UNIVERSITY OF HAWAI‘I
CANCER CENTER

Artificial Intelligence Predicts Mammographic Breast Density in Clinical Breast Ultrasound Images

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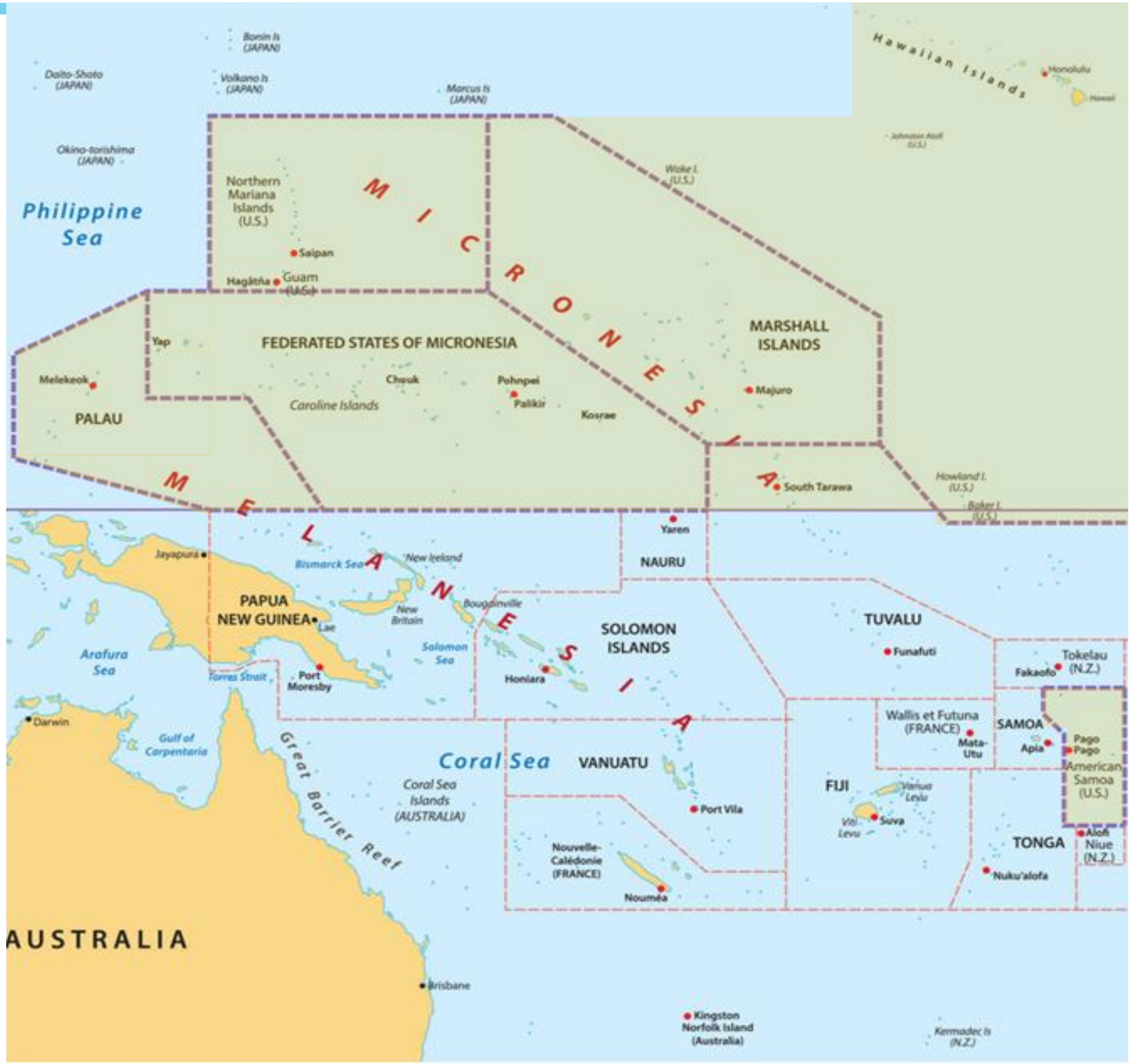
Motivation

University of Hawai‘i Cancer Center Catchment Area

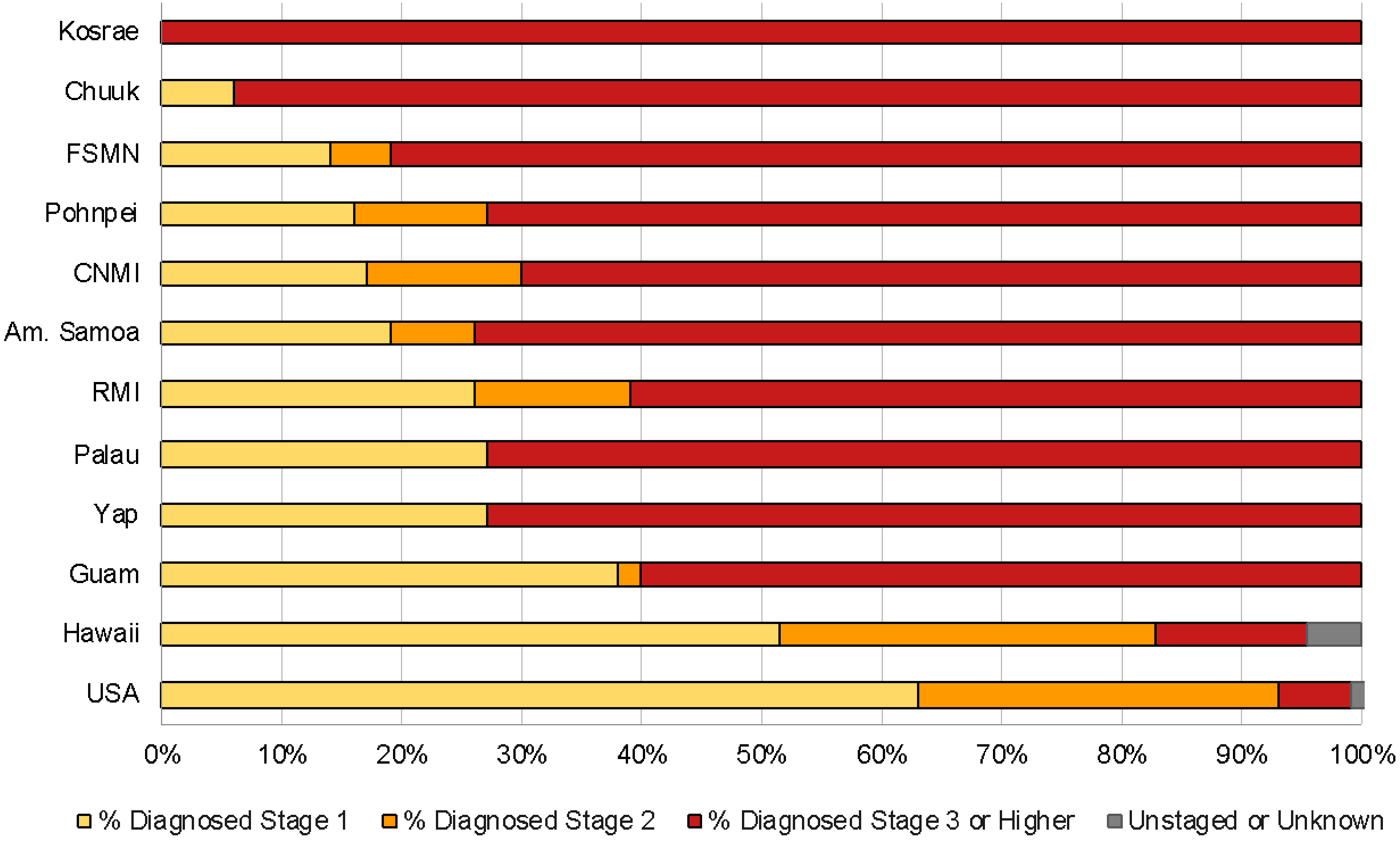
U.S. Affiliated Pacific Islands

- **Advanced stage breast cancer rates in the Pacific are higher than in the USA mainland**, especially where mammography is inaccessible
  - Palau: 77% of breast cancer cases are diagnosed at an advanced stage
  - Republic of the Marshall Islands: 72%
  - Federated States of Micronesia: 82%

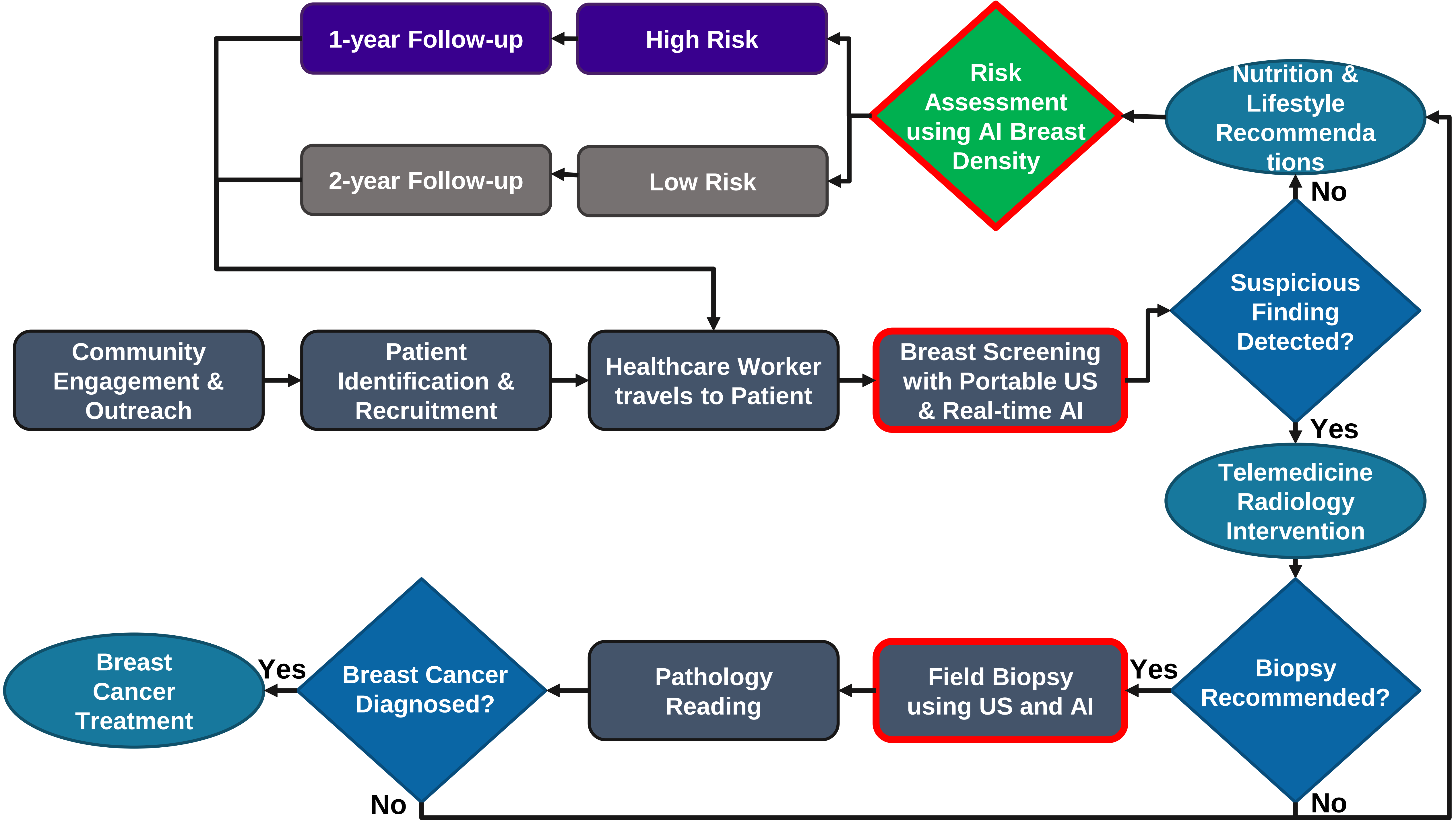
- Ultrasound is a viable alternative imaging modality
  - Requires: sonographer and interpreting radiologist
  - **Can AI soften the requirements?**



Reducing Advanced-Stage Cancer Rates



Time period is 2007-2017 for the Pacific, 2013-2017 for Hawaii, and 2010-2016 for the USA. (Sources: SEER*Stat Database: Hawaii 1975-2017 and SEER Cancer Statistics Review 1975-2017). Courtesy of Hernandez and Buenconsejo-Lum.



1-year Follow-up
High Risk
Risk Assessment using AI Breast Density
Nutrition & Lifestyle Recommendations
2-year Follow-up
Low Risk
No
Suspicious Finding Detected?
Community Engagement & Outreach
Patient Identification & Recruitment
Healthcare Worker travels to Patient
Breast Screening with Portable US & Real-time AI
Yes
Telemedicine Radiology Intervention
Breast Cancer Treatment
Yes
Breast Cancer Diagnosed?
Pathology Reading
Field Biopsy using US and AI
Yes
Biopsy Recommended?
No
No

Problem Statement

Goal: Identify the mammographic breast density of a patient

- It is well-established that higher mammographic breast density is associated with higher risk of breast cancer
- The paradigm of getting a measure defined on mammography from BUS seems only applicable in settings without mammography

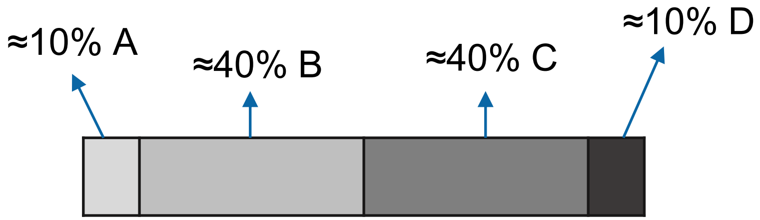
Data Source

- The data used in this study are sourced from the Hawaiʻi and Pacific Islands Mammography Registry (HIPIMR)
  - Prospective cohort of women
  - Collects breast imaging and breast health information (2009-*present*)
  - Linked to the Hawaiʻi Tumor Registry to identify cases

- HIPIMR data consist of imaging, metadata, clinical variables, patient characteristics, and biopsy-confirmed cancer status

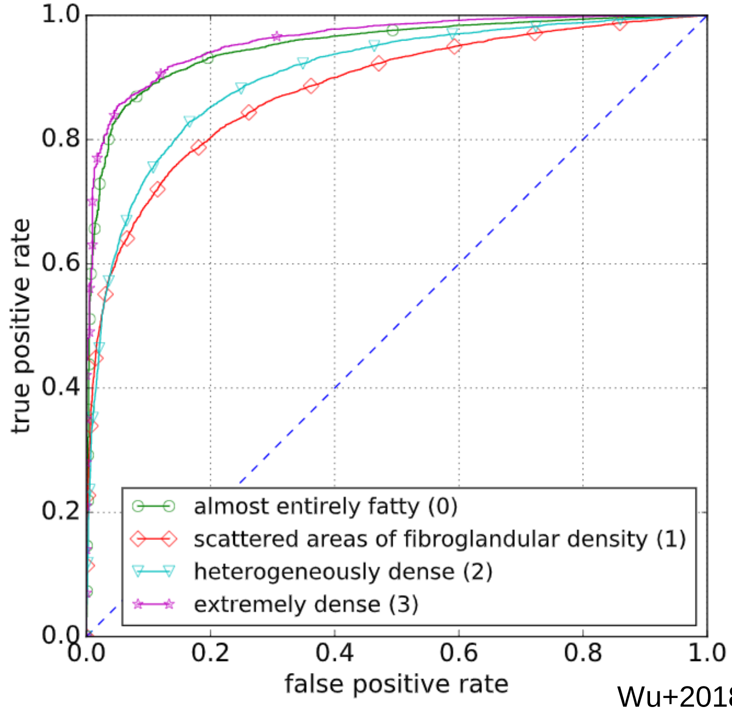
Data Description

- Includes clinical and AI-derived breast density labels
  - Clinical labels are assigned based on visual assessment by the radiologist
  - AI-derived labels are sourced from NYU breast density algorithm
- Split 60%-20%-20% by case-control set, stratified by AI-derived density



AI-derived $y = [p(y = A|x) \quad p(y = B|x) \quad p(y = C|x) \quad p(y = D|x)]$

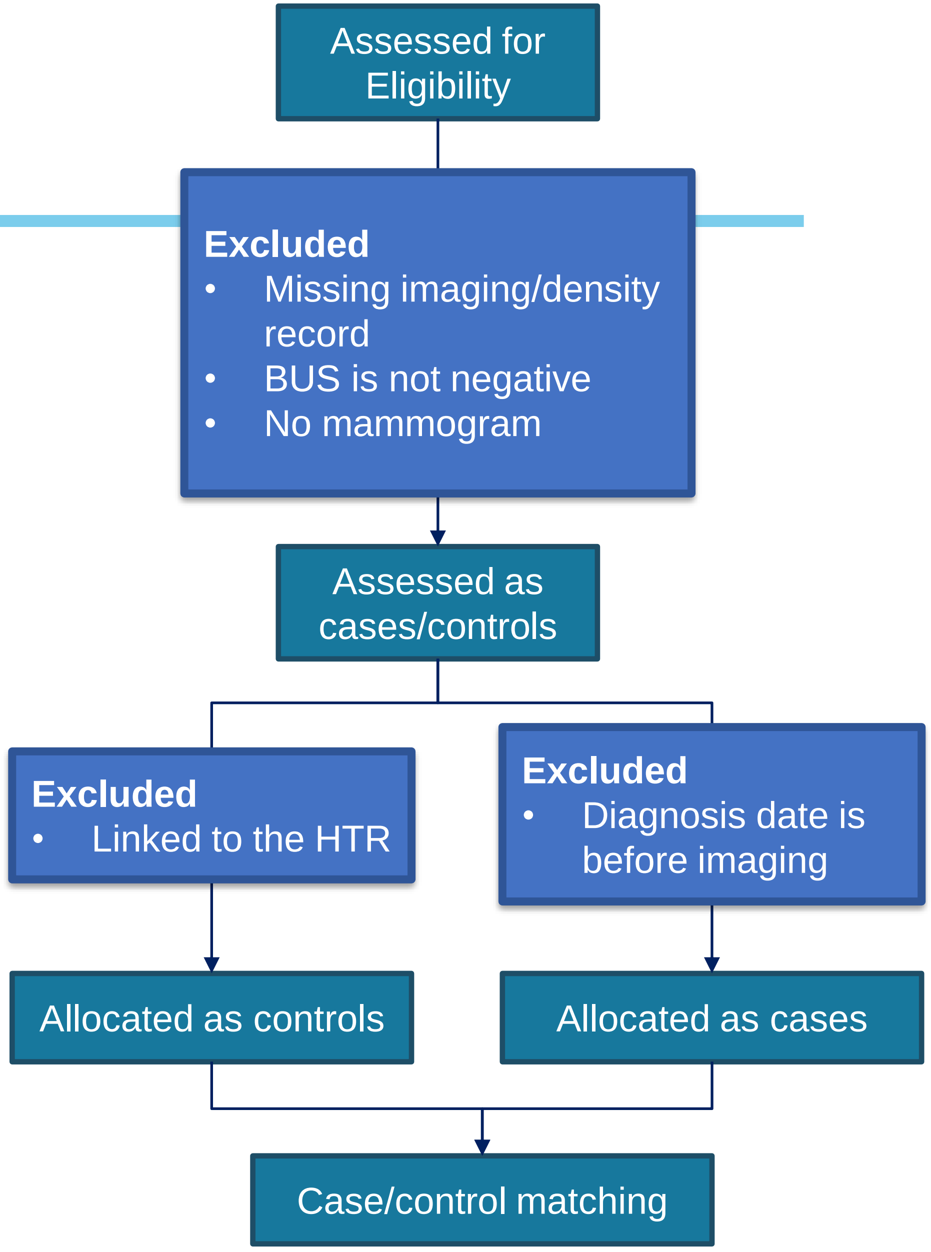
Clinical $y \in \{A, B, C, D\}$



Wu+2018

Selection Criteria

- Population is all patients with a record of BUS imaging in the HIPIMR
- Exclusion Criteria
  - No mammogram <1 year from BUS imaging
  - Missing density record <1 year from imaging
  - BUS is not negative (BI-RADS 1 or 2)
  - Diagnosis date is before imaging date
  - Missing imaging
- 1:10 case-control matching on birth year and BUS machine type



Gray-level Feature Models

Data

- 32 evenly-spaced gray-level bins
- Trained with discrete density labels

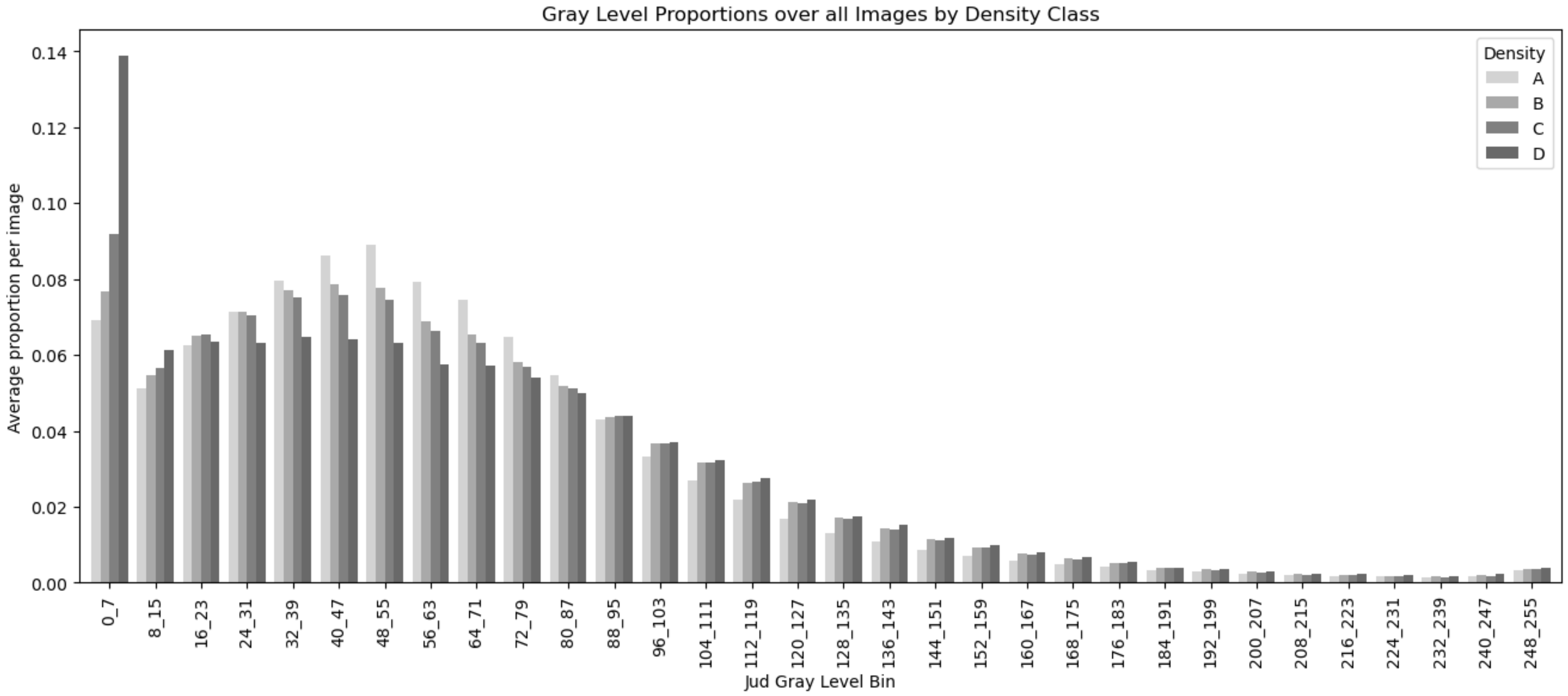
Models

1. Logistic Regression
2. Multi-Layer Perceptron

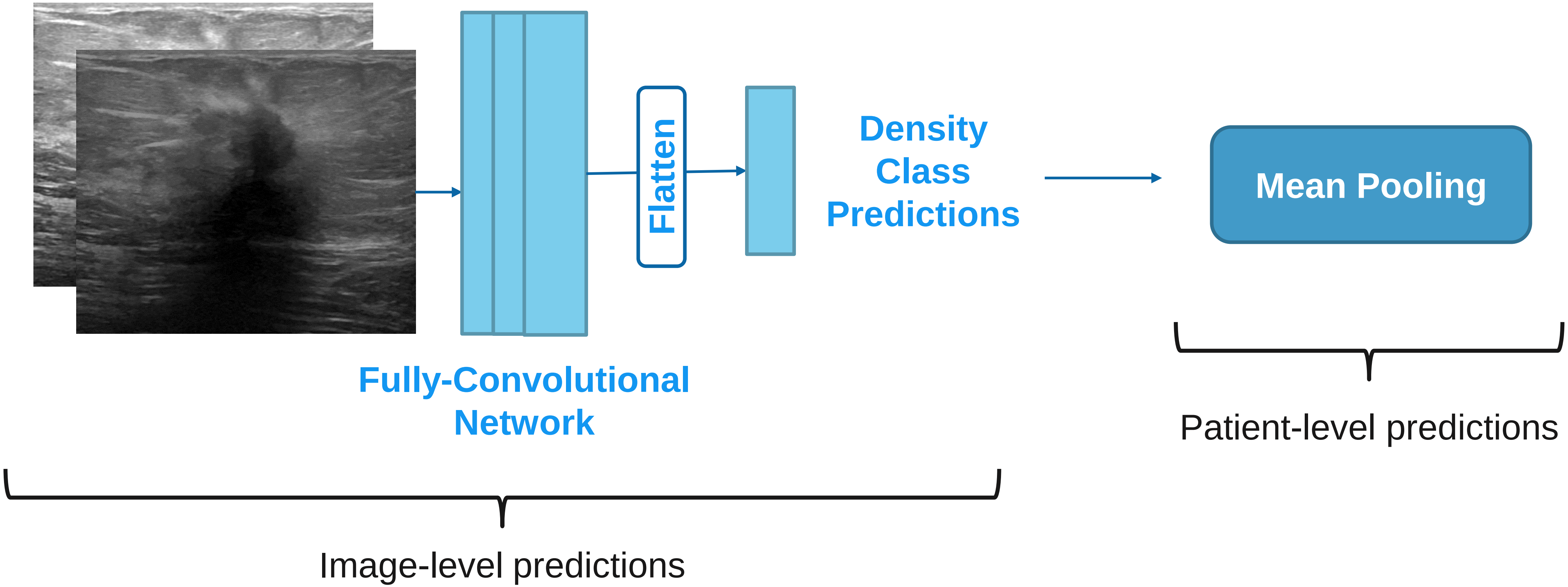
Correlates of mammographic density in B-mode ultrasound and real time elastography

Sebastian Michael Jud[a,c], Lothar Häberle[a,c], Peter A. Fasching[a,e,c],

Jud+2012



CNN Model



Flatten
Density Class Predictions
Mean Pooling
Fully-Convolutional Network
Patient-level predictions
Image-level predictions

Data Selection Results

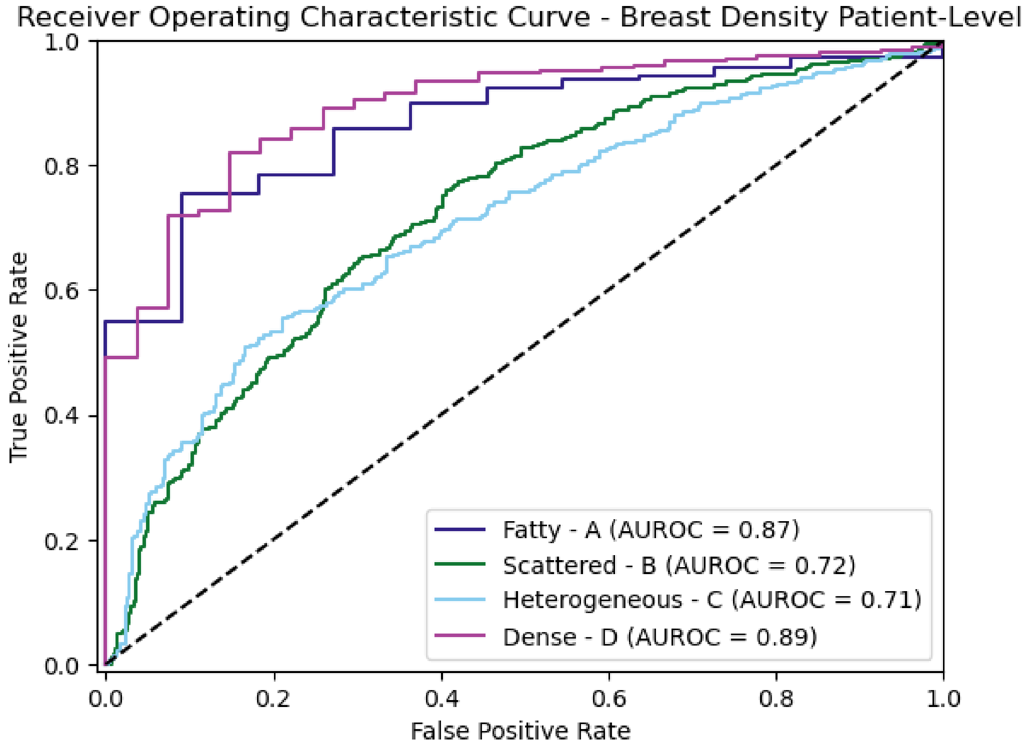
Characteristic, Unit	Cancer Cases	Controls
Women, N	378	3,722
Women with fatty/A breasts, N	3	60
Women with scattered/B breasts, N	194	1,932
Women with heterogeneous/C breasts, N	166	1,606
Women with dense/D breasts, N	15	124
Images, N	11,273	93,692
Images with fatty/A breasts, N	32	1,387
Images with scattered/B breasts, N	5,521	45,295
Images with heterogeneous/C breasts, N	5,245	43,577
Images with dense/D breasts, N	475	3,433

Modeling Results – Patient Level

- Image-level predictions were mean-pooled to form a single density class distribution prediction per patient
- The four-tuple labels were condensed into a single value, representing the class for which they predicted the largest probability

One vs. Rest AUROC (95% C.I.)

	Model		
Density	**LogReg**	**MLP**	**CNN**
A	0.50 (0.31, 0.69)	0.55 (0.39, 0.70)	0.87 (0.79, 0.95)
B	0.60 (0.56, 0.64)	0.66 (0.62, 0.70)	0.72 (0.69, 0.76)
C	0.58 (0.54, 0.62)	0.65 (0.61, 0.69)	0.71 (0.67, 0.74)
D	0.74 (0.65, 0.84)	0.80 (0.72, 0.88)	0.89 (0.84, 0.94)



Future Work

1. Can we predict cancer risk directly from BUS images?
2. Are there other risk factors for breast cancer defined on BUS we can estimate with AI?
3. Can we use AI to derive whole breast-level measures of density from BUS?

Mahalo nui loa!

SHEPHERD RESEARCH LAB

AI PRECISION HEALTH INSTITUTE
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AIM AHEAD

#OT2OD032581

References

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Jud SM, Häberle L, Fasching PA, Heusinger K, Hack C, Faschingbauer F, Uder M, Wittenberg T, Wagner F, Meier-Meitinger M, Schulz-Wendtland R, Beckmann MW, Adamietz BR. Correlates of mammographic density in B-mode ultrasound and real time elastography. European Journal of Cancer Prevention. 2012;21(4):343-9.