



UNIVERSITY OF HAWAI'I  

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CANCER CENTER

# Developing a Data Standardization Pipeline for Evaluation of Mammography AI in Hawaii

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A Cancer Center Designated by the  
National Cancer Institute



# Motivation - Improving Breast Cancer AI for Women in Hawai'i

1. Most breast cancer AI is developed on datasets of White women from the continental US and Europe. **In Hawai'i, we are powered to look at ANHPI subgroups.**
2. Personal growth: Significant opportunity to use computer vision & AI techniques while actively contributing to the project.

BCSC 5-year risk	White N = 91,308	Filipina N = 6,551	Chinese N = 24,051	Japanese N = 2,485
	% of invasive cancers discovered within 5 years			
<1.67% chance of developing cancer in the next 5 years	54	90	93	89
≥1.67% chance of developing cancer in the next 5 years	46	10	7	11





# Modern Breast Radiology & AI

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1. Computer-aided diagnosis and detection systems using artificial intelligence (AI) have transformed breast radiology in recent years.
2. **HOWEVER**, clinical imaging data often contains *necessary* artifacts that hinder accurate algorithmic evaluation.



# Big Ideas & Significance

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✓ Large repository of *clinical* mammogram images for **ANHPI**

✗ Data cleaning → ✗ Reliable verification of AI models with diverse data sets

**REAL LIVES DEPEND ON THIS!!!**



# Research Question & Hypothesis

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**How can we address this lack of standardization in HIPIMR mammograms?**

Our Hypothesis:

**A fully-automatic pipeline for cleaning mammography images can be developed for the HIPIMR.**



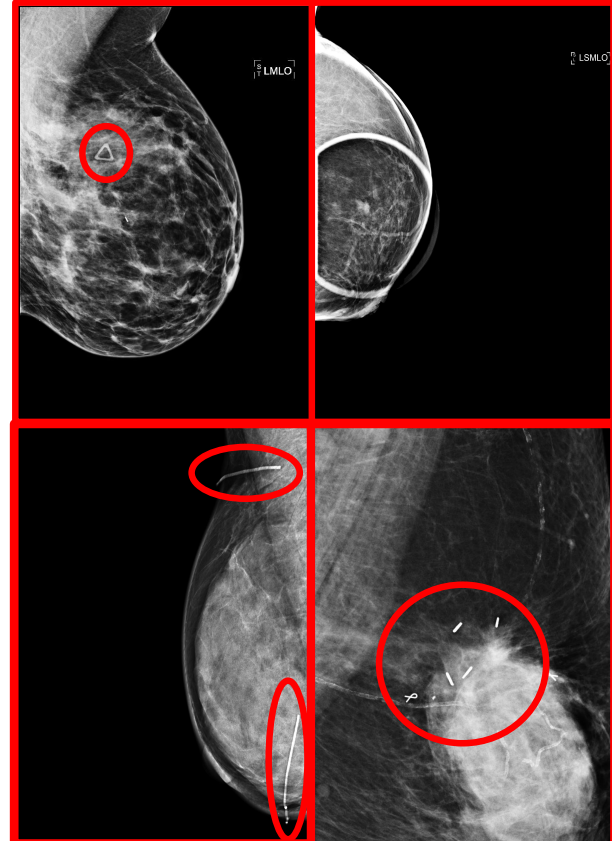
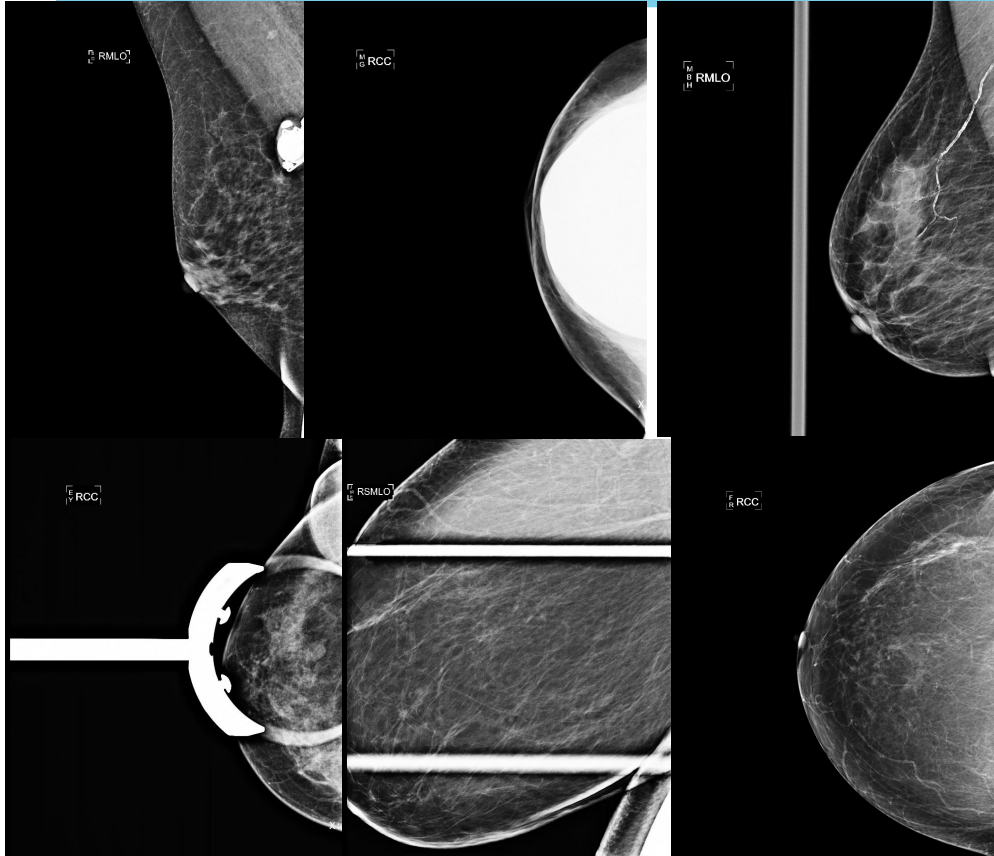
# MammoClean - Project Overview

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- This project focuses on answering how to develop an ***automated pipeline*** for cleaning and standardizing HIPIMR mammograms.
- This project involves:
  - Labelling data with anomalies
  - Developing methods to identify anomalies
    - Computer Vision (CV)
    - Deep Learning



# Anomalous Mammography Types





# Annotations & Labelling

- We annotated our large dataset, individually identifying regions of interest and labelling them respectively by hand.

Project Annotation View Help

Region Shape

Project

Name: via\_project\_19Nov2025\_

All files regular expression

[37]  
[38]  
[39]  
**[40]**  
[41]  
[42]  
[43]  
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[45]  
[46]

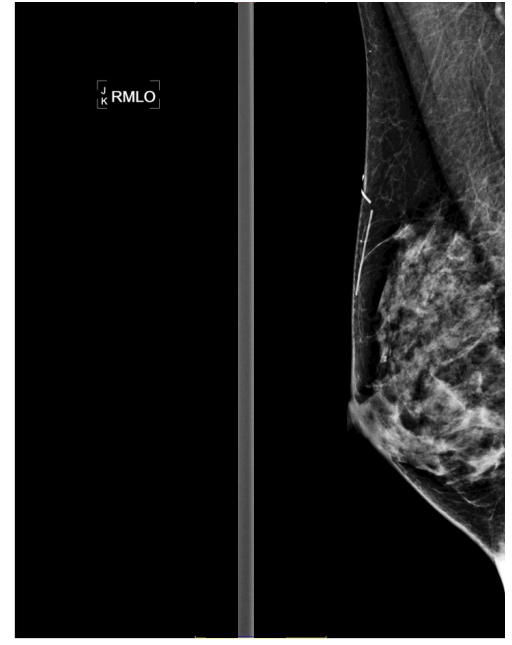
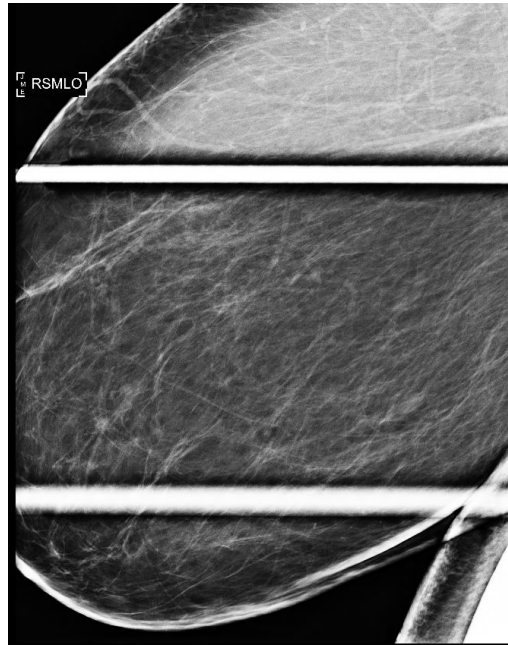
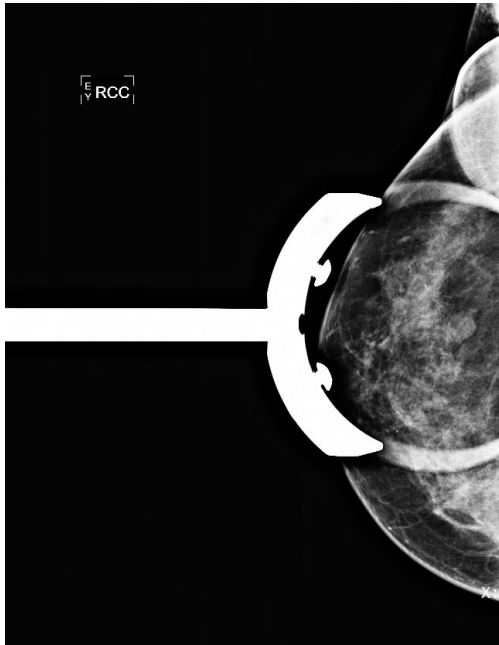
Annotations Other Anomalies

filename	Type of anomaly
p3_xal_dcm_241126_images_8bit/0bd3d244efea7b740a91de1003f61fba17c00041.png	<input type="checkbox"/> Implant <input type="checkbox"/> Compression paddle <input type="checkbox"/> Spot compression paddle <input type="checkbox"/> Small breast compression paddle <input type="checkbox"/> Thyroid shield <input type="checkbox"/> Cardiac device <input type="checkbox"/> Other



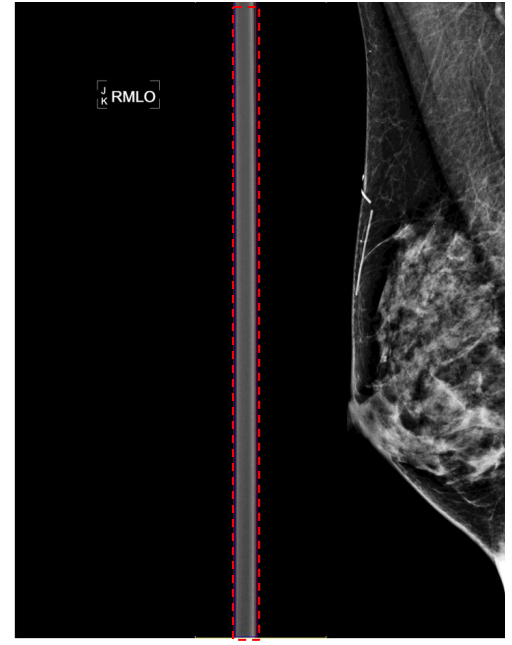
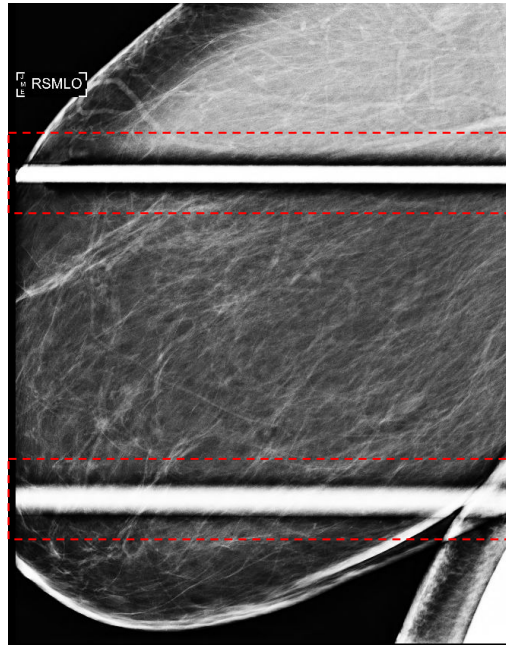
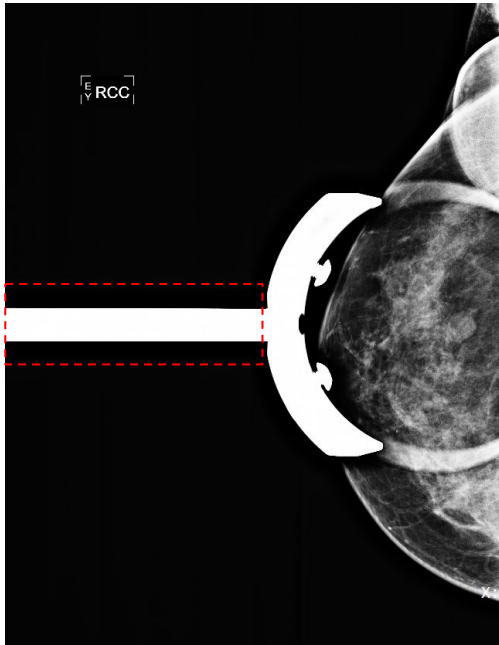
# Computer Vision Methods

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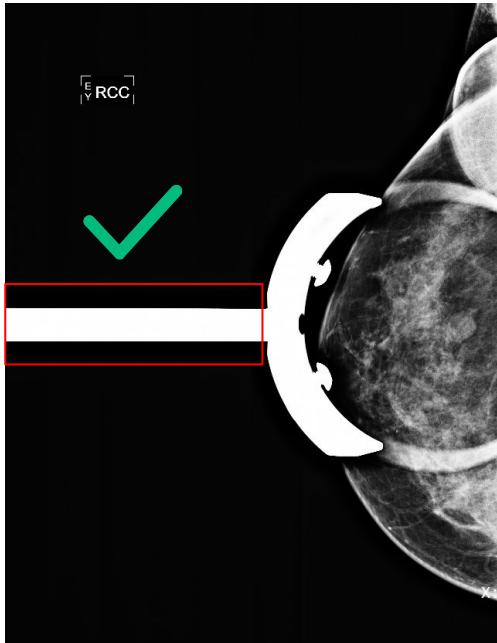
# Computer Vision Methods



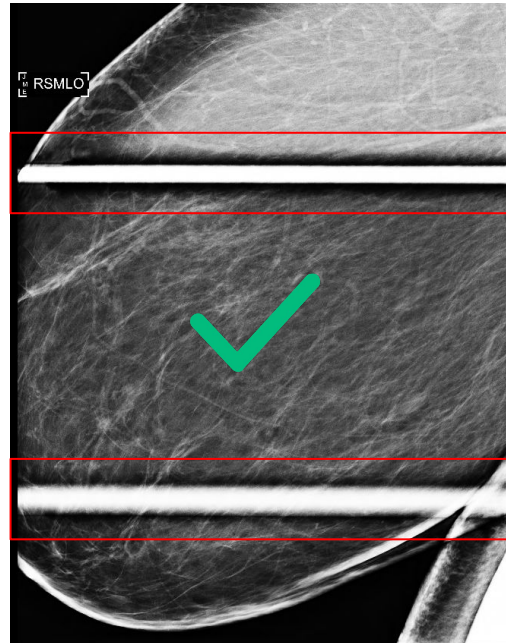


# Computer Vision Methods

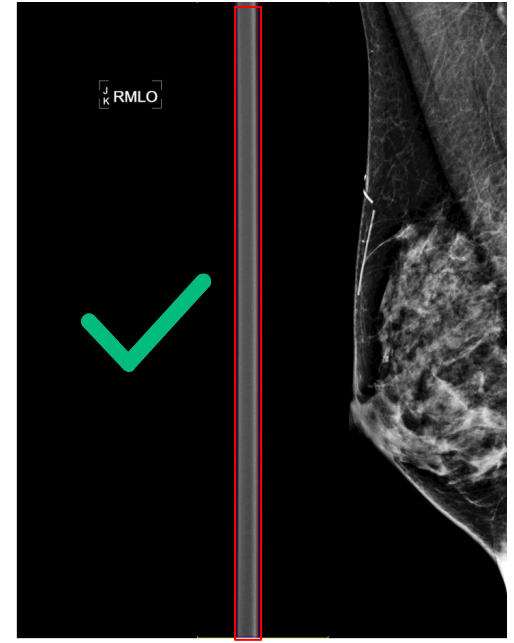
Is it bright?



Is it bright?



Is it straight?



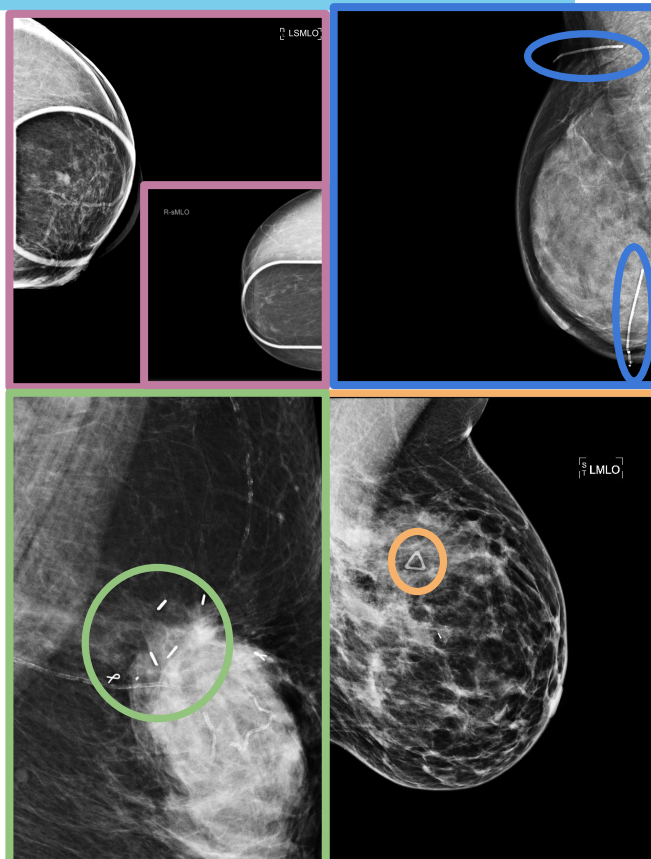


# Deep Learning Methods

- **Granular Anomalies**
  - Palpable lump markers
  - Post biopsy clips
  - Wire Marker
- **Handless spot compression paddles**
  - Traditional & Rectangular

**Problem:** Too heterogeneous to automate using traditional computer vision methods.

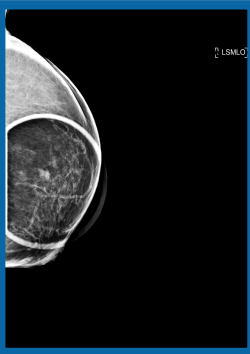
**Solution:** Train a deep learning model to more effectively identify these anomalies.



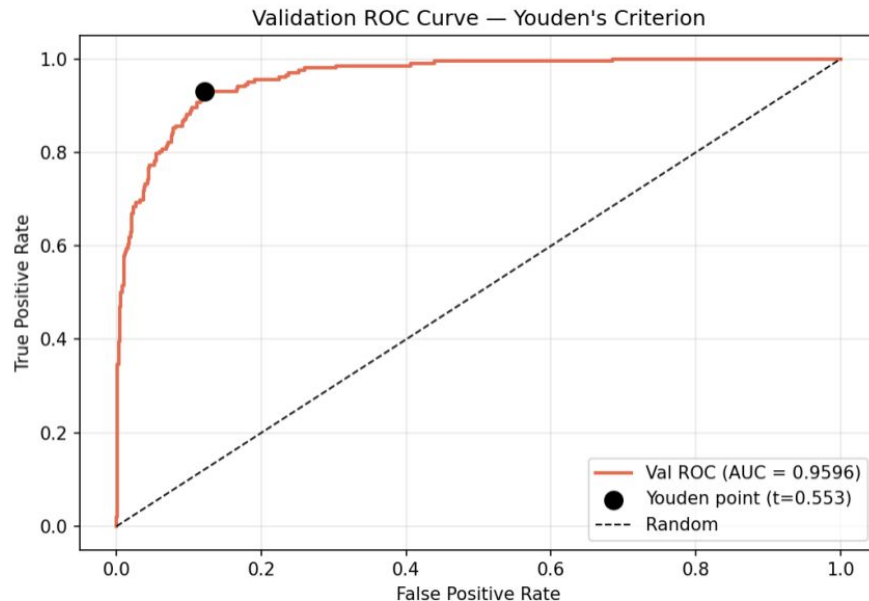


# ResNet50 Spot Compression Model

## A Binary Classification of Spot Compression Paddles



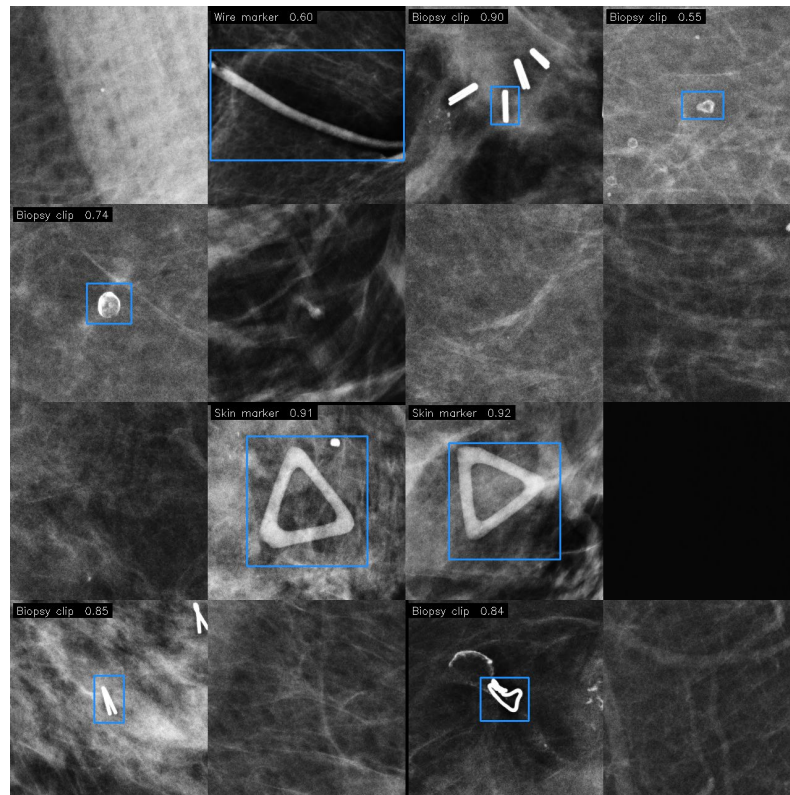
- Trained and compared 4 pre-trained models
  - **ResNet50** achieved the best performance
- Achieved an accuracy of **96.0%**





# Skin Marker & Post Bx Clip Detection Model

- Detection of fine grained anomalies
  - **Post-Biopsy Clips**
  - **Wire Markers**
  - **Skin Markers**
- Trained a **RT-DETR** model
- **97% sensitivity** for skin markers and biopsy clips **81% sensitivity** for wire markers





# Overall Results

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- Performance of the classical CV methods was evaluated on a randomly selected, hand-labeled validation subset of 2,649 images:
  - The CV methods achieved great performance with accuracy and precision **exceeding 95%** for all anomalies.
- The classification model achieved an impressive 96% ROC-AUC score in accurately identifying Spot Compression paddles.
- The detection model achieved a 97% sensitivity for skin markers and post biopsy clips and 81% sensitivity for wire markers.



# Quantitative Performance

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- Performance metrics of the MammoClean pipeline by artifact category on the validation set.
- Best results are highlighted in bold.

<b>Artifact Type</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-Score</b>	<b>Balanced Acc</b>	<b>MCC</b>
Spot Compression	1.00	0.71	0.83	0.85	0.81
Regular Paddle	<b>1.00</b>	0.97	0.98	0.98	0.98
Small Breast Paddle	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Breast Implants	0.96	0.79	0.87	0.90	0.87

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# Conclusion

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- **MammoClean:**
  - **Rule-based computer vision.**
    - Transparent and explainable method.
  - **Deep Learning methods** for more difficult anomalies.
  - **Near-perfect detection** for standard compression artifacts.
- A dataset of 9,000 labelled mammograms to train & validate AI models specifically for **ANHPI** women.
  - Addresses critical limitation where mammograms of ANHPI women are not typically included in training.



# Acknowledgement

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## Undergraduate Research Opportunities Program

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Office of the Vice Provost for Research & Scholarship  
University of Hawai'i at Mānoa





# References

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- Gary Bradski. The opencv library. *Dr. Dobb's Journal of Software Tools*, 25(11):120–123, 2000. 3
- Arianna Bunnell, Kailee Hung, John A. Shepherd, and Peter Sadowski. Busclean: Open-source software for breast ultrasound image pre-processing and knowledge extraction for medical ai. *PLOS ONE*, 19(12):e0315434, 2024. 2
- B.N. Hellquist et al. Effectiveness of population-based service screening with mammography for women ages 40 to 49 years: Evaluation of the swedish mammography screening in young women (scry) cohort. *Cancer*, 117(4):714–722, 2011. 1
- Epimack Michael et al. Breast cancer segmentation methods: Current status and future potentials. *BioMed Research International*, 2021:9962109, 2021. 1
- Vaijyanthi Nagarajan et al. Feature extraction based on empirical mode decomposition for automatic mass classification of mammogram images. *Medicine in Novel Technology and Devices*, 1:100004, 2019. 1
- Ziad Obermeyer, Brian Powers, Christine Vogeli, and Sendhil Mullainathan. Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464): 447–453, 2019. 1, 5
- S.J. Otto et al. Mammography screening and risk of breast cancer death: a population-based case-control study. *Cancer Epidemiology, Biomarkers & Prevention*, 21(1):66–73, 2012. 1
- Said Pertuz et al. Open framework for mammography-based breast cancer risk assessment. In *2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, pages 1–4. IEEE, 2019. 1
- Laszlo Tabar et al. Swedish two-county trial: impact of mammographic screening on breast cancer mortality during 3 decades. *Radiology*, 260(3):658–663, 2011. 1
- World Health Organization. Breast cancer. <https://www.who.int/news-room/fact-sheets/detail/breast-cancer>, 2025. Accessed: 2025-10-15. 1