The TOMMY Study:
Understanding the Value of Digital breast Tomosynthesis using Machine Learning

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Main Objectives

- **We aim at using machine learning and data from TOMMY trial to answer the following questions…**

Which women benefit the most from DBT imaging?
Age and **breast** density groups

How does breast density affect the informativeness of DBT imaging for different age groups?

What is the informativeness of DBT for different types of lesions?

Background

- **Limitations of standard 2D mammography:** overlapping dense Fibroglandular tissue can decrease visibility of malignant abnormalities or simulate the appearance of an abnormality.

Negative impact on:

Sensitivity

False negatives

15–30% of cancers are not detected by standard screening.

Worse for women aged under **50 years** and in women with **dense** breasts

Specificity

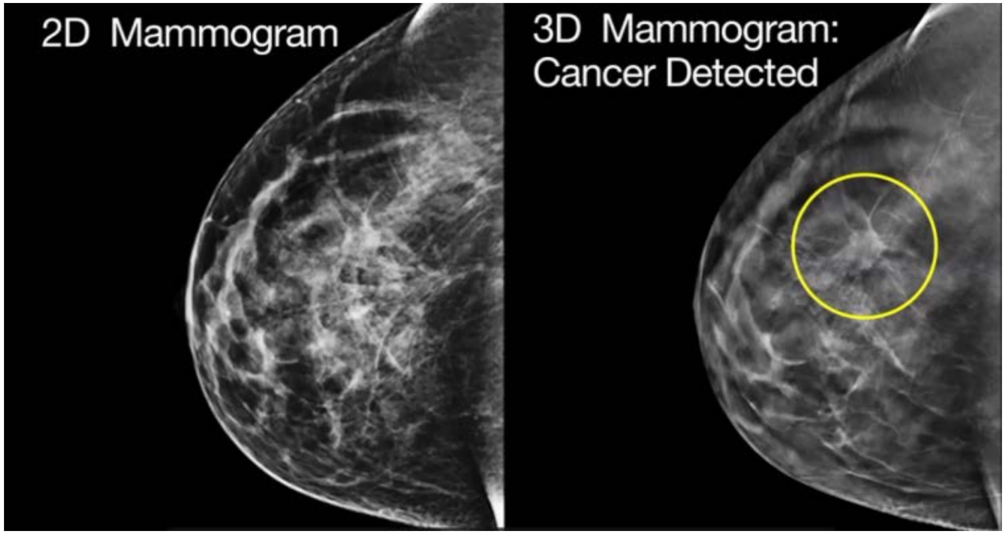
False positives

Unnecessary extra screening/biopsy

Digital Breast Tomosynthesis (DBT)

- Improve the accuracy of mammography by reducing overlapping shadows from breast tissue that degrade the image quality in standard 2D projection imaging.

- **Better differentiation between malignant and non-malignant features.**



Digital Breast Tomosynthesis (DBT)

The Expectations from DBT are

Better Sensitivity

Small cancers obscured by normal Fibroglandular tissue in standard 2D imaging should be detected using DBT

Beneficial for women with dense breasts!

Better Specificity

Identify features such as asymmetrical density (ASD) on 2D imaging as normal composite shadows and thereby decrease the number of false-positive recalls

Is DBT Beneficial for ALL Women?

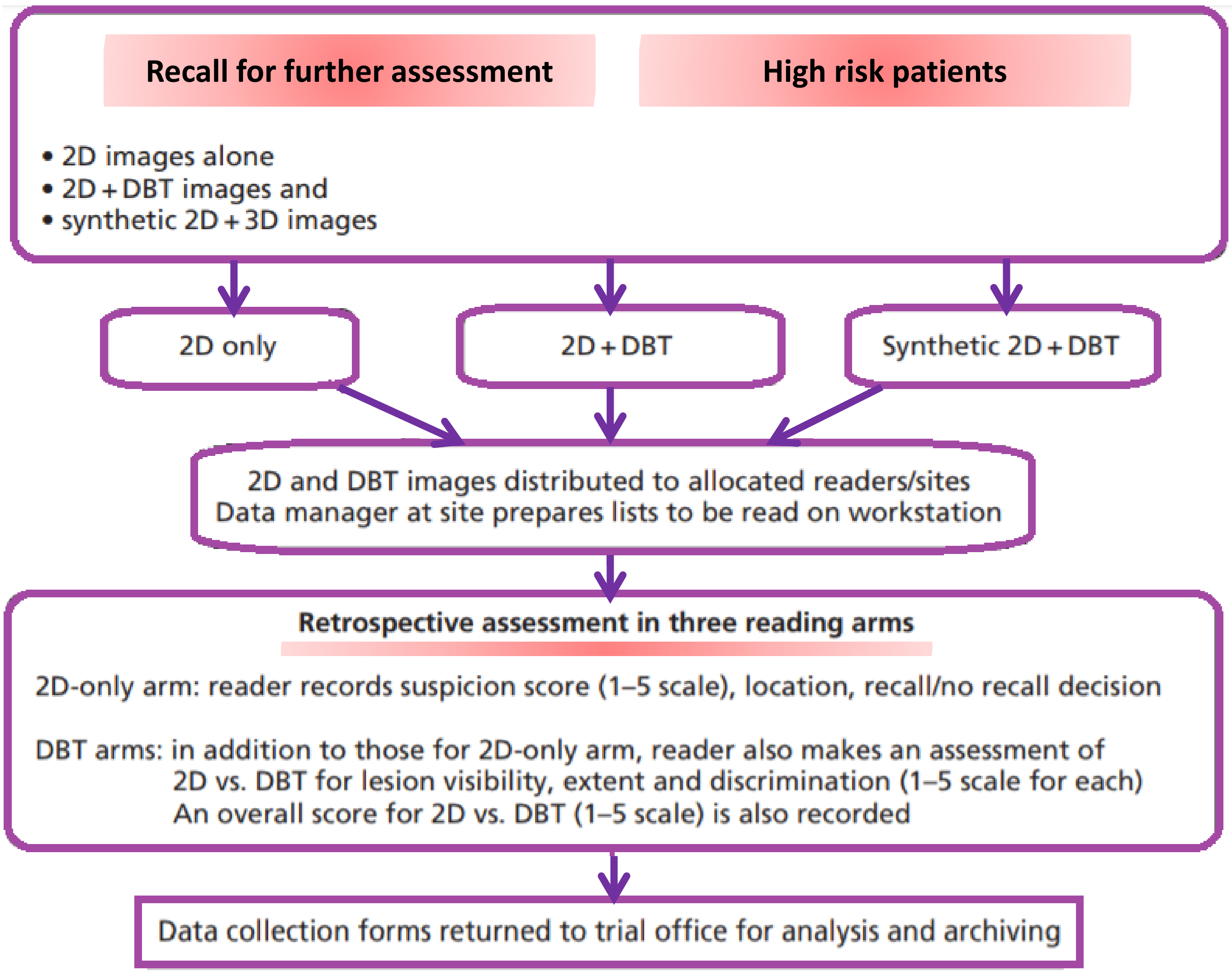
- **Using machine learning + data from TOMMY trial to answer the following questions…**

Which women benefit the most from DBT imaging?
Age and breast density groups

How does breast density affect the informativeness of DBT imaging for different age groups?

What is the informativeness of DBT for different types of lesions?

The TOMMY Study Design: Reading Study



Data used in our Analysis

Data files

final_assessment_
prospective

final_retrospectiv
edata_02.09.13_s
n

8,171 rows

7,393 rows

- Age
- Breast density
- 2D and DBT features
- Pathology variables

- 2D and DBT features
- Pathology variables
- Cancer/no cancer
- Exclusion criteria

Data files matched on R2ID

6,067 patients

1,106 cancers

All with 2D + DBT

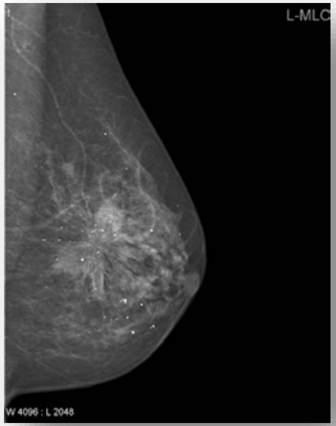
Study Population: Imaging Features

- **Two view mammography:**
  - Mediolateral oblique (MLO)
  - Craniocaudal (CC)

Many 2D views to give a 3D picture of potential lesions.

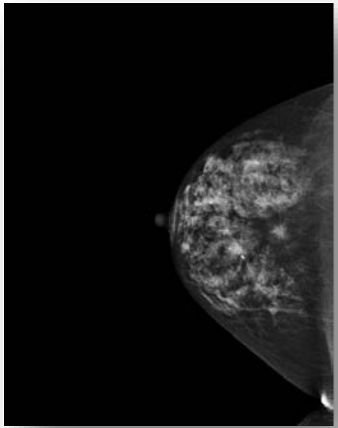
Mediolateral oblique (MLO)

Oblique angled view.



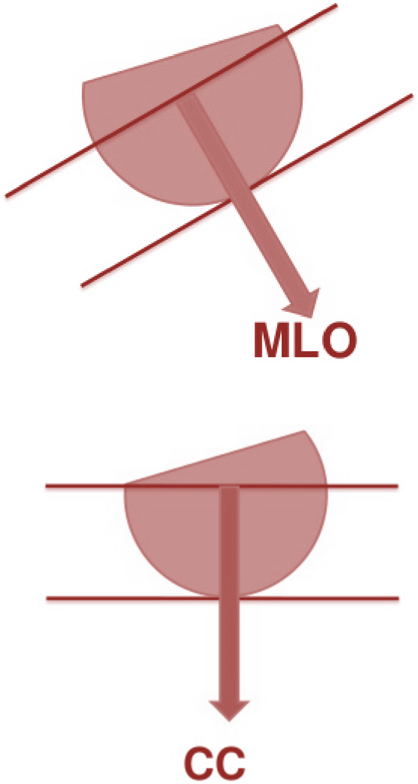
Craniocaudal (CC)

Medial part as well the external lateral portion of the breast.

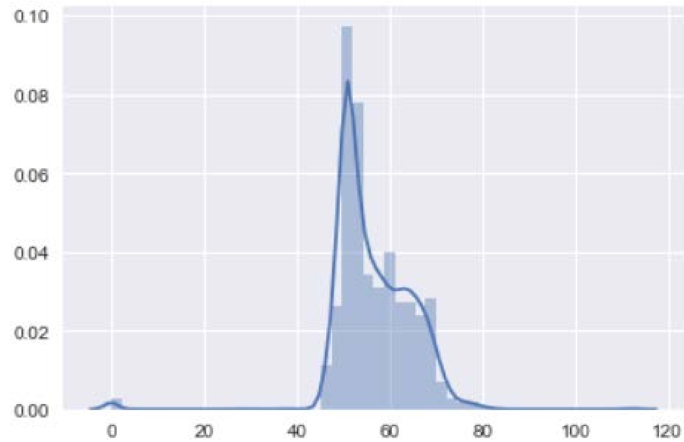


Study Population: Imaging Features

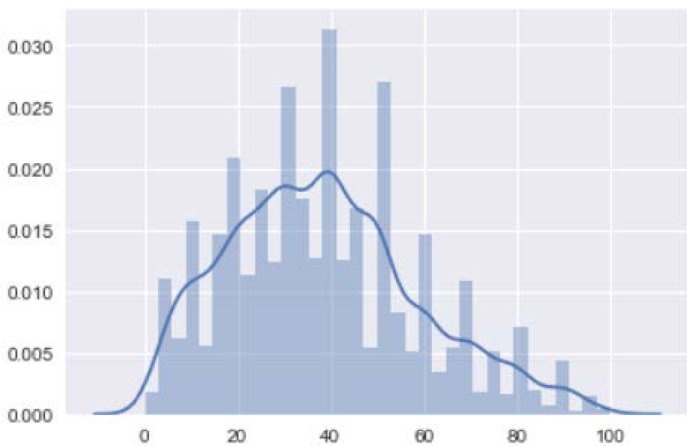
DBT-related	2D-related
MLO sign	MLO sign
MLO suspicion	MLO suspicion
MLO conspicuity	MLO conspicuity
CC sign	CC sign
CC suspicion	CC suspicion
CC conspicuity	CC conspicuity



Study Population: Distribution of Age and Breast Density



Age



Density

≤ 50 years	19.69 %
50-59 years	47.20 %
≥ 60 years	33.10 %

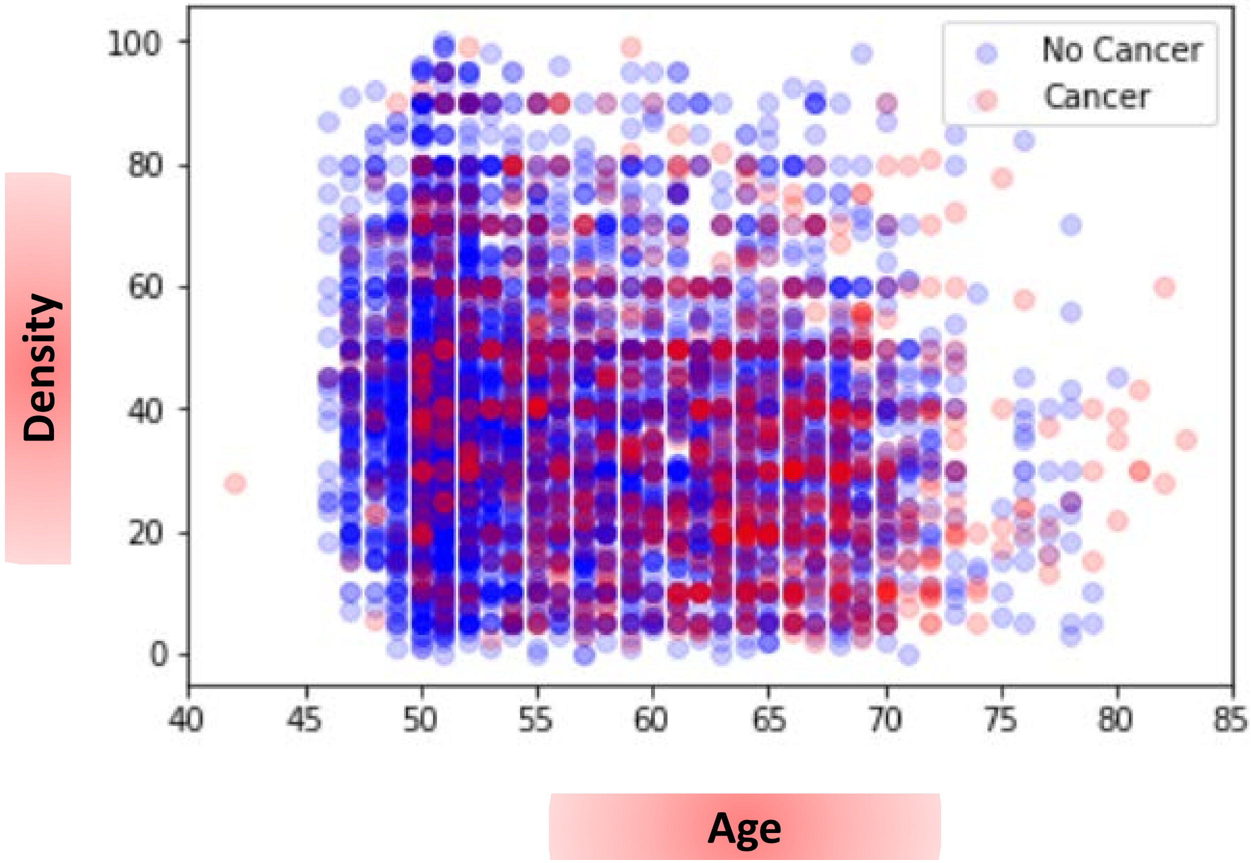
Prognostic Modeling with non-Imaging Features
(Age and breast density)

Prognostic Model	AUC-ROC	Prognostic Model	AUC-ROC
Logistic Regression	0.676 ± 0.009	**Multinomial Naïve Bayes**	0.567 ± 0.027
SGD Perceptron	0.557 ± 0.109	**AdaBoost**	0.676 ± 0.009
KNN	0.590 ± 0.017	**Bagging**	0.590 ± 0.023
Decision Tree	0.561 ± 0.026	**Gradient Boosting**	0.673 ± 0.012
Linear SVM	0.547 ± 0.010	**XGBoost**	0.674 ± 0.013
Gauss. Naïve Bayes	0.669 ± 0.010	**MLP**	0.532 ± 0.045
Bern. Naïve Bayes	0.500 ± 0.001	**Random Forest**	0.598 ± 0.027
LDA	0.676 ± 0.009	**AutoPrognosis**	**0.681 ± 0.012**

Prognostic Modeling with non-Imaging Features
(Age and breast density)

Prognostic Model	AUC-PR	Prognostic Model	AUC-PR
Logistic Regression	0.314 ± 0.021	Multinomial Naïve Bayes	0.241 ± 0.013
SGD Perceptron	0.184 ± 0.069	AdaBoost	0.314 ± 0.020
KNN	0.233 ± 0.019	Bagging	0.234 ± 0.018
Decision Tree	0.219 ± 0.015	Gradient Boosting	0.318 ± 0.014
Linear SVM	0.240 ± 0.010	XGBoost	0.316 ± 0.015
Gauss. Naïve Bayes	0.304 ± 0.019	MLP	0.173 ± 0.016
Bern. Naïve Bayes	0.182 ± 0.007	Random Forest	0.241 ± 0.021
LDA	0.313 ± 0.023	**AutoPrognosis**	**0.318 ± 0.012**

Prognostic Modeling with non-Imaging Features
(Age and breast density)



Prognostic Modeling with non-Imaging Features
(2D only)

Prognostic Model	AUC-ROC	Prognostic Model	AUC-ROC
Logistic Regression	0.899 ± 0.023	Multinomial Naïve Bayes	0.604 ± 0.049
SGD Perceptron	0.872 ± 0.026	AdaBoost	0.911 ± 0.021
KNN	0.863 ± 0.020	Bagging	0.887 ± 0.028
Decision Tree	0.865 ± 0.036	Gradient Boosting	0.913 ± 0.019
Linear SVM	0.881 ± 0.026	XGBoost	0.915 ± 0.018
Gauss. Naïve Bayes	0.884 ± 0.030	MLP	0.910 ± 0.019
Bern. Naïve Bayes	0.715 ± 0.029	Random Forest	0.892 ± 0.024
LDA	0.898 ± 0.022	**AutoPrognosis**	**0.915 ± 0.018**

Prognostic Modeling with non-Imaging Features (2D only)

Prognostic Model	AUC-PR	Prognostic Model	AUC-PR
Logistic Regression	0.742 ± 0.057	Multinomial Naïve Bayes	0.296 ± 0.035
SGD Perceptron	0.719 ± 0.067	AdaBoost	0.765 ± 0.061
KNN	0.689 ± 0.060	Bagging	0.735 ± 0.051
Decision Tree	0.675 ± 0.053	Gradient Boosting	0.772 ± 0.057
Linear SVM	0.729 ± 0.058	XGBoost	0.775 ± 0.057
Gauss. Naïve Bayes	0.716 ± 0.059	MLP	0.760 ± 0.065
Bern. Naïve Bayes	0.286 ± 0.021	Random Forest	0.735 ± 0.063
LDA	0.743 ± 0.058	**AutoPrognosis**	**0.776 ± 0.051**

Prognostic Modeling with non-Imaging Features
(DBT only)

Prognostic Model	AUC-ROC	Prognostic Model	AUC-ROC
Logistic Regression	0.934 ± 0.007	**Multinomial Naïve Bayes**	0.661 ± 0.059
SGD Perceptron	0.917 ± 0.016	**AdaBoost**	0.941 ± 0.012
KNN	0.907 ± 0.018	**Bagging**	0.929 ± 0.016
Decision Tree	0.903 ± 0.024	**Gradient Boosting**	0.941 ± 0.009
Linear SVM	0.923 ± 0.018	**XGBoost**	0.942 ± 0.009
Gauss. Naïve Bayes	0.923 ± 0.014	**MLP**	0.941 ± 0.010
Bern. Naïve Bayes	0.739 ± 0.023	**Random Forest**	0.932 ± 0.017
LDA	0.932 ± 0.008	**AutoPrognosis**	**0.943 ± 0.009**

Prognostic Modeling with non-Imaging Features (DBT only)

Prognostic Model	AUC-PR	Prognostic Model	AUC-PR
Logistic Regression	0.797 ± 0.043	Multinomial Naïve Bayes	0.347 ± 0.058
SGD Perceptron	0.797 ± 0.043	AdaBoost	0.808 ± 0.052
KNN	0.723 ± 0.057	Bagging	0.793 ± 0.047
Decision Tree	0.745 ± 0.042	Gradient Boosting	0.804 ± 0.045
Linear SVM	0.780 ± 0.030	XGBoost	812 ± 0.047
Gauss. Naïve Bayes	0.774 ± 0.046	MLP	0.812 ± 0.052
Bern. Naïve Bayes	0.304 ± 0.020	Random Forest	0.797 ± 0.048
LDA	0.799 ± 0.043	**AutoPrognosis**	**0.812 ± 0.042**

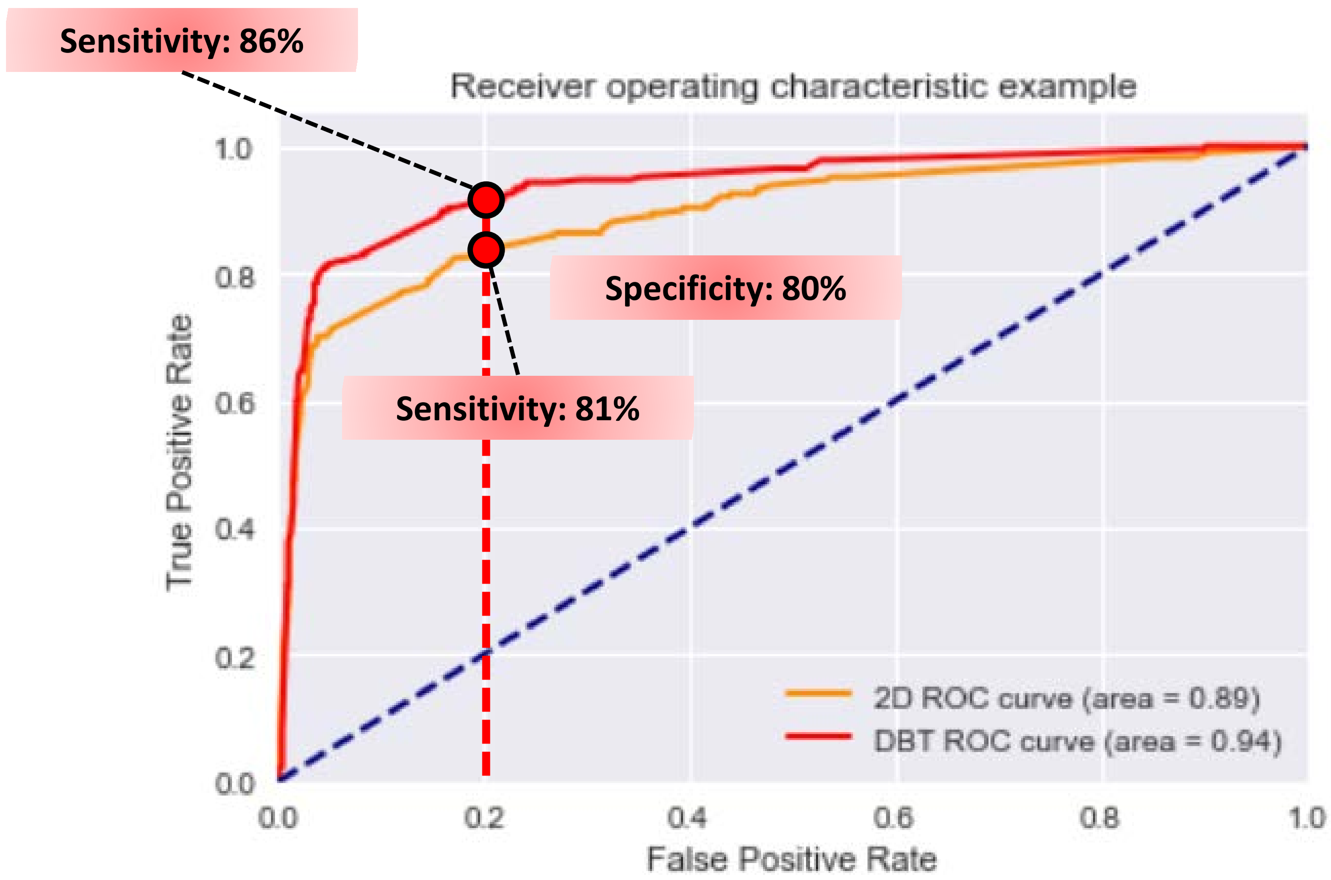
Prognostic Modeling with non-Imaging Features (2D + DBT)

Prognostic Model	AUC-ROC	Prognostic Model	AUC-ROC
Logistic Regression	0.933 ± 0.008	**Multinomial Naïve Bayes**	0.712 ± 0.048
SGD Perceptron	0.896 ± 0.041	**AdaBoost**	0.938 ± 0.012
KNN	0.910 ± 0.012	**Bagging**	0.923 ± 0.020
Decision Tree	0.860 ± 0.029	**Gradient Boosting**	0.941 ± 0.010
Linear SVM	0.926 ± 0.014	**XGBoost**	0.941 ± 0.009
Gauss. Naïve Bayes	0.917 ± 0.018	**MLP**	0.939 ± 0.008
Bern. Naïve Bayes	0.737 ± 0.027	**Random Forest**	0.925 ± 0.015
LDA	0.931 ± 0.010	**AutoPrognosis**	**0.943 ± 0.009**

Prognostic Modeling with non-Imaging Features
(Age + Density + 2D + DBT)

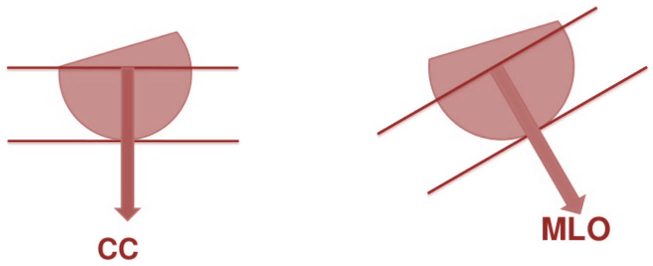
Prognostic Model	AUC-ROC	Prognostic Model	AUC-ROC
Logistic Regression	0.936 ± 0.007	**Multinomial Naïve Bayes**	0.819 ± 0.019
SGD Perceptron	0.904 ± 0.013	**AdaBoost**	0.941 ± 0.010
KNN	0.890 ± 0.012	**Bagging**	0.909 ± 0.018
Decision Tree	0.800 ± 0.024	**Gradient Boosting**	0.947 ± 0.007
Linear SVM	0.915 ± 0.011	**XGBoost**	0.915 ± 0.008
Gauss. Naïve Bayes	0.919 ± 0.018	**MLP**	0.916 ± 0.007
Bern. Naïve Bayes	0.737 ± 0.027	**Random Forest**	0.914 ± 0.016
LDA	0.935 ± 0.008	**AutoPrognosis**	**0.947 ± 0.007**

2D vs. DBT Diagnostic Accuracy



MLO vs. CC Diagnostic Accuracy

- **Which of the two views (CC and MLO) is more informative?**



2D-CC	0.888 ± 0.025
2D-MLO	0.892 ± 0.023
2D-CC+MLO	0.915 ± 0.018

MLO is slightly more informative

Both CC and MLO are complementary

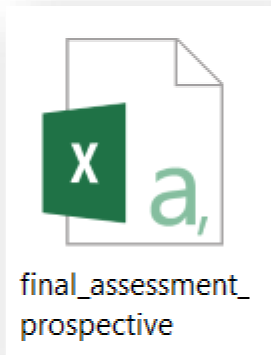
DBT-CC	0.918 ± 0.014
DBT-MLO	0.932 ± 0.009
DBT-CC+MLO	0.942 ± 0.009

MLO is slightly more informative

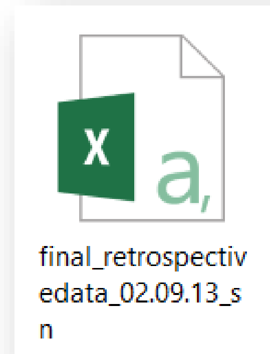
Both CC and MLO are complementary

Pending Issues: Where are synthetic 2D features?

Data files



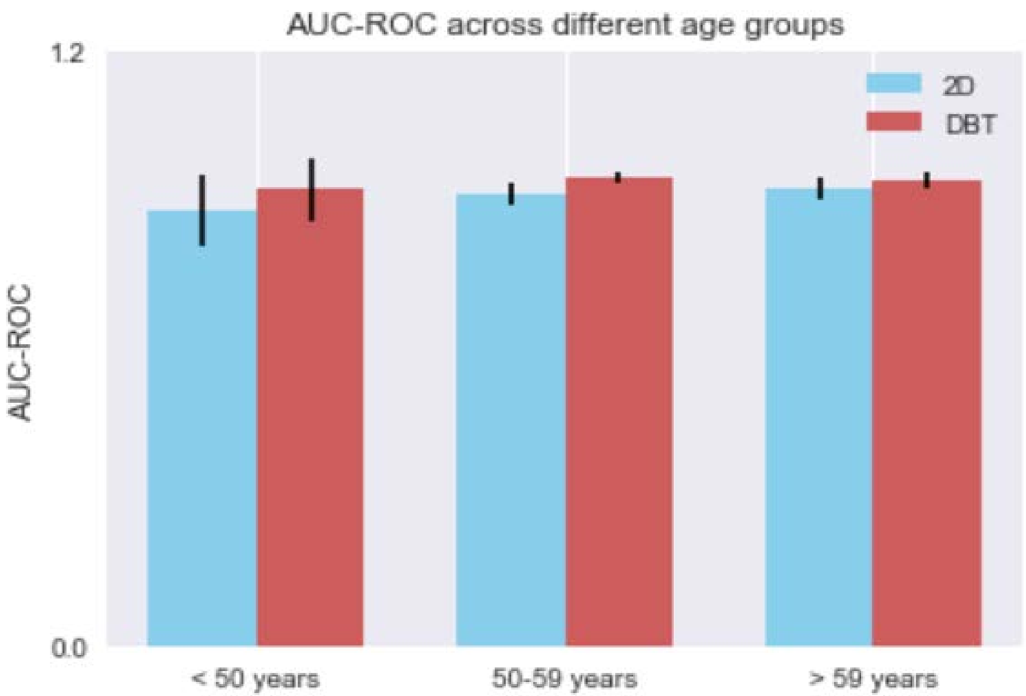
No clear synthetic features



Need data dictionary for synthetic features

Which Women Benefit the most from DBT Imaging?

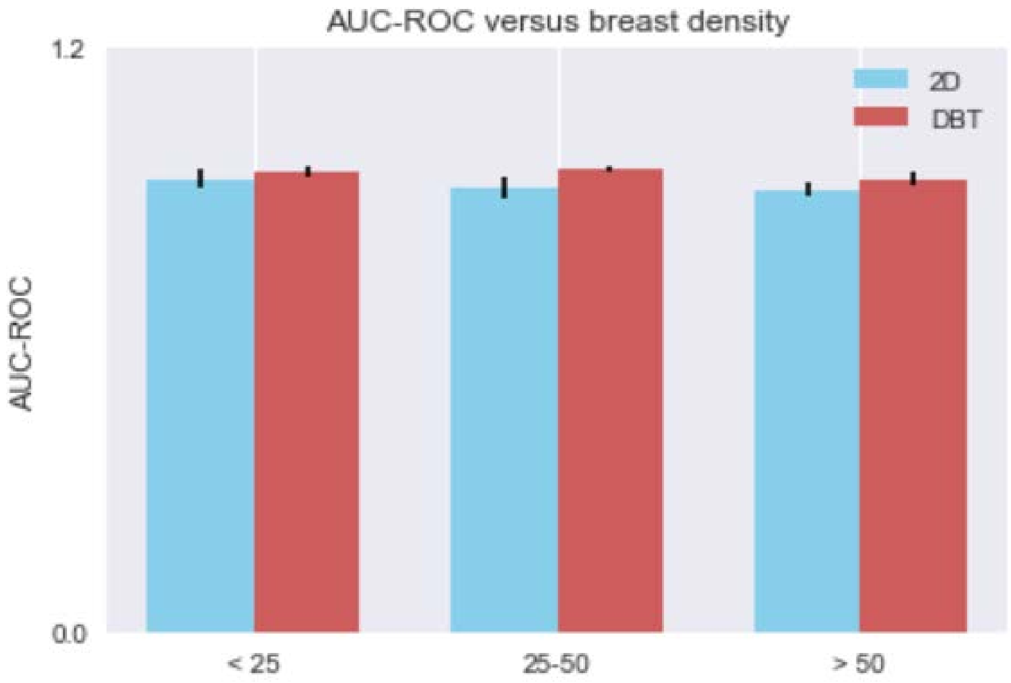
Which women benefit the most from DBT imaging?
Age and **breast** density groups



Younger age groups benefit more from DBT

Which Women Benefit the most from DBT Imaging?

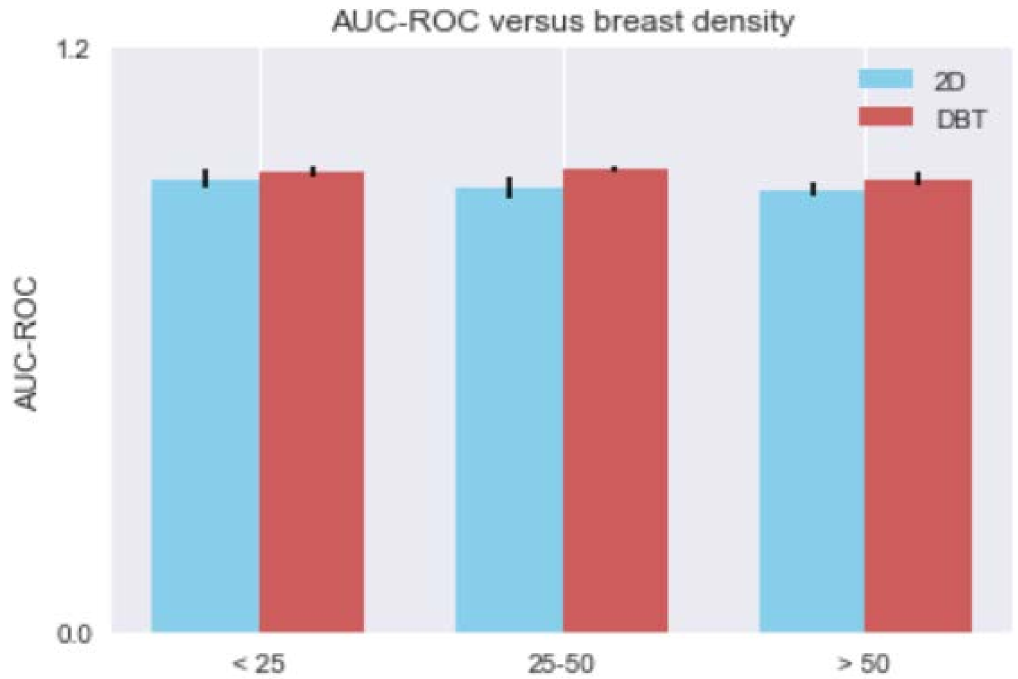
Which women benefit the most from DBT imaging?
Age and **breast** density groups



Group with density 25-50 benefits most from DBT

Which Women Benefit the most from DBT Imaging?

How does breast density affect the informativeness of DBT imaging for different age groups?



Average age 58.1 years

Average age 56.5 years

Average age 54.8 years

Adjustment?

Which Women Benefit the most from DBT Imaging?

What is the informativeness of DBT for different types of lesions?

Three types of Malignant Tumors

Invasive ductal	
Invasive lobular	
Invasive (other)	• Medullary • Mucinous • Tubular • Intracystic papillary • Lymphoma • Ductal In situ

Which Women Benefit the most from DBT Imaging?

What is the informativeness of DBT for different types of lesions?

Three types of Malignant Tumors

	Invasive ductal	Invasive lobular	Invasive other
2D	0.919 ± 0.021	0.873 ± 0.014	0.875 ± 0.035
DBT	0.943 ± 0.011	0.905 ± 0.015	0.894 ± 0.029