UNIVERSITY OF HAWAI'I
CANCER CENTER

Adaptation of a Histopathology Foundation AI Model for Cytopathology Interpretation of Breast Cancer to Improve Diagnostic Access

Arianna Bunnell[1,2], Samuel Yang[2], Nusrat Zemi[1], Dustin Valdez[1], Brenda Hernandez[1], Peter Sadowski[2], John Shepherd[1,2]

[1]University of Hawai'i Cancer Center, [2]University of Hawai'i at Mānoa

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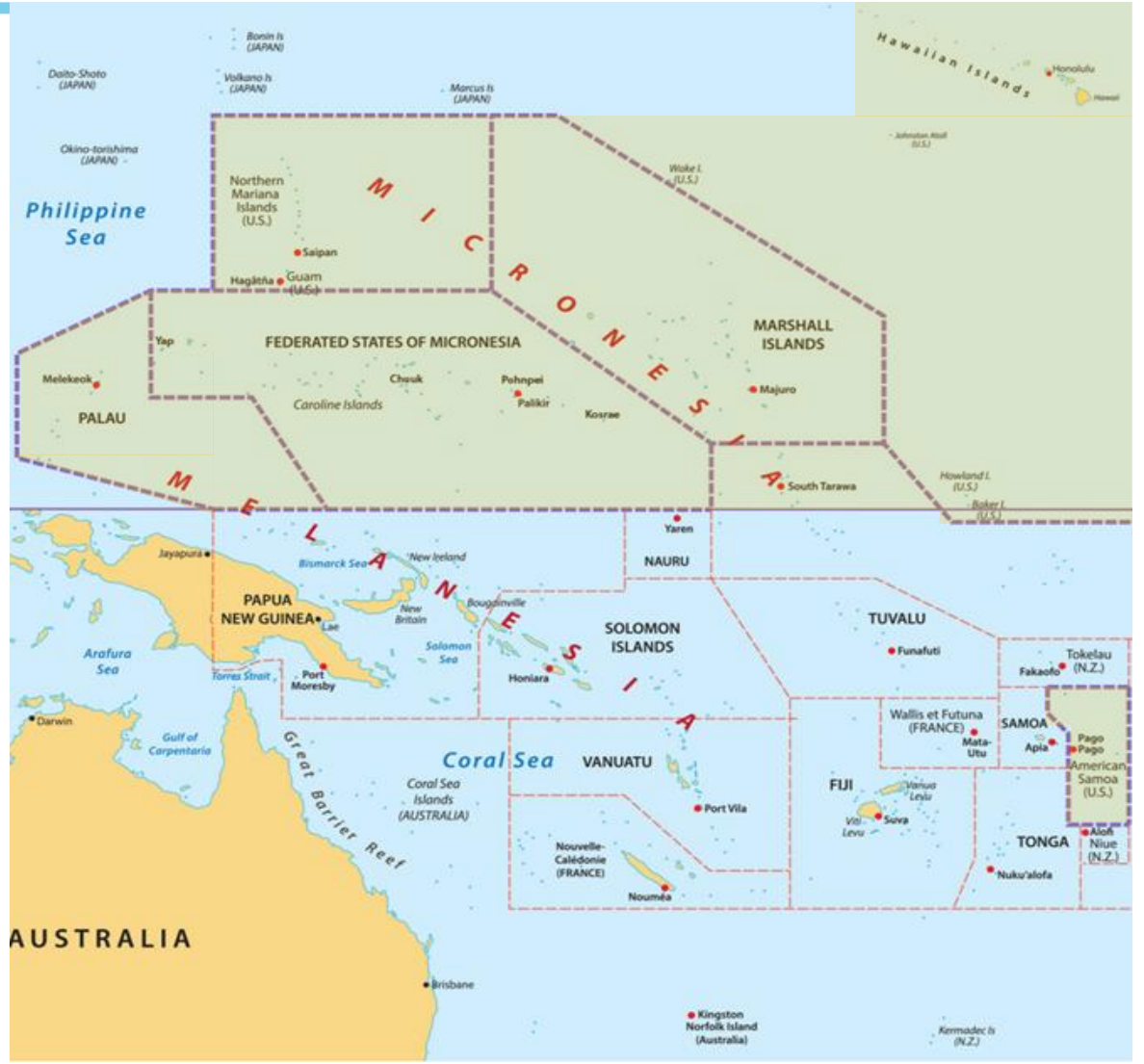
Motivation

University of Hawai‘i Cancer Center Catchment Area

– – – – U.S. Affiliated Pacific Islands

- **Advanced stage breast cancer rates in the Pacific are exceedingly high**, 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 for both lesion detection and FNA guidance.



https://www.123rf.com/profile_rusak

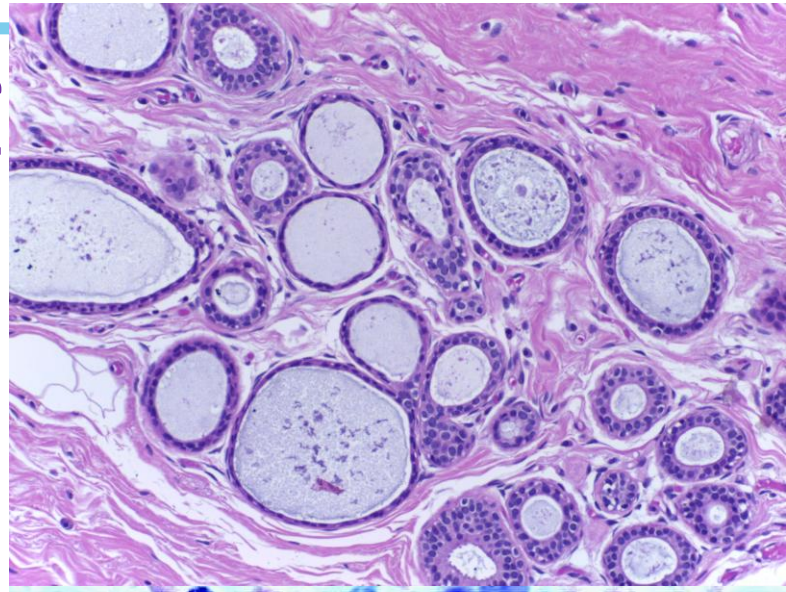
Triple Assessment for Breast Cancer

	Standard of Care	Adaptation for USAPI
1. Clinical Examination	CBE or BSE, combined with symptom evaluation and risk assessment.	CBE or BSE, combined with symptom evaluation and risk assessment.
2. Imaging	Mammography; optional supplemental US or MRI	US
3. Pathological Assessment	Core needle biopsy under US or stereotactic guidance	Fine needle aspiration cytology under US guidance

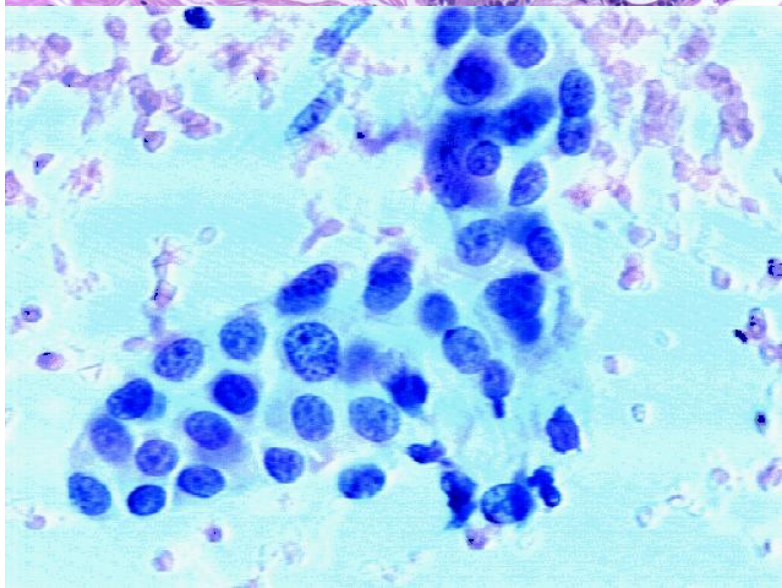
Fine Needle Aspiration Cytology

- FNAC is collected via aspiration of a lesion and smearing of sample onto a slide for examination.
- The sample contains individual cells, not tissue block as in core needle biopsy.
- Can be used to diagnose invasive cancer.
- Collected and examined by a cytotechnologist or pathologist.

Core needle biopsy



Fine needle aspirate



Histology images from Aresta+ (2019). Bach: Grand challenge on breast cancer histology images.

Cytology Assessment

Bedside

Stage 1: ROSE assessment – is the sample adequate?

- Residual background staining
- Cytoplasmic detail
- Nuclear membrane
- Chromatin texture

Stage 2: Pap, Giesma, or H&E stain – is the lesion malignant?

Can we use AI to soften the expertise requirements for cytological assessment?

Problem Statement

Goal: Can the cytotechnologists collecting samples also provide preliminary rule-outs of clearly benign samples with AI assistance?

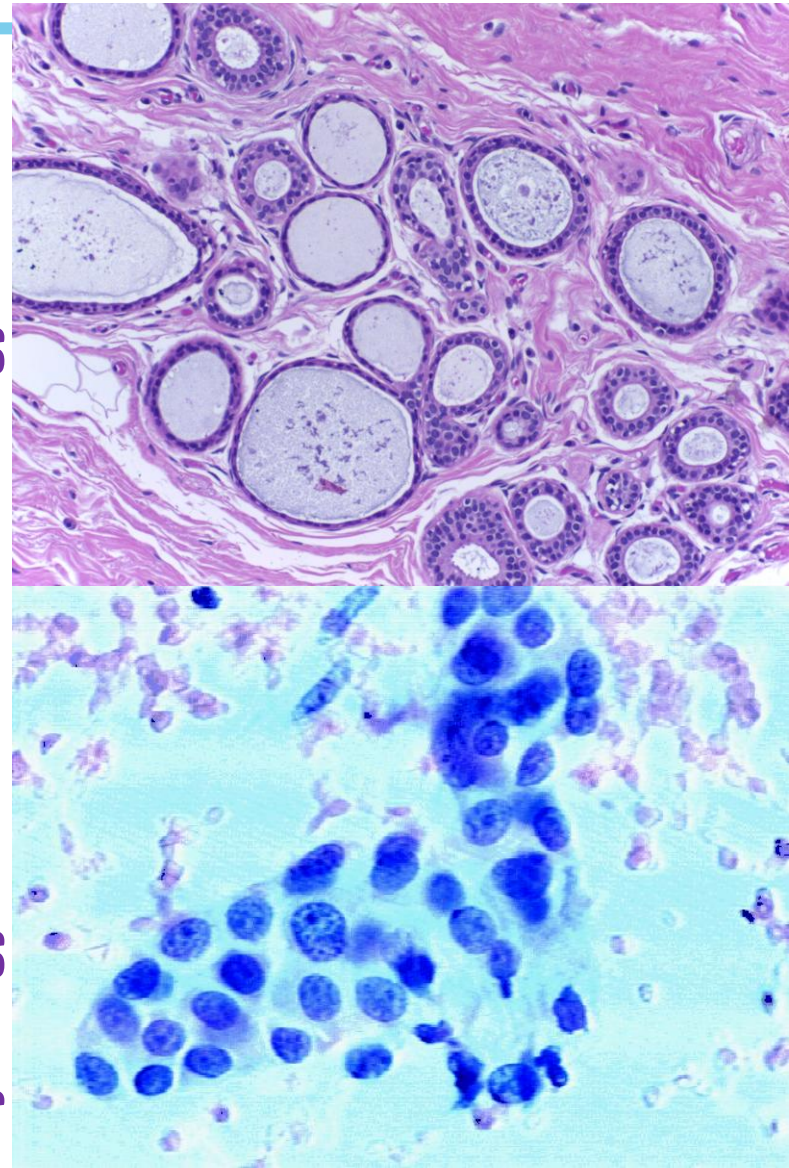
Aim: Determine malignancy of a breast fine needle aspiration cytology smear with AI.

Rationale: Limited telepathology resources and time can be saved for suspicious samples.

Digitized Cytology is Rare!

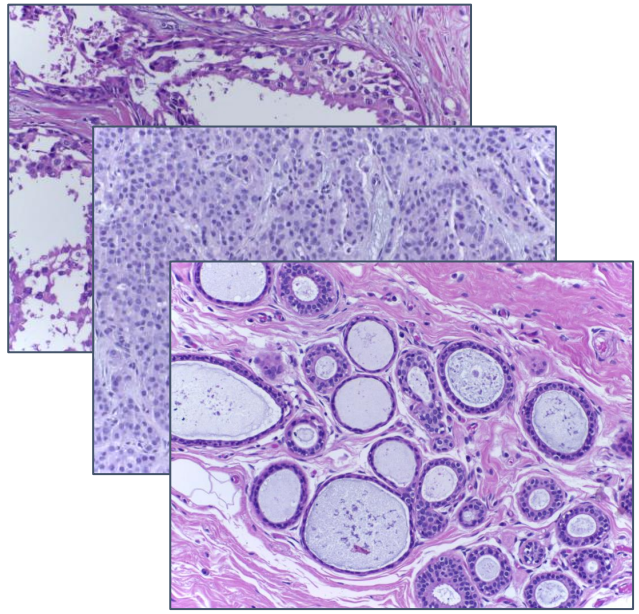
- Cytology smears are not typically digitized or preserved.
- Digital pathology on whole-slide histology images is well-studied – 16 foundation models trained on over 7M whole-slide images.

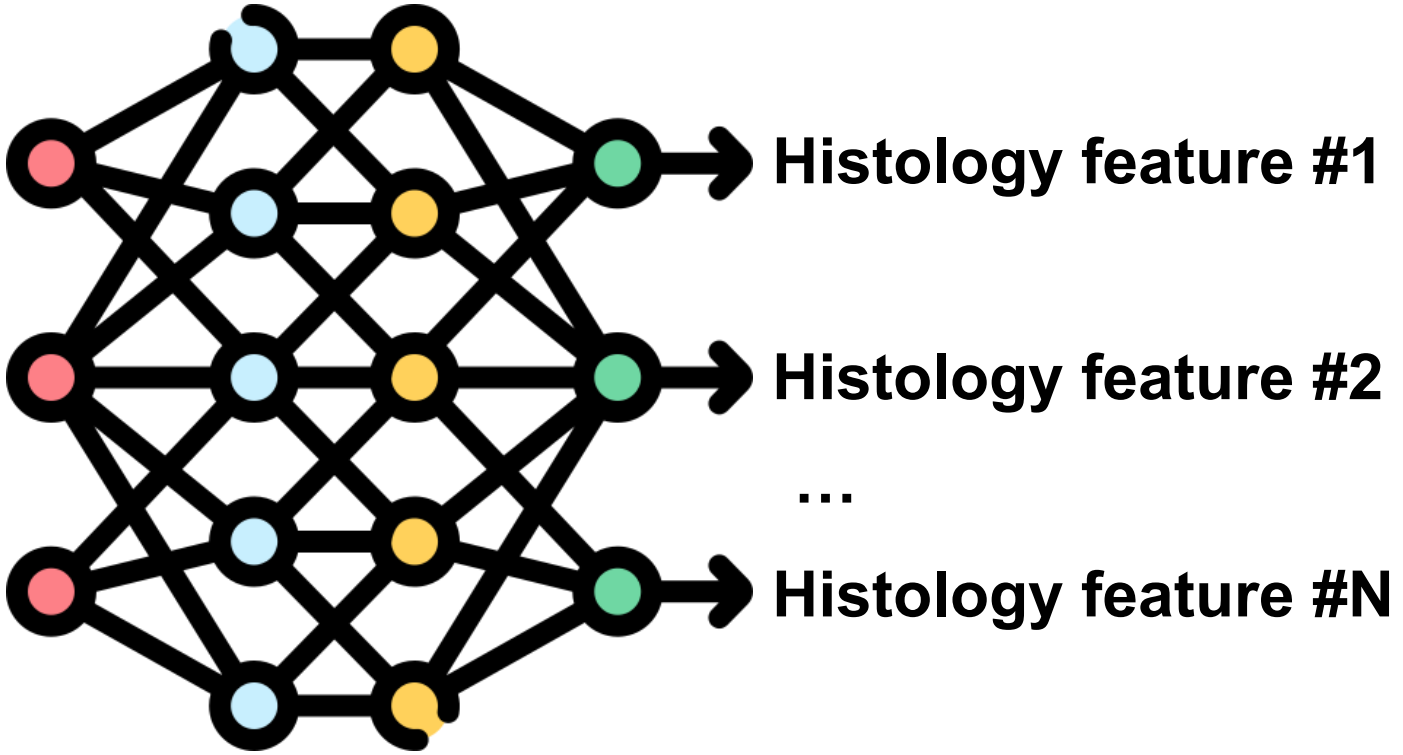
Can we use methods from histology to cope with low data volume in cytology for AI development?



Zimmermann+ (2024) *arXiv:2408.00738*

Adapting a Histology Foundation Model – Virchow2

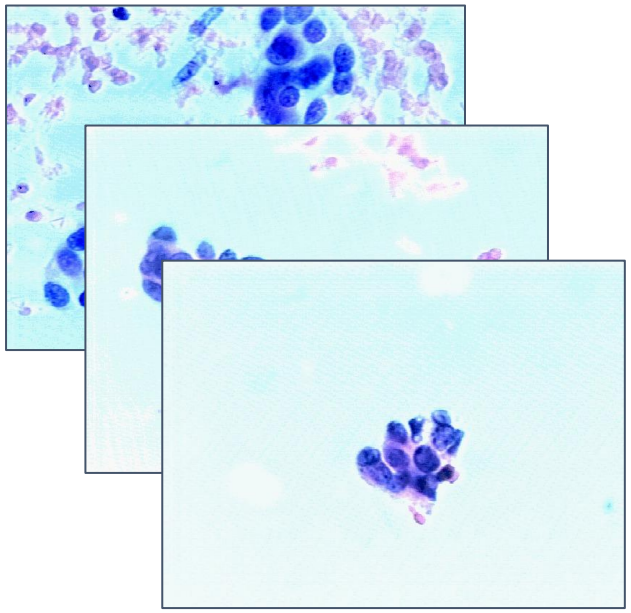


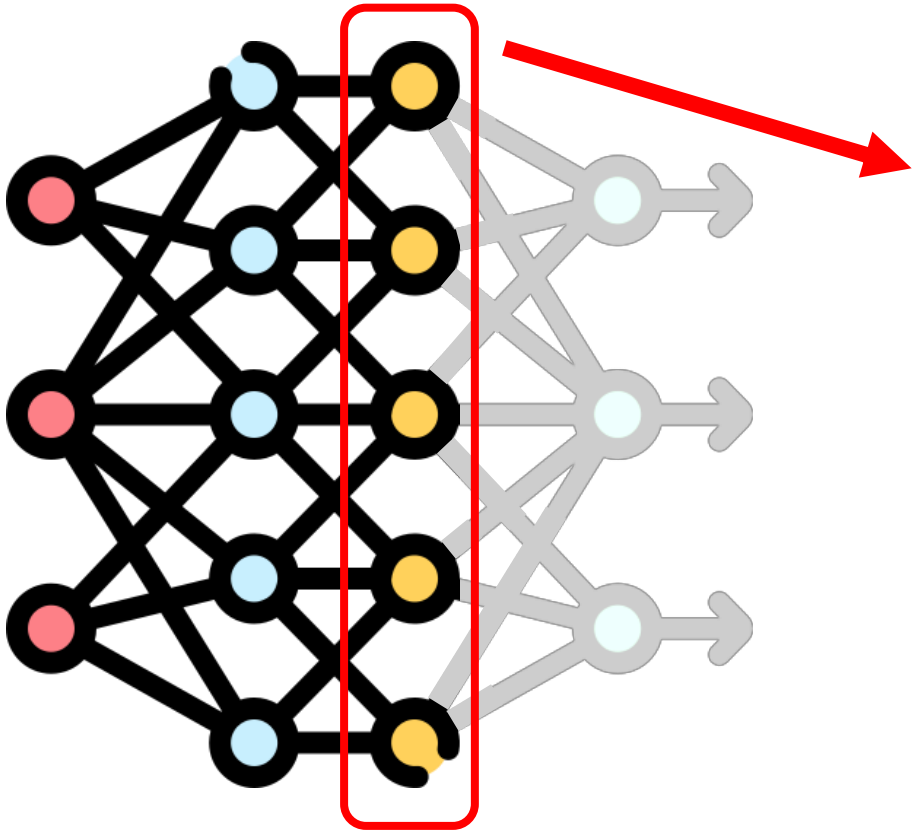


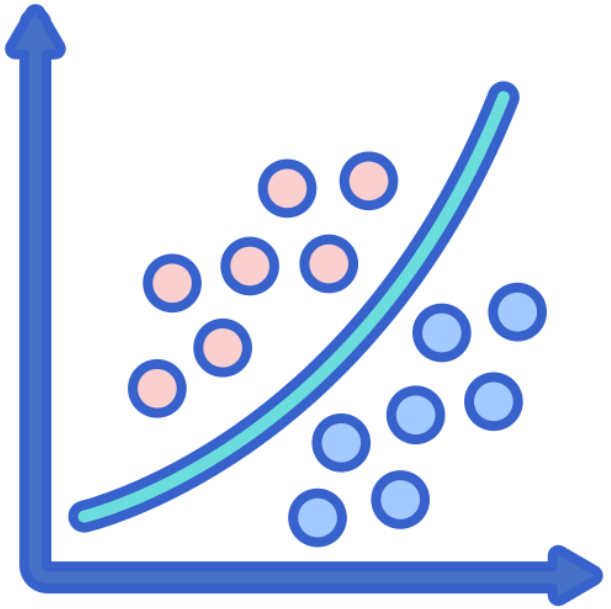
Icons from Freepik- Flaticon

Histology images from Aresta+ (2019). Bach: Grand challenge on breast cancer histology images.

Adapting a Histology Foundation Model – Virchow2







Logistic Regression Classifier

Icons from Freepik- Flaticon

Street+ (1993) *SPIE:10.1117/12.148698*

Zimmermann+ (2024) *arXiv:2408.00738*

Data

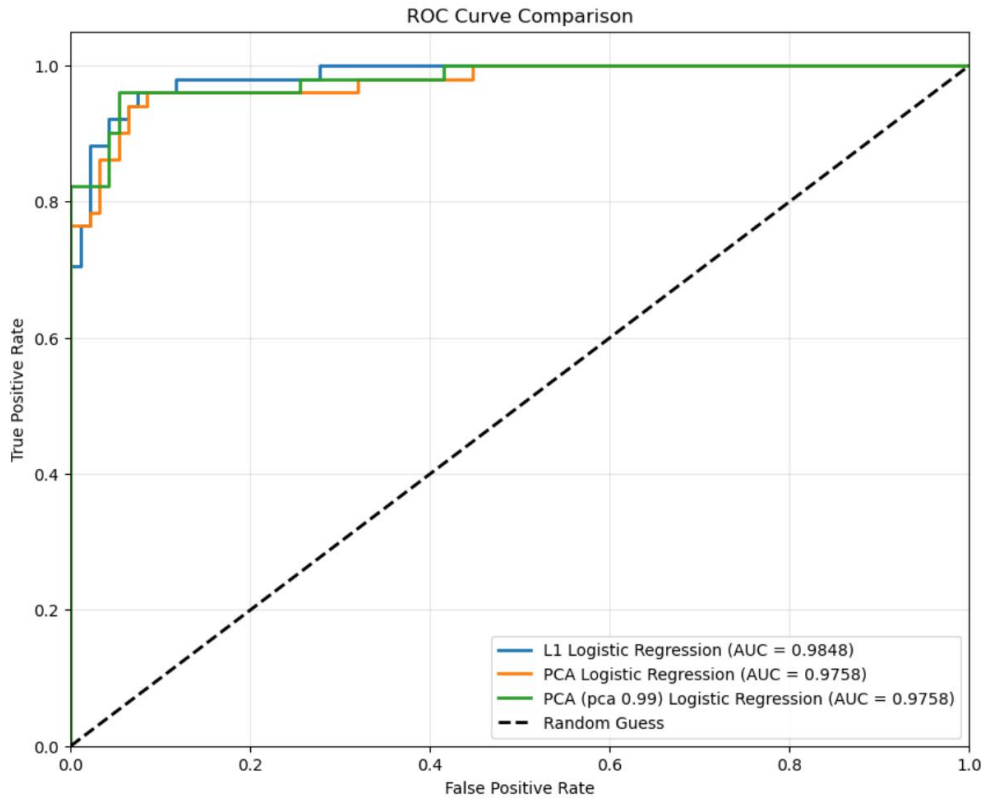
- The data used in this study are sourced from the Wisconsin Diagnostic Breast Cancer Dataset.
- 482 digitized images of smears
  - 312 benign samples
  - 170 malignant samples
- Data were split 70% into training/validation and 30% into testing.
- Hyperparameter and model selection was done via 5-fold CV on the training/validation set.

Street+ (1993) *SPIE:10.1117/12.148698*

Results

- We tested the following models:
  - Decision Tree
  - Logistic regression
  - XGBoost
  - Decision Tree + PCA
  - Logistic regression + PCA
  - XGBoost + PCA

Decreasing interpretability



Results from external test set

The most successful model was logistic regression with L1 regularization which achieved an AUROC of 0.98.

Limitations

- We do not yet have a model or data for Stage 1: ROSE sample adequacy assessment.
- The Wisconsin dataset is highly curated. We don’t know how this model performs on real-world data.
- The features from the histology space are unexplainable.

Mahalo nui loa!

SHEPHERD RESEARCH LAB

Sadowski Group

AI PRECISION HEALTH INSTITUTE
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