CUSTOMIZATION OF AI-BASED BREAST CANCER RISK MODELS FOR VALIDATION IN AANHPI WOMEN

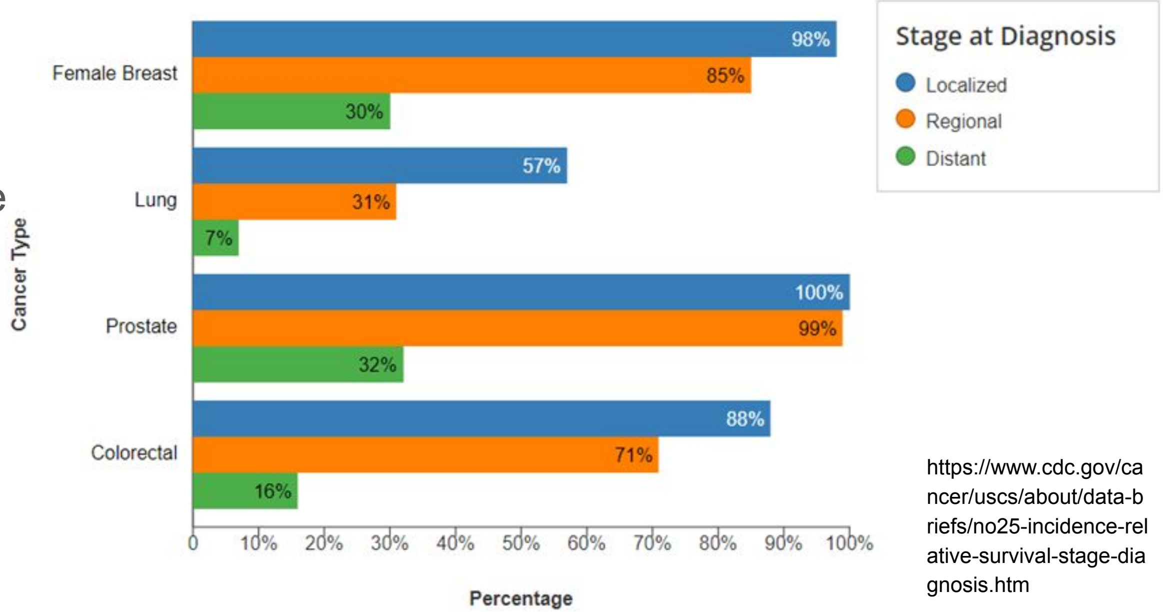
MARC
at UH MĀNOA
Maximizing Access to Research Careers

Cade Kane
SURE Symposium 2024

Breast Cancer Risk Assessment

- Ultimate goal: catch breast cancer earlier, when there’s a higher chance of survival for the patient.
- 5-year or lifetime risk assessments

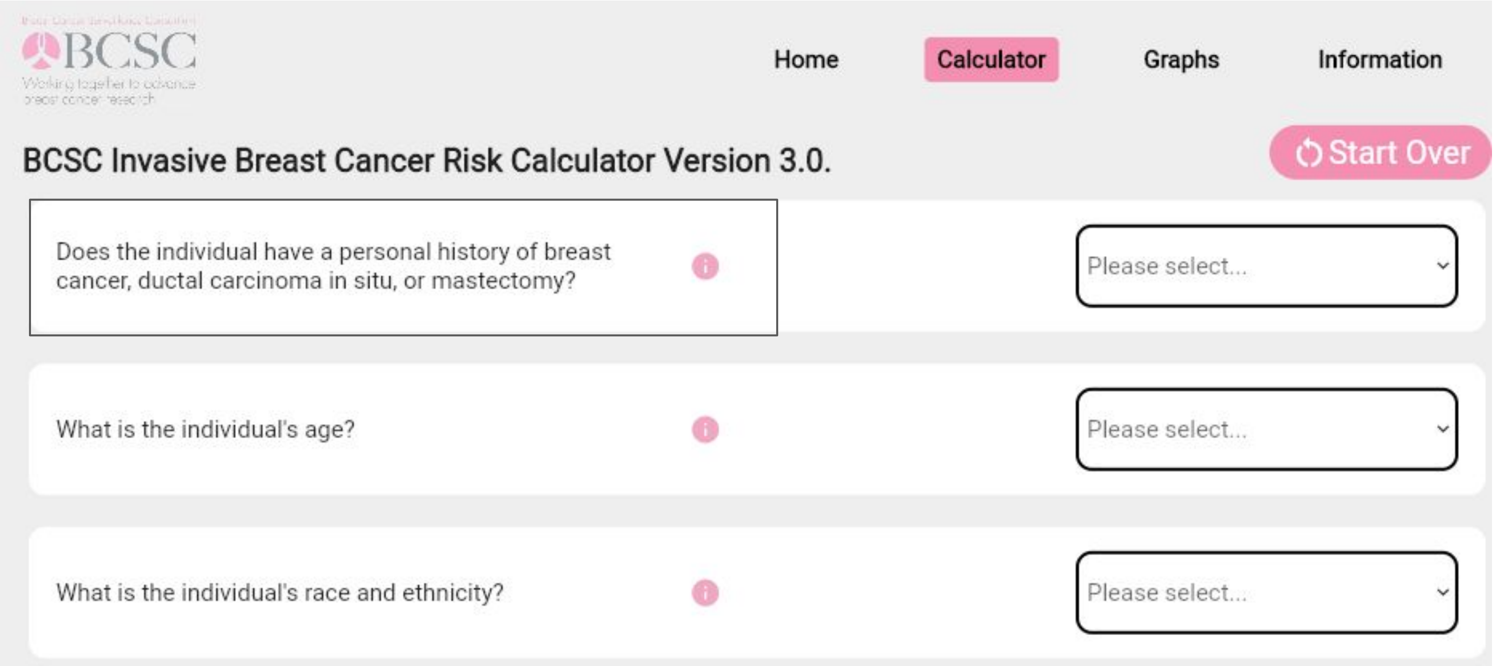
5-year relative survival estimates the percentage of cancer patients who will have **not** died from their cancer **5 years** after diagnosis



https://www.cdc.gov/cancer/uscs/about/data-briefs/no25-incidence-relative-survival-stage-diagnosis.htm

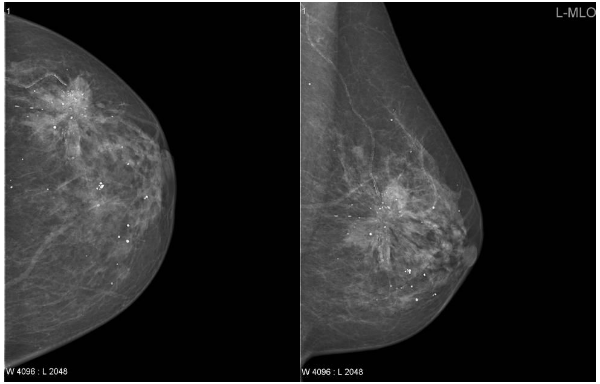
Clinical Breast Cancer Risk

- Demographics and clinical risk factors only
- Can be extended polygenic risk scores



Mammography

- Mammography is the recommended primary breast cancer screening modality for women in the U.S.
- Mammography consists of a low-dose x-ray of the breast tissue
- Mammography has four views: R-CC, R-MLO, L-CC, L-MLO

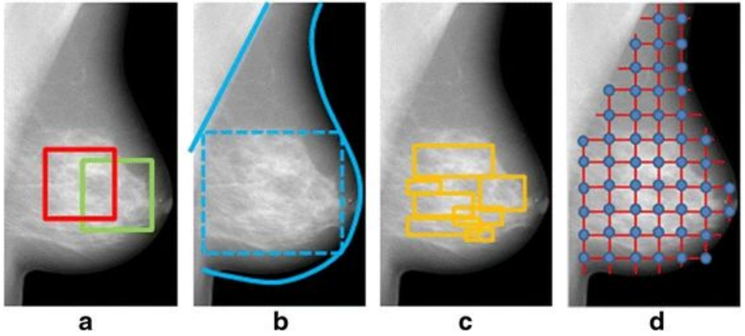


L-CC L-MLO

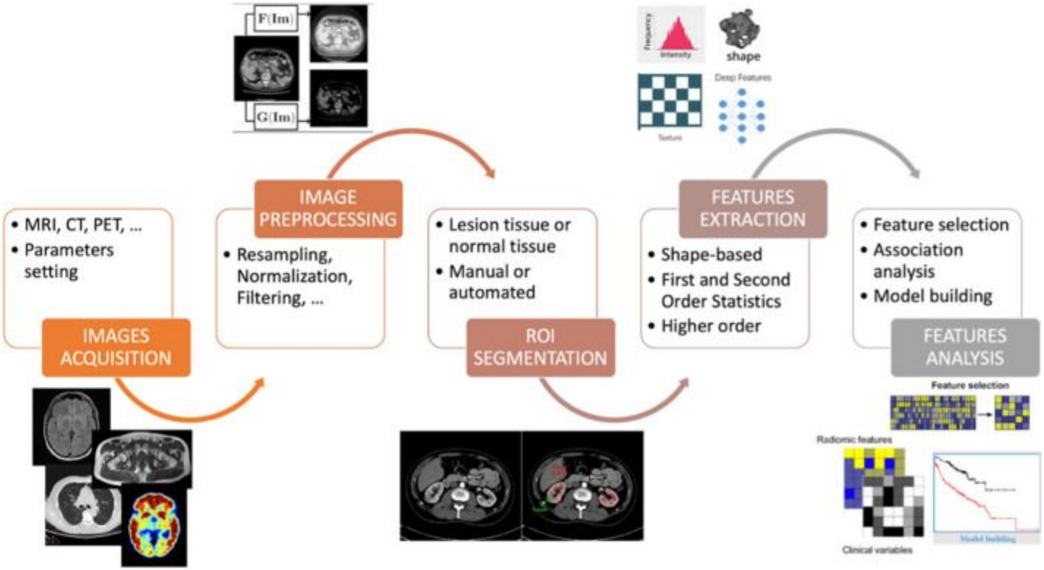
(Radswiki, 2011)

Breast Cancer Risk with Radiomics/AI

- BC risk can be found from radiomics through calculation of traditional computer vision features or AI-derived features from breast imaging.



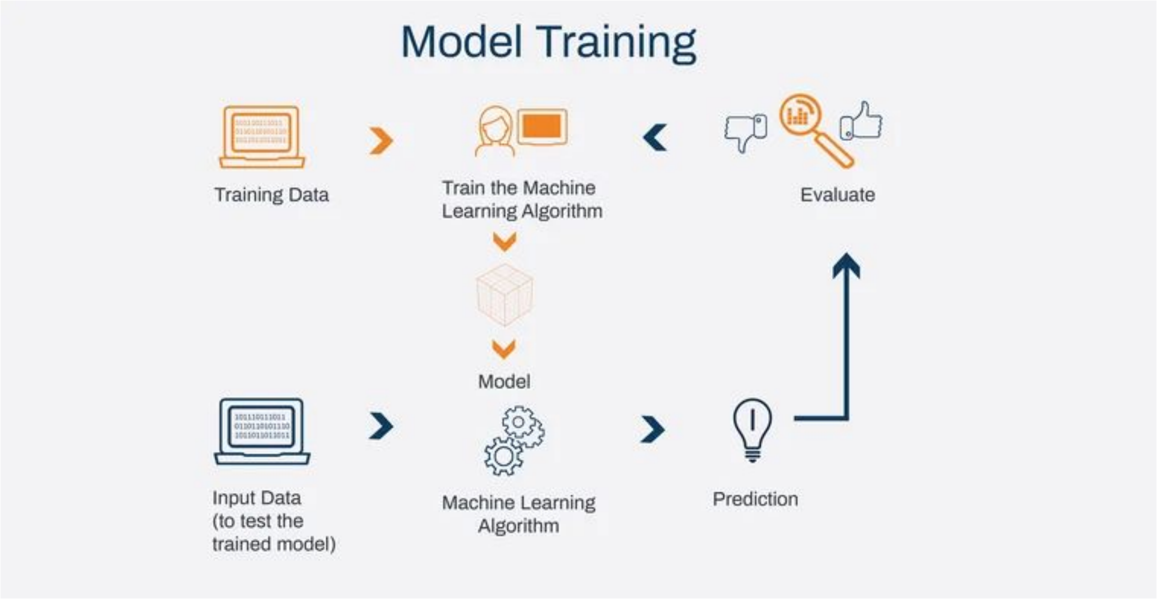
(Pertuz et al., 2019)



(Scapicchio et al., 2021)

Machine Learning and AI in Breast Cancer Risk Prediction

- Pattern recognition → *Learning patterns and features*
- A trained model can be given NEW data to evaluate its performance



(Chaitanya, n.d.)

Breast Cancer Risk by Ethnicity/Race

- Due to high proportion of women of Asian descent in HI we can **disaggregate** the “**AANHPI**” ethnicity group into **specific subgroups**: i.e., Japanese, Chinese, etc.
- In HI we have populations which aren’t seen in statistically significant numbers on the continental US (NHPI), allowing us to do **subgroup analysis**.

BCSC 5-year risk	White N=91,308	Filipina N=6,551	Chinese N=24,051	Japanese N=2,485
	Invasive cancers %			
<1.67%	54	90	93	89
≥1.67%	46	10	7	11

UCSF breast cancer surveillance consortium risk model

Overall Problem Statement

Examine clinical and radiomic risk factors (family history of breast cancer, BMI, BI-RADS breast density) and their association with breast cancer risk in women undergoing breast cancer screening by **Asian and Native Hawaiian/Pacific Islander** ancestry <u>compared</u> to non-Hispanic **White**, non-Hispanic **Black**, and **Hispanic** women.

Hawaii & Pacific Islands Mammography Registry (HIPIMR)

- Collects breast imaging and breast health information (2009-present)

- Linked to the Hawaiʻi Tumor Registry to identify cases

- Consist of imaging, metadata, clinical variables, patient characteristics, and biopsy-confirmed cancer status

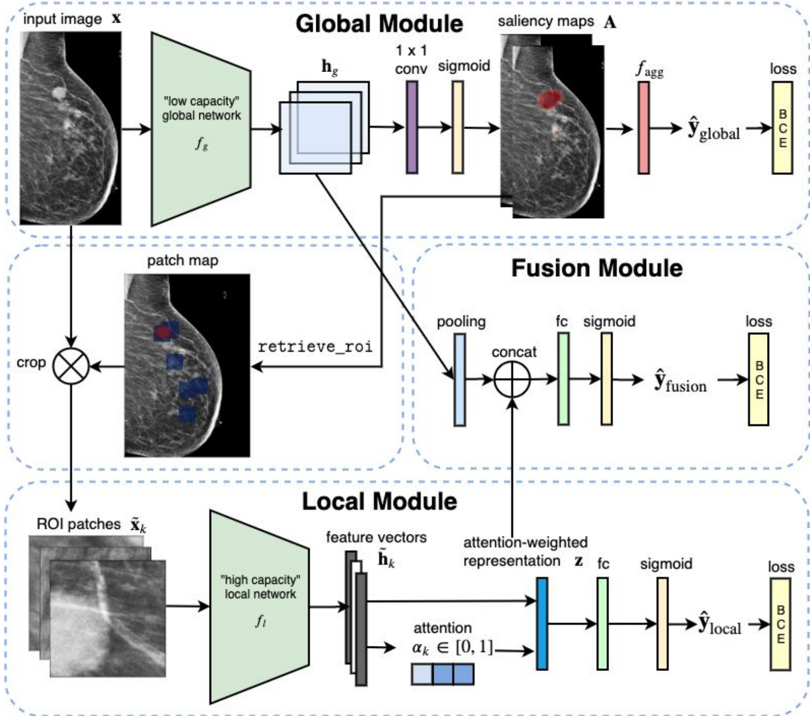
Model	***Required Views***	***Processed or Raw***	***File Format***
Transpara	R/L MLO/CC	Processed	DICOM or JPEG
iCAD (ProFound AI)	R/L MLO/CC	Processed (Dimensions)	DICOM
Malkov Features	R/L CC	Processed	PNG
OpenBreast	R/L MLO/CC	Processed	DICOM
CaPTk	Any	Processed or Raw	DICOM
LIBRA	Any	Processed or Raw	DICOM
Geras Density	R/L MLO/CC	Processed	PNG
Xun	R/L MLO/CC	Raw (Proc2Pres)	DICOM
Mirai	R/L MLO/CC	Processed	DICOM or PNG
Geras Classifier (GMIC)	R/L MLO/CC	Processed	PNG
RADIFUSION	R/L MLO/CC	Processed	DICOM

An interpretable classifier for high-resolution breast cancer screening images utilizing weakly supervised localization

Yiqiu Shen[a], Nan Wu[a], Jason Phang[a], Jungkyu Park[a], Kangning Liu[a], Sudarshini Tyagi[d], Laura Heacock[b,e], S. Gene Kim[b,c,e], Linda Moy[b,c,e], Kyunghyun Cho[a,d,f], Krzysztof J. Geras[b,c,a]

- GMIC: globally-aware multiple instance classifier

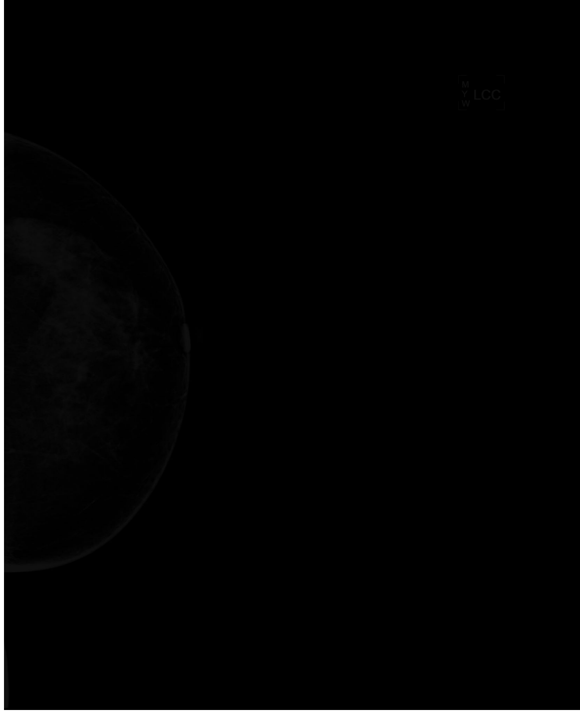
- Input: mammogram PNG + exam list
- Output: cropped mammograms, probability of malignant and benign



GMIC Pipeline Alterations

- Preprocessing:
  - DICOM conversion to PNG format
    - Bit difference 12 bit vs. 16 bit
  - CSV conversion to exam list

- Wrapper script
  - Base directory
  - DICOM directory
  - Path to CSV



Mammogram

CSV Input Data Example

Image_file	ANALYSIS_ID	CANCER_STATUS	ViewPosition	ImageLaterality	StudyInstanceUID	Visit
1.2.840.114191.6.!	100685956	0	CC	R	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100685956	0	CC	L	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100685956	0	MLO	L	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100685956	0	MLO	R	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100689996	1	CC	R	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100689996	1	MLO	L	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100689996	1	CC	L	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100689996	1	MLO	R	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100689996	1	MLO	R	1.2.840.114191.6.9(	1
1.2.840.114191.6.!	100689996	1	MLO	L	1.2.840.114191.6.9(	1
1.2.840.114191.6.!	100689996	1	CC	L	1.2.840.114191.6.9(	1
1.2.840.114191.6.!	100689996	1	CC	R	1.2.840.114191.6.9(	1
1.2.840.114191.6.!	100985944	0	CC	R	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100985944	0	CC	L	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100985944	0	MLO	L	1.2.840.114191.6.9(	0
1.2.840.114191.6.!	100985944	0	MLO	R	1.2.840.114191.6.9(	0

GMIC Pipeline Results Example

image_index	benign_pred	malignant_pred	benign_label	malignant_label
0_L-CC	0.1356	0.0081	0	0
0_R-CC	0.8928	0.3259	1	0
0_L-MLO	0.2368	0.0335	0	0
0_R-MLO	0.9509	0.1812	1	0
1_L-CC	0.0508	0.0144	0	0
1_R-CC	0.5679	0.9965	0	1
1_L-MLO	0.0545	0.0154	0	0
1_R-MLO	0.4722	0.7178	0	1
2_L-CC	0.0746	0.016	0	0
2_R-CC	0.3551	0.0884	1	0
2_L-MLO	0.0953	0.0086	0	0
2_R-MLO	0.2267	0.0395	1	0
3_L-CC	0.6162	0.8992	0	1
3_R-CC	0.2945	0.2116	0	0
3_L-MLO	0.6677	0.722	0	1

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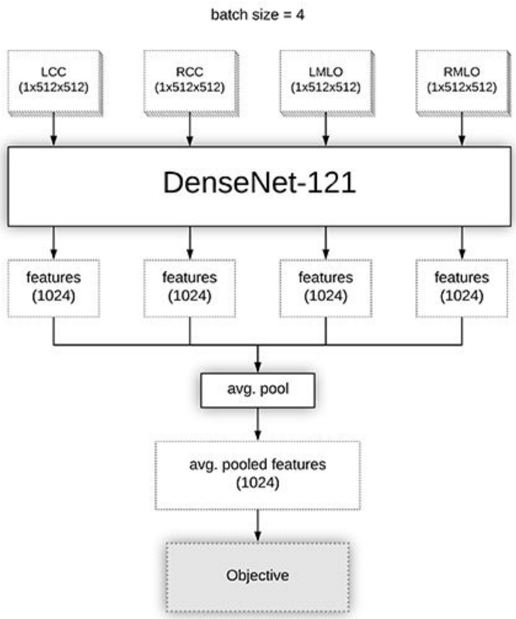
1_L-CC	0.0508	0.0144	0	0
1_R-CC	0.5679	0.9965	0	1
1_L-MLO	0.0545	0.0154	0	0
1_R-MLO	0.4722	0.7178	0	1
2_L-CC	0.0746	0.016	0	0
2_R-CC	0.3551	0.0884	1	0
2_L-MLO	0.0953	0.0086	0	0
2_R-MLO	0.2267	0.0395	1	0
3_L-CC	0.6162	0.8992	0	1
3_R-CC	0.2945	0.2116	0	0
3_L-MLO	0.6677	0.722	0	1
3_R-MLO	0.0722	0.0303	0	0

Deep Learning Predicts Interval and Screening-detected Cancer from Screening Mammograms: A Case-Case-Control Study in 6369 Women

Xun Zhu, Thomas K. Wolfgruber, Lambert Leong, Matthew Jensen, Christopher Scott, Stacey Winham, Peter Sadowski, Celine Vachon, Karla Kerlikowske, John A. Shepherd

- Interval-based breast cancer
- Clinical factors
- Engineering differences (Xun uses Proc2Pres)

A



Xun Pipeline Alterations

- Preprocessing
  - Adjusting CSV column names and paths
  - Add acquisition_date and acquisition_time to patient metadata’
  - Use patient_id_acq_time as the unique identifier

- Convolutional Neural Network (CNN) Model
  - Use a MyDenseNet object that Arianna wrote instead of Xun’s code

CSV Input Example for Xun

path_to_dicom	patient_id	CANCER_STATUS	view_position	image_laterality	dicom_id	Visit	acquisition_date	acquisition_time
/mnt/srl-oahu-1/disk/a	100685956	0	CC	R	1.2.840.114191	0	20200612	152301
/mnt/srl-oahu-1/disk/a	100685956	0	CC	L	1.2.840.114191	0	20200612	152301
/mnt/srl-oahu-1/disk/a	100685956	0	MLO	L	1.2.840.114191	0	20200612	152301
/mnt/srl-oahu-1/disk/a	100685956	0	MLO	R	1.2.840.114191	0	20200612	152301
/mnt/srl-oahu-1/disk/a	100689996	1	CC	R	1.2.840.114191	0	20210713	105623
/mnt/srl-oahu-1/disk/a	100689996	1	MLO	L	1.2.840.114191	0	20210713	105623
/mnt/srl-oahu-1/disk/a	100689996	1	CC	L	1.2.840.114191	0	20210713	105623
/mnt/srl-oahu-1/disk/a	100689996	1	MLO	R	1.2.840.114191	0	20210713	105623
/mnt/srl-oahu-1/disk/a	100689996	1	MLO	R	1.2.840.114191	1	20221025	90505
/mnt/srl-oahu-1/disk/a	100689996	1	MLO	L	1.2.840.114191	1	20221025	90505
/mnt/srl-oahu-1/disk/a	100689996	1	CC	L	1.2.840.114191	1	20221025	90505
/mnt/srl-oahu-1/disk/a	100689996	1	CC	R	1.2.840.114191	1	20221025	90505
/mnt/srl-oahu-1/disk/a	100985944	0	CC	R	1.2.840.114191	0	20170203	131502
/mnt/srl-oahu-1/disk/a	100985944	0	CC	L	1.2.840.114191	0	20170203	131502
/mnt/srl-oahu-1/disk/a	100985944	0	MLO	L	1.2.840.114191	0	20170203	131502
/mnt/srl-oahu-1/disk/a	100985944	0	MLO	R	1.2.840.114191	0	20170203	131502

Xun Output Example

patient_id_acq_time	label	group	LCC	RCC	LMLO	RMLO	n_dicoms	prob_cancer
100685956_152301	0	test	1.2.840.	1.2.840.1	1.2.840.11	1.2.840.114	4	0.19794065
100689996_105623	1	test	1.2.840.	1.2.840.1	1.2.840.11	1.2.840.114	4	0.11494599
100689996_90505	1	test	1.2.840.	1.2.840.1	1.2.840.11	1.2.840.114	4	0.14777811
100985944_131502	0	test	1.2.840.	1.2.840.1	1.2.840.11	1.2.840.114	4	0.14504619

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- Arianna Bunnell

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References

Shen, Y., Wu, N., Phang, J., Park, J., Liu, K., Tyagi, S., Heacock, L., Kim, S. G., Moy, L., Cho, K., & Geras, K. J. (2021). An interpretable classifier for high-resolution breast cancer screening images utilizing weakly supervised localization. *Medical Image Analysis*, *68*, 101908. https://doi.org/10.1016/j.media.2020.101908

Zhu, X., Wolfgruber, T. K., Leong, L., Jensen, M., Scott, C., Winham, S., Sadowski, P., Vachon, C., Kerlikowske, K., & Shepherd, J. A. (2021). Deep Learning Predicts Interval and Screening-detected Cancer from Screening Mammograms: A Case-Case-Control Study in 6369 Women. *Radiology*, *301*(3), 550–558. https://doi.org/10.1148/radiol.2021203758

Images Cited

Chaitanya, N. (n.d.). *Critical steps to training and evaluating AI and ML models*. Retrieved July 31, 2024, from https://www.columbusglobal.com/en/blog/critical-steps-to-training-and-evaluating-ai-and-ml-models

Pacifici S, Murphy A, Hacking C, et al. Mediolateral oblique view. Reference article, Radiopaedia.org (Accessed on 30 Jul 2024) https://doi.org/10.53347/rID-15338

Pertuz, S., Torres, G. F., Tamimi, R., & Kamarainen, J. (2019). Open Framework for Mammography-based Breast Cancer Risk Assessment. *2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, 1–4. https://doi.org/10.1109/BHI.2019.8834599

Scapicchio, C., Gabelloni, M., Barucci, A., Cioni, D., Saba, L., & Neri, E. (2021). A deep look into radiomics. *La Radiologia Medica*, *126*(10), 1296–1311. https://doi.org/10.1007/s11547-021-01389-x

Mahalo!
Questions?

BREAST DENSITY CLASSIFICATION WITH DEEP CONVOLUTIONAL NEURAL NETWORKS

Nan Wu[1], *Krzysztof J. Geras*[1], *Yiqiu Shen*[1], *Jingyi Su*[1], *S. Gene Kim*[3,4], *Eric Kim*[3], *Stacey Wolfson*[3], *Linda Moy*[3,4] & *Kyunghyun Cho*[1,2]