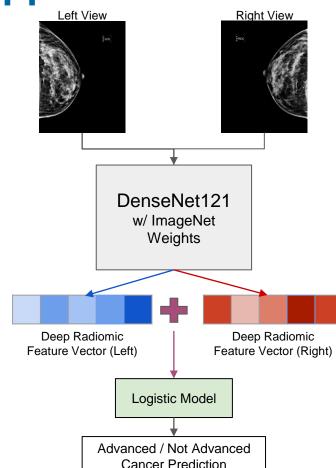
 Al-derived labels are sourced from NYU breast density algorithm

Wu N. et. Al Breast Density Classification with Deep Convolutional Neural Networks. 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP); 2018 2018-04-01: IEEE.

#### Clinical & AI-Derived Breast Density

# Image-based Modeling Approach

- Imaging/deep radiomic feature extractor
  - Base architecture
    - DenseNet121
    - Pretrained ImageNet
    - Weights locked
- Logistic models take in both
  L and R views



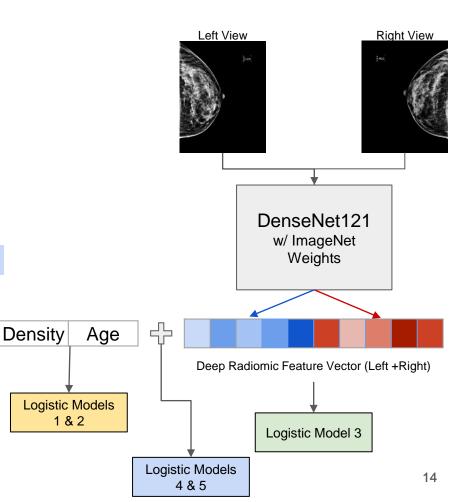


#### We built 5 logistic models

- Clinical density only model
  Al-derived density only model
  Image feature only model
  Combined clinical density and

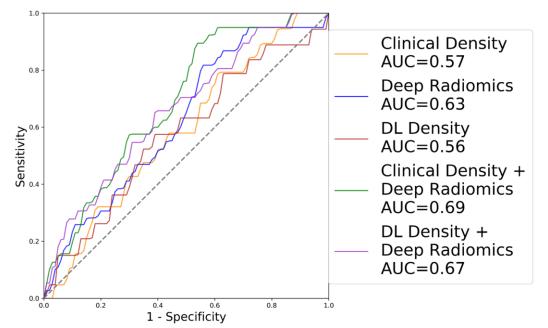
- image features
- 5. Combined dl density and image features

All models which include density were age adjusted





- Image features perform better than density only models
- Combined models performed best
  - Imaging contains signals of risk unique to density





- Imaging contains predictive information related to risk of advanced cancer
  - Information is unique to breast density
- Such models can be used to identify high risk women and intervene appropriately

## **Caveats:**

- Not all common risk factors were available
- Small number of cancers with category D density
  So we combined C and D when computing odds ratios
- Small number of advanced cancer cases





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  - HIPIMR R01CA263491 and U54CA143728
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